

POLITECNICO DI TORINO



MASTER'S DEGREE IN BIOMEDICAL ENGINEERING BIOMEDICAL INSTRUMENTATION



Development and validation of a multimodal wearable system for MMG monitoring and compensatory gait analysis using piezoelectric AlN-based and IMU sensors

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INTRODUCTION

*“What we observe is not Nature itself,
but Nature exposed to our method of questioning.”*
— *Werner Heisenberg*

Human gait is a highly coordinated motor task involving the interaction of the musculoskeletal, neural, and sensory systems to ensure efficient and stable locomotion. Understanding the biomechanical and neuromuscular mechanisms underlying gait is essential for identifying physiological movement patterns, detecting compensatory strategies, and assessing functional recovery in both healthy and pathological populations. In particular, gait analysis has become an important tool in rehabilitation and post-surgical assessment, such as following total hip arthroplasty (THA), where patients frequently adopt compensatory strategies to restore stability and reduce discomfort.

To characterize these adaptations, reliable monitoring of muscle activity is required. Surface electromyography (sEMG) is widely regarded as the reference technique for assessing muscle electrical activation; however, its use in long-term wearable monitoring is often limited by electrode placement, skin preparation requirements, and sensitivity to motion artifacts. Consequently, increasing attention has been devoted to complementary sensing modalities capable of providing additional information on muscle function.

Among these techniques, mechanomyography (MMG) has recently regained interest owing to advances in wearable technologies and miniaturized sensors. Unlike sEMG, which measures the electrical activity of muscles, MMG captures the mechanical oscillations generated during muscle contraction, potentially providing complementary information on muscle mechanics, loading conditions, and motor control strategies. The integration of MMG with inertial sensing and sEMG therefore represents a promising multimodal approach for wearable gait analysis.

Within this context, the present thesis investigates a multimodal wearable system integrating surface electromyography, inertial measurement units (IMUs), and an aluminum nitride (AlN)-based piezoelectric MMG sensor developed at the Istituto Italiano di Tecnologia – Center for Biomolecular Nanotechnologies. The objective of this work is to evaluate the feasibility of using the proposed MMG sensor during gait, assess its relationship with conventional sEMG measurements, and explore its potential contribution to wearable neuromuscular monitoring. Furthermore, the study investigates the possibility of estimating phase-dependent muscle behavior using MMG and IMU signals alone, laying the groundwork for future applications in rehabilitation and clinical gait assessment.

The thesis is structured according to a progressive approach, moving from the theoretical foundations to the technological implementation, experimental validation, signal processing, and discussion of the obtained results. *Chapter 1* introduces the biomechanical principles underlying human gait and muscle function. *Chapter 2* reviews the technological background, focusing on wearable sensing systems, piezoelectric MMG sensors, and inertial sensing, thereby motivating the adoption of a multimodal approach. *Chapter 3* presents the design of the developed wearable platform and its sensing modules, while *Chapter 4* describes the experimental protocols used for static and dynamic data acquisition. *Chapter 5* details the complete signal processing framework, from signal conditioning to gait-event detection, gait-cycle normalization, multimodal signal comparison, and MMG-based gait reconstruction. Finally, *Chapter 6* presents the experimental findings, discusses their physiological interpretation, highlights the strengths and limitations of the proposed methodology, and outlines future research directions.

CHAPTER 1

BIOMECHANICAL BACKGROUND

“The human gait is the most subtle harmony of strength, balance, and proportion.”

— *Leonardo Da Vinci*

The following biomechanical framework provides the basis for understanding how the human body achieves controlled, stable, and efficient movement. In this section, the fundamental principles of human movement and biomechanics are described in detail, introducing the organization of the gait cycle, the distinction between stance and swing phases, and the underlying kinematic and kinetic interactions that characterize physiological locomotion. Building upon these foundations, the chapter also explores the clinical implications of gait analysis in the context of hip arthroplasty, where the primary goal is the surgical restoration of joint function. Understanding these biomechanical alterations is essential for designing effective monitoring and recovery protocols. In addition, the physiological basis of movement is examined through the mechanisms of motor unit activation and muscle contraction, since their coordinated patterns characterize every phase of locomotion. The chapter also describes the electrical and mechanical processes responsible for force generation, highlighting how neural input is translated into muscle activation. This comprehensive biomechanical and physiological framework underpins the analytical approaches developed in the following chapters, where the integration of sensor-based measurements is used to detect, quantify, and interpret compensatory gait patterns after hip arthroplasty.

1.1 FUNDAMENTALS OF HUMAN MOVEMENT AND BIOMECHANICS

Human locomotion is based on the gait cycle, defined as the sequence of movements occurring between two consecutive contacts of the same foot with the ground. Each gait cycle includes two main phases: the stance phase (approximately 60% of the cycle) and the swing phase (about 40%).

Motions in *stance phase* are closed-chain, as the distal segment is fixed by ground-reaction forces, while swing phase motions are open-chain, with the limb moving freely.

The stance phase, during which the foot touches the ground, is further divided into five sub-periods:

1. Initial contact (or Heel Strike)
2. Loading response (or Foot Flat)
3. Mid-stance
4. Terminal stance (or Heel Off)
5. Pre-swing (or Toe Off)

During the *swing phase* one foot is not in contact with the ground and the body weight is borne by the other leg and foot. It includes [1]:

1. Early swing
2. Mid-swing
3. Late swing/Deceleration

During a complete gait cycle, both feet maintain foot-ground adhesion for about 20% of the time: 10% at the start and 10% at the end of the stance phase. These intervals are called *double-support* periods, while the remaining 80% of the cycle corresponds to *single support*. The gait cycle characterization is shown in **Figure 1.1**. Given that more than 5,000 gait cycles occur daily, walking represents one of the most repetitive motor behaviors in human life. From an evolutionary perspective, stance phase control is an acquired skill that involves practice and sensory experience, although swing phase movement patterns are instinctive and evident from birth. Throughout childhood, motor efficiency gradually improves. Even at the same walking pace, a three-year-old uses around

33% more oxygen than an adult, and energy costs only reach adult levels by the age of ten [2].

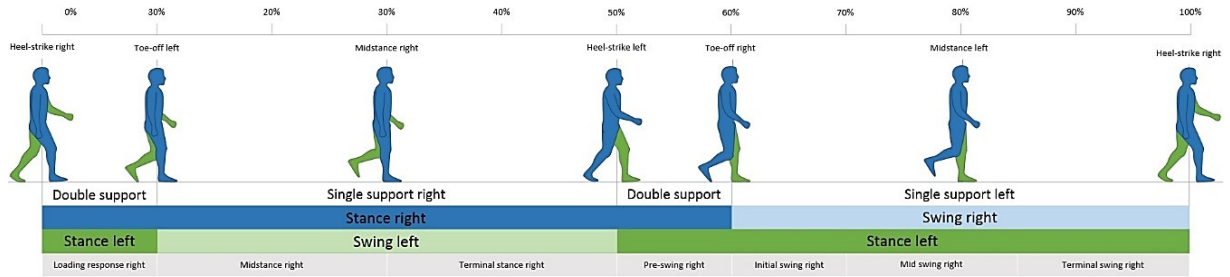


Figure 1.1: Gait Cycle definitions.

1.1.1 Spatio-temporal parameters

Spatio-temporal parameters provide quantitative insights into gait performance and are widely used for clinical and biomechanical characterization of human locomotion. These parameters describe the timing, distance, and speed characteristics of walking, enabling an objective assessment of gait efficiency, symmetry, and stability [3], [4]. The most important parameters are:

- **Lengths**
 - *Step Length [cm]*: distance between the initial contacts of two consecutive opposite feet; it reflects stride symmetry and limb coordination.
 - *Stride Length [cm]*: distance between successive contacts of the same foot; it indicates the overall distance covered in a single gait cycle.
- **Gait Parameters**
 - *Stance phase [%]*: percentage of the gait cycle during which the foot is in contact with the ground; it indicates weight-bearing duration.
 - *Swing Phase [%]*: percentage of the gait cycle when the foot is off the ground; it reflects limb advancement and clearance.
 - *Single Support [%]*: portion of the gait cycle when only one foot is in contact with the ground, critical for balance assessment.
 - *Total double support [%]*: combined duration when both feet are on the ground; lower values often indicate faster or more confident walking.
 - *Pre-Swing [%]*: final phase of stance prior to toe-off, important for push-off dynamics.

- **Time Parameters**

- *Step Time [sec]*: time taken to complete a single step, useful for evaluating rhythm and cadence.
- *Gait Cycle [%]*: total duration of a complete gait cycle that allows normalization across individuals.
- *Cadence [steps/min]*: number of steps per minute that reflects walking rhythm and pace.

- **Speed Parameters**

- *Walking Speed [m/s]*: distance covered per unit time. It integrates stride length and cadence, representing overall gait performance.
- *Average Speed [m/s]*: mean velocity over a walking trial, commonly used to track functional mobility and rehabilitation progress.

1.1.2 Hip Range of Motion

The intrinsic mobility of the hip joint plays a critical role in facilitating smooth and energy-efficient gait. From a physiological perspective, the hip joint – a *ball-and-socket* articulation between the femoral head and the acetabulum – provides a wide range of motion (ROM) that is essential for normal gait mechanics [5]. Hip movements (**Figure 1.2**) include:

- **Flexion** (110-120°)
- **Extension** (10-15°)
- **Abduction** (30-50°)
- **Adduction** (25-30°)
- **Internal/Medial Rotation** (30-40°)
- **External/Lateral Rotation** (40-60°)

These motions occur in three anatomical planes (sagittal, frontal and transverse), allowing multidirectional control of the lower limb during both stance and swing phases. During walking, approximately 30° of flexion and 10° of extension are typically required, along with minor contributions from abduction, adduction and rotation. The most stable position of the hip is the normal standing position, characterized by hip extension, slight abduction

and slight internal rotation. In contrast, the resting positions of the hip ranges between 10° - 30° of flexion, 10 - 30° of abduction and 0 - 5° of external rotation.

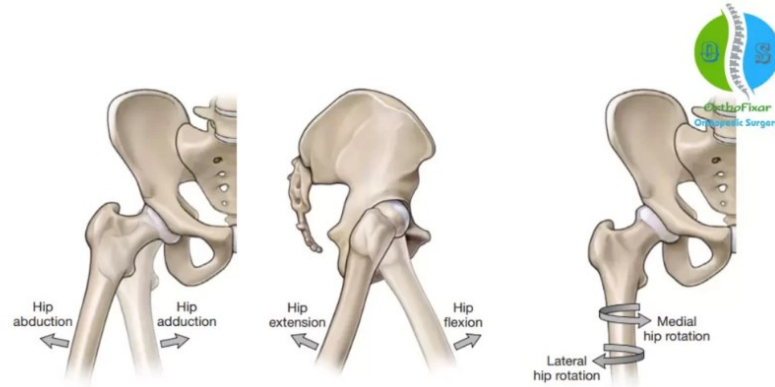


Figure 1.2: Hip Range of Motion.

1.1.3 COM, COG, COP and the Six Determinants of Gait

Human gait is governed by the interaction of gravitational forces, body mass distribution, and ground reaction forces, depicted in **Figure 1.3**. The *center of mass (COM)* represents the point at which the mass of the human body is evenly distributed and around which balance and motion are controlled. During locomotion, maintaining the COM within the base of support is essential for stability, while the *center of gravity (COG)* and *pressure distribution (center of pressure - COP)* determine how forces are transmitted in the body-ground interaction [6].

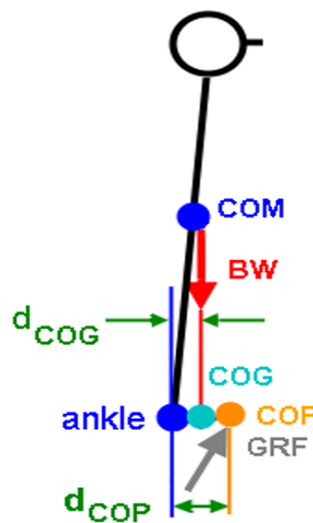


Figure 1.3: Relative positions of COM, COG, and COP with respect to the ankle joint during quiet stance.

Metabolic efficiency in gait is achieved when the COM follows the smoothest possible trajectory through space, thereby minimizing energy expenditure. This is accomplished through coordinated joint adjustments, known as the *six determinants of gait* [7]:

1. **Pelvic rotation:** rotation of the pelvis in the transverse plane during walking; it lengthens stride and slightly reduces vertical COM displacement, improving energy efficiency.
2. **Pelvic tilt:** downward tilt of the pelvis on the side opposite the leg; it reduces vertical excursion of the COM, smoothing the gait.
3. **Knee flexion during stance phase:** knee flexes $\sim 15\text{-}20^\circ$ after heel strike; this acts as a shock absorber, lowers the COM, and smooths the transition from heel strike to midstance.
4. **Coordinated hip-knee-ankle interactions:** foot and ankle motion mainly contribute to shock absorption, forward propulsion, and smoothing the COM trajectory. Knee motion during swing ensures foot clearance and proper stride length.
5. **Lateral pelvic displacement:** side-to-side shift of the pelvis toward the stance leg; it keeps the COM over the supporting foot, maintaining balance and characteristic pelvic sway.
6. **Hip adduction:** frontal-plane movement of the hip toward the midline during stance; it works with lateral pelvic displacement to regulate mediolateral COM motion and maintain balance, particularly during single-leg support.

As a result, an adequate hip ROM ensures efficient bipedal locomotion, shock absorption, and smooth COM progression, while restrictions, such as those caused by degenerative changes, pain, or prosthetic constraints, can alter pelvic degrees of freedom.

1.1.4 Compass Gait and Inverted Pendulum Models

A first theoretical framework explaining how kinematic mechanisms contribute to the COM's smooth progression is the *compass gait model*, illustrated in **Figure 1.4**. In this simplified geometrical model, the trajectory of the COM in the sagittal plane can be approximated by a rigid leg swinging like a compass, with only hip flexion and extension occurring [8]. According to this elementary configuration, stance knee flexion, pelvic

rotation, and pelvic tilt act to reduce the excessive vertical displacement predicted by the idealized compass gait, while foot and ankle mechanisms serve to smooth the COM path during transitions between single and double support. This model highlights the kinematic contributions of the six determinants of gait in maintaining stability and minimizing vertical oscillations.

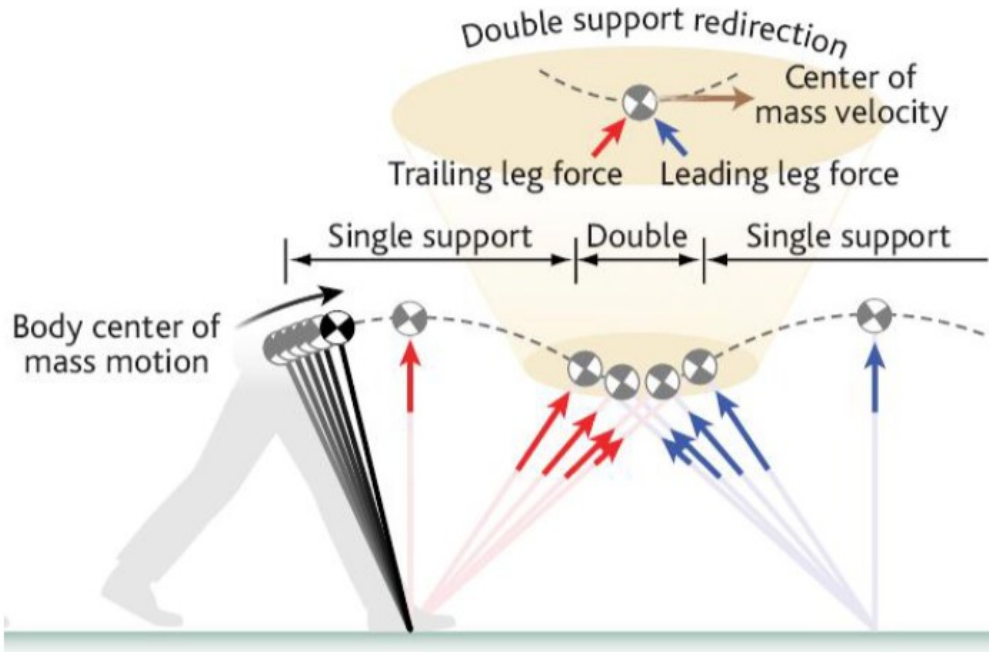


Figure 1.4: Conceptual schematic of the compass gait model of human walking.

Complementing the compass gait, the *inverted pendulum model* provides a physiological and energetic perspective on walking (**Figure 1.5**). In this framework, the stance leg behaves as a rigid pendulum that pivots about the foot in contact with the ground [9], [10], [11]. During the stance moment:

- At **initial contact**, the COM is low, kinetic energy is minimal, and potential energy begins to increase as the body rises.
- During **mid-stance**, the COM reaches its maximum height, with potential energy peaking while kinetic energy decreases.
- At **terminal stance** and **pre-swing**, potential energy is converted back to kinetic energy as the body accelerates forward into the swing phase.

This pendulum-like motion enables an efficient exchange between the body's kinetic and potential energy, thereby reducing muscular effort. Deviations from this pattern, such as

reduced stance-phase knee flexion, limited hip extension, or abnormal pelvic motion, disrupt the pendulum trajectory.

By considering both models, it is possible to understand gait from two complementary perspectives: the compass gait emphasizes the kinematic role of determinants, while the inverted pendulum explains the energetic efficiency and smoothness of human locomotion. Within this elementary geometrical configuration, stance-phase knee flexion, pelvic rotation, and pelvic list act to reduce the excessive vertical displacement predicted by the idealized compass gait, whereas foot and knee mechanisms serve to smooth the COM trajectory during the transition between single and double support. Furthermore, hip adduction has been identified as the primary determinant of the mediolateral COM displacement.

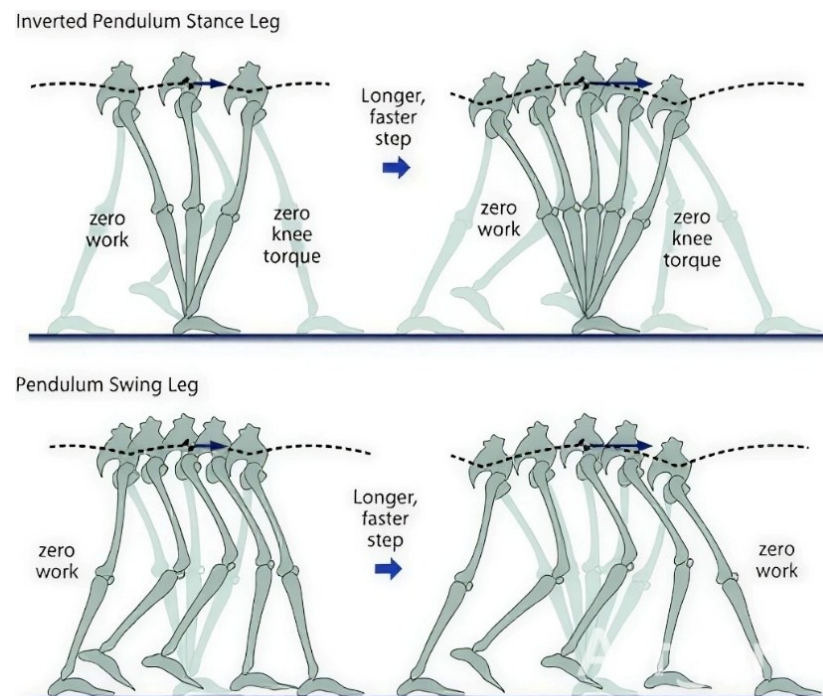


Figure 1.5: A) Inverted-pendulum behavior of the stance leg. B) Pendular-ballistic motion of the swing leg during walking.

By evaluating the distinct contributions of each determinant to the three-dimensional COM displacement across a range of walking speeds, recent quantitative analyses have refined and expanded these traditional concepts. The primary factors influencing COM motion in the sagittal plane have been demonstrated to be hip flexion, stance-phase knee flexion, and ankle-foot interactions, including ankle plantarflexion, toe flexion, and the anterior translation of the COP. In contrast, pelvic rotation and pelvic list have only a minor effect on the vertical trajectory of the COM, whereas hip adduction and pelvic list play a crucial role in regulating mediolateral displacement within the frontal plane. Overall, these findings

suggest that the smoothness and energetic efficiency of human walking are maximized through the coordinated interaction of multiple lower-limb and pelvic mechanisms rather than by the action of a single determinant [12].

1.1.5 Kinetics and Muscle Activity

Beyond kinematics, gait analysis also encompasses kinetics, which describes the forces and moments that produce or result from motion. While kinematics focuses on the geometry of movement – such as joint angles, segment displacements, and COM trajectories, kinetics provides insight into how and why these movements occur, revealing the underlying mechanical demands on the body. Kinetic analysis plays an important role for understanding the control, stability, and efficiency of human locomotion through the evaluation of several key contributions:

- **Ground Reaction Forces (GRFs)** measure the forces exerted by the ground on the body, influencing joint loading and propulsion.
- **Joint Moments and Inertial Forces** are generated by muscles and body segments; they control limb motion, absorb impact, and stabilize the body during stance. For example, the ankle plantar-flexor moment contributes to push-off, while the knee extensor moment supports weight acceptance.
- **Joint Power** represents the rate of mechanical energy generation or absorption at each joint. During walking, positive power at the ankle during late stance produces forward propulsion, whereas negative power at the knee absorbs shock at heel strike.
- **Muscle Activity:** regulates joint motion, controls the trajectory of the COM, and stabilizes posture through coordinated activation patterns.

Even the simple task of initiating the gait requires complex interactions between proprioceptive and motor systems, as the central nervous system executes a stereotyped sequence of motor recruitment known as the *gait-initiation motor control program*.

In particular, the calf and hip abductor muscles shift the COP laterally and posteriorly, first toward the swing limb and then toward the stance limb. Because this posterior COP displacement occurs without a perceptible movement of the COM, the body inclines slightly

forward, effectively pivoting about its COM [2]. This mechanism is represented schematically in **Figure 1.6**.

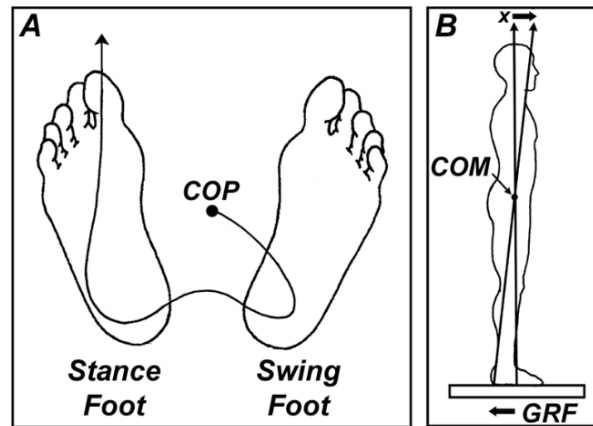


Figure 1.6: A) COP shifts laterally and posteriorly from swing to stance foot. B) Posterior COP shift tilts the body slightly forward, pivoting around the COM.

This coordinated muscle activity is further organized into specific muscle groups, each contributing distinct functions during the gait cycle, as outlined below:

- **Hip extensors:** *Gluteus Maximus – GMAX, Biceps Femoris – BF, Semitendinosus – ST*. They actively stabilize the pelvis in the sagittal plane and generate forward propulsion during the stance phase, controlling trunk lean and facilitating efficient transfer of body weight over the supporting limb.
- **Hip abductors:** *Gluteus Medius – GMED, Tensor Fascia Lata – TFL*. They maintain frontal-plane pelvic stability by preventing the contralateral side of the pelvis from dropping during single-leg stance, ensuring balance and smooth lateral transfer of body weight.
- **Hip flexors:** *Rectus Femoris – RF, Tensor Fascia Lata – TFL, Iliopsoas – IP*. They elevate and accelerate the thigh during the swing phase, contributing to foot clearance and proper limb trajectory for the upcoming stance phase.
- **Knee extensors:** *Vastus Lateralis – VL, Vastus Medialis – VM, Rectus Femoris – RF*. All three muscles are part of the *quadriceps femoris* group. They control knee extension during stance, absorb impact at heel strike, and provide stability to the limb, allowing safe load bearing and energy transfer through the leg.
- **Knee flexors:** *Biceps Femoris – BF, Semitendinosus – ST*

They assist in shock absorption at initial contact and help decelerate the leg during late swing, facilitating a smooth transition from stance to swing.

- **Ankle dorsiflexors:** *Tibialis Anterior – TA*

Lift the foot during swing to prevent toe drag and prepare the ankle for controlled initial contact with the ground.

- **Ankle plantar-flexors:** *Gastrocnemius – GAS, Soleus – SOL*

They generate propulsion at the end of stance by pushing the body forward, contributing to step length and forward momentum.

- **Trunk stabilizers:** *Erector Spinae – ES*

They maintain upright trunk posture and proper trunk, pelvis alignment throughout gait, facilitating coordinated movement of the lower limbs and upper body.

As illustrated in **Figure 1.7**, during relaxed standing, passive tension in the hip and knee ligaments provides most of the support, with minimal muscle activity required to maintain balance. The feet form a stable base of support, and body weight is distributed around a COG located slightly anterior to the ankle joint axes.

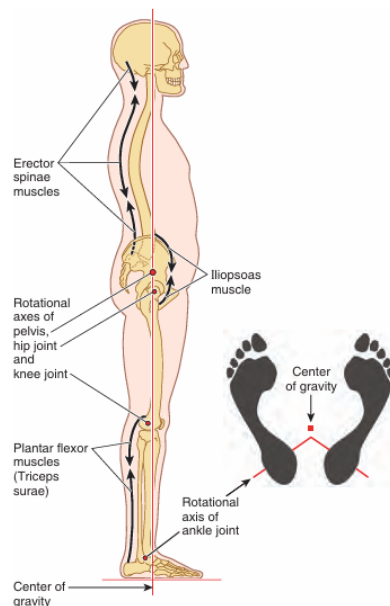


Figure 1.7: Muscular groups involved in relaxed standing.

Overall, muscles act in concert to ensure smooth transitions between gait phases: the gluteal muscles control lateral pelvic tilt, the quadriceps support knee extension during stance, and the dorsiflexors prevent foot drop during swing. The integration of trunk and pelvic stabilizers is therefore crucial not only for maintaining balance but also for coordinating force transmission and ensuring efficient progression of the COM throughout locomotion. The following **Table 1.1**, **Table 1.2** and **Table 1.3** summarize the key biomechanical and muscular events during locomotion, highlighting joint motions, forces, and muscle actions across each phase and subphase of the gait cycle.

Joint	Motion	Ground Reaction Force	Internal Moment	Power	Major Muscle Activity
Hip	Extends from +20°–+30° to 0°	Anterior to posterior	Extensor to neutral	Generation (hip extensors)	Gluteus maximus Hamstrings
Knee	Flexes from 0° to +15°, then extends +15° to +5°	Anterior to posterior to anterior	Flexor, then extensor then flexor	Generation (knee flexors) Absorption (knee extensors) Generation (knee extensors) Absorption (knee flexors)	Hamstrings Quadriceps Hamstrings Gastrocnemius
Ankle	Plantarflexes from 0° to –5°, then dorsiflexes to +5°	Posterior to anterior	Dorsiflexor, then plantarflexor	Absorption (dorsiflexors) Generation (plantarflexors)	Tibialis anterior Soleus Gastrocnemius
Joint	Motion	Ground Reaction Force	Moment	Power	Major Muscle Activity
Hip	Extends from 0° to –20° extension, then begins to flex	Posterior	Flexor	Absorption (flexors) Generation (flexors)	Iliopsoas Rectus femoris Iliopsoas Rectus femoris
Knee	From +5° extends a few degrees, then flexes to about +45°	Posterior	Flexor, then extensor	Absorption (extensors) Small generation (knee flexors) Large absorption (extensors)	Vastus Gastrocnemius Rectus femoris
Ankle	From +5° dorsiflexion, dorsiflexes a few more degrees, then rapidly plantarflexes to –25°	Anterior	Plantarflexor	Very small absorption (plantarflexors) Large generation (plantarflexors)	Soleus Gastrocnemius Soleus Gastrocnemius

Table 1.1: Kinematics and kinetics of gait.

Table 1.2: Biomechanical and kinematic analysis of the stance phase.

Main Phase	Sub-Phase	% of Cycle	Foot–Ground Contact	Biomechanical Events	Functional Role	Kinematics	Muscle Action
STANCE (≈ 60%)	Initial Contact (Heel Strike)	0-2%	Heel only	Heel touches the ground; limb positioned to accept load.	Initiation of stance and preparation for shock absorption.	Hip flexed ~30°, knee ~5° flexed, ankle neutral.	TA controls plantar-flexion; QUAD stabilize knee; GMAX controls hip flexion.
	Loading Response (Foot Flat)	2-12%	Entire foot	Weight transferred onto stance limb; shock absorbed.	Weight acceptance and stability.	Hip begins to extend; knee flexes to ~15°; ankle plantarflexes to ~10°.	QUAD absorb shock; TA controls foot lowering; GMED stabilizes pelvis.
	Mid-Stance	12-31%	Full foot	Body progresses over stationary foot; contralateral limb in swing.	Single-limb support and body advancement.	Hip and knee extend; ankle dorsiflexes gradually.	GAS and SOL (eccentric) control tibial advancement; GMED maintains pelvic stability.
	Terminal Stance (Heel-Off)	31-50%	Forefoot	Heel lifts; body advances beyond supporting foot.	Propulsion and forward progression.	Hip in extension (~10-20°); knee near full extension; ankle dorsiflexed (~10°).	Calf muscles (GAS, SOL) act concentrically to propel body forward.
	Pre-Swing (Toe-Off)	50-62%	Toes only	Weight transferred to opposite limb; toe-off occurs.	Transition to swing and initiation of limb advancement.	Hip flexes; knee flexes to ~40°; ankle plantarflexes (~20°).	IP and RF initiate hip flexion; plantar-flexors generate push-off.

Legend: TA: tibialis anterior / QUAD: quadriceps / GMAX: gluteus maximus / GMED: gluteus medius / GAS: gastrocnemius / SOL: soleus / IP: iliopsoas / RF: rectus femoris / BF: biceps femoris / HAM: hamstring

Table 1.3: Biomechanical and kinematic analysis of the swing phase.

Main Phase	Sub-Phase	% of Cycle	Foot–Ground Contact	Biomechanical Events	Functional Role	Kinematics	Muscle Action
SWING (≈ 40%)	Initial Swing	2-75%	No contact	Foot leaves ground; limb accelerates forward.	Limb advancement and clearance.	Hip flexes rapidly; knee flexes to ~60°; ankle neutral.	IP and RF flex hip; BF short head flexes knee; TA maintains dorsiflexion.
	Mid-Swing	5-87%	No contact	Thigh advances; knee begins to extend; foot clears ground.	Continued limb progression and toe clearance.	Hip flexed ~30°; knee extends to ~25° flexion; ankle neutral.	Hip flexors maintain limb advancement; dorsiflexors hold neutral foot position.
	Terminal Swing (Deceleration)	87-100%	No contact	Knee extends; limb decelerates before heel strike.	Prepare for controlled initial contact.	Hip flexed ~30°; knee extends to near 0°; ankle neutral.	HAM (eccentric) decelerate limb; QUAD prepare for heel contact; TA positions foot.

1.2 CLINICAL CONTEXT: HIP ARTHROPLASTY AND COMPENSATORY GAIT PATTERNS

Hip arthroplasty is one of the most common and successful orthopedic procedures, performed to treat advanced osteoarthritis and approximately one-third of hip fracture cases. In 2010, over 330,000 procedures were performed in the United States, and more than 100,000 primary hip replacements are carried out annually in Italy. The surgery aims to relieve pain, restore joint mobility, and improve quality of life, enabling early weight bearing and mobilization.

The artificial hip joint is composed of distinct mechanical components that replicate the anatomical articulation of the native hip. These include the *acetabular cup*, *liner*, *femoral head*, and *femoral stem*, which together ensure stability, effective load transmission, and smooth articulation. The main structural elements of hip prosthesis are illustrated in the following **Figure 1.8**.

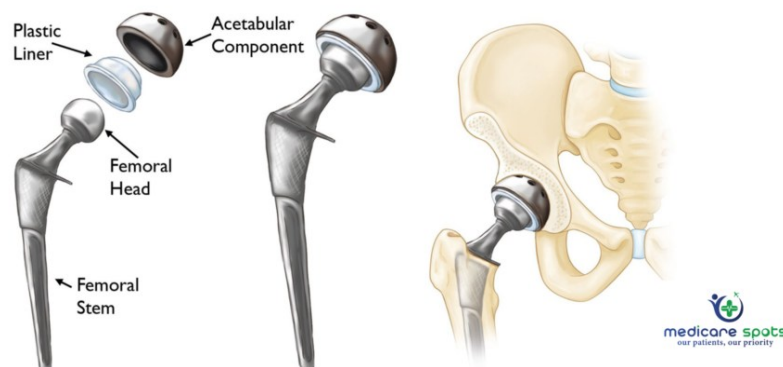


Figure 1.8: Hip replacement surgery.

Hip arthroplasty procedures can be broadly categorized into:

- **Hemiarthroplasty**
- **Total Hip Arthroplasty (THA)**

In hemiarthroplasty, only the femoral head and neck are replaced while the native acetabulum is preserved. Variants include *unipolar hemiarthroplasty* (a fixed prosthetic head articulating with the native acetabulum), *bipolar hemiarthroplasty* (a dual articulation system with a polyethylene-lined metal cup), and *resurfacing hemiarthroplasty* (replacement

of only the femoral head). Representative radiographs of the three hemiarthroplasty variants are provided in **Figure 1.9**, corresponding to unipolar, bipolar, and resurfacing hemiarthroplasty, respectively.

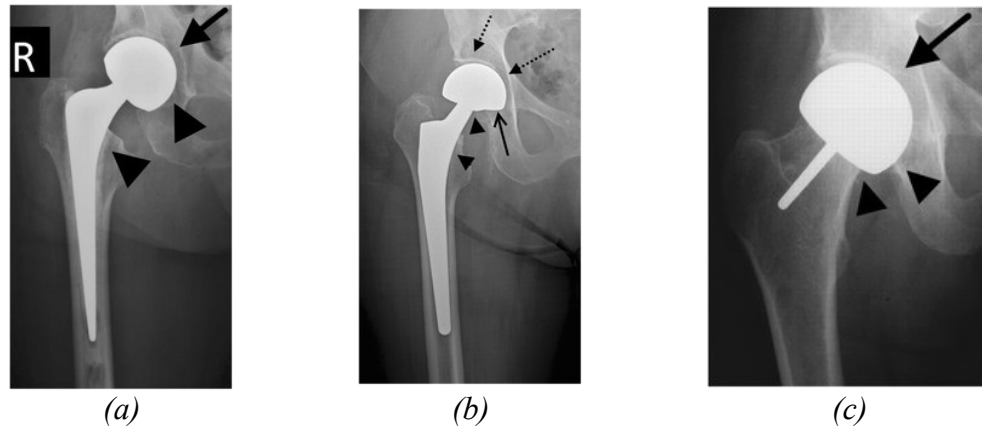


Figure 1.9: a) Anteroposterior (AP) radiograph. Cemented unipolar hemiarthroplasty: femoral stem with fixed head articulates directly with the native acetabulum; b) Cementless bipolar hemiarthroplasty: femoral stem with fixed head articulates with a polyethylene-lined metal cup, which in turn articulates with the native acetabulum; c) Cementless resurfacing hemiarthroplasty: only the femoral head is replaced, articulating with the native acetabulum.

In THA, both the femoral and acetabular components are replaced. Resurfacing total hip arthroplasty preserves the femoral neck while replacing the femoral head and acetabulum, often using *metal-on-metal* bearing surfaces. Bearing surfaces may include metal or ceramic for durability, or polyethylene to reduce friction, although the latter is associated with higher wear over time [13]. Fixation methods can be cemented, uncemented, or hybrid, depending

on patient bone quality and surgical planning. Examples of different total hip arthroplasty configurations and bearing surfaces are illustrated in **Figure 1.10**.

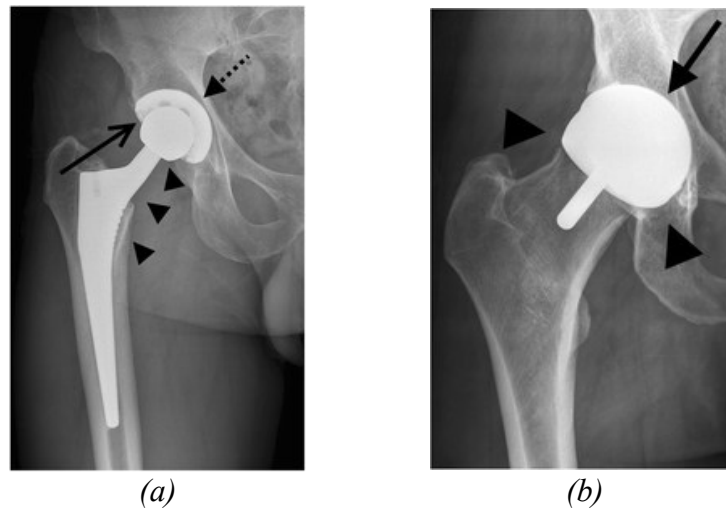


Figure 1.10: a) Cementless total hip arthroplasty: Both femoral head and neck, as well as the acetabulum, are replaced. A radiolucent polyethylene cup is visible at the joint. b) Cementless resurfacing hip arthroplasty: Femoral head and acetabulum are replaced, but the femoral head is preserved with no radiolucent area at the joint (metal-on-metal bearing surface).

Total hip arthroplasty is most frequently indicated for degenerative joint disease, while the choice between THA and hemiarthroplasty for hip fractures remains debated. Since Charnley's pioneering developments in the 1960s, surgical techniques, implant designs, and imaging modalities have evolved significantly, leading to improved patient outcomes.

Despite the overall success of hip arthroplasty, functional recovery remains a complex process that depends not only on implant integrity but also on the effectiveness of postoperative rehabilitation. Although rehabilitation is universally recognized as essential, there is limited consensus regarding the optimal timing, intensity, and duration of interventions. The most substantial improvements in physical impairments, activity limitations, and social participation are typically observed within the first three months following THA, with only marginal gains thereafter. Functional recovery progresses most rapidly during the initial six postoperative months, although gradual improvements in gait symmetry and walking velocity may continue up to twelve months after surgery. Nevertheless, clinical studies have reported that a subset of patients continue to experience residual pain, limited joint range of motion, muscle weakness, and functional deficits – such as reduced gait speed and impaired postural stability – up to one year postoperatively. These

findings emphasize that while the early postoperative period represents the most responsive phase for rehabilitation, long-term follow-up and individualized interventions remain essential to ensure optimal recovery and functional outcomes after THA. Understanding compensatory gait patterns is therefore fundamental for optimizing rehabilitation strategies, promoting symmetrical locomotion, and improving long-term functional outcomes after hip arthroplasty [14], [15], [16]. Moreover, post-operative complications can significantly affect functional recovery and influence compensatory gait patterns, making early detection and appropriate management crucial for effective rehabilitation [17]. The most common complications include:

- **Periprosthetic lucencies**

- *Aseptic loosening or osteolysis*: progressive radiolucent lines or bone resorption caused by wear debris, indicating implant instability (**Figure 1.11**).



Figure 1.11: AP radiograph, 3 years postoperatively. Cementless bipolar hemiarthroplasty. Aseptic loosening, radiographically seen as periprosthetic lucencies in a Gruen zone 5/6 (arrows).

- *Infection*: may appear as irregular, rapidly progressing lucencies or periosteal reaction around the prosthesis.
- **Sclerosis and bone proliferation**
 - *Heterotopic bone formation*: abnormal bone deposition in soft tissues surrounding the joint, potentially restricting motion.
 - *Spot welding*: localized reactive sclerosis at the bone–prosthesis interface, often representing stable fixation.

- *Stress shielding*: adaptive bone resorption or cortical thinning due to altered load distribution (**Figure 1.12**).

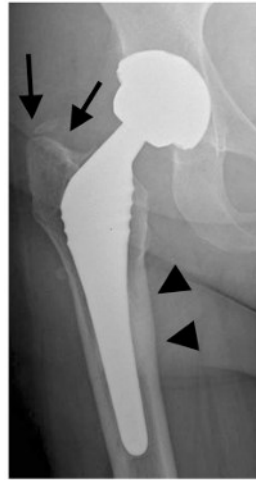


Figure 1.12: AP radiograph. Cementless total hip arthroplasty. Stress shielding. Cortical hypertrophy (arrowheads zone) and adaptive atrophy (arrows zone) as different parts of reactive bone remodelling.

- **Component failure and fractures**

- *Linear wear*: asymmetric femoral head position within the acetabular cup on radiographs, typical of hard-on-soft or soft-on-soft bearings (**Figure 1.13**).

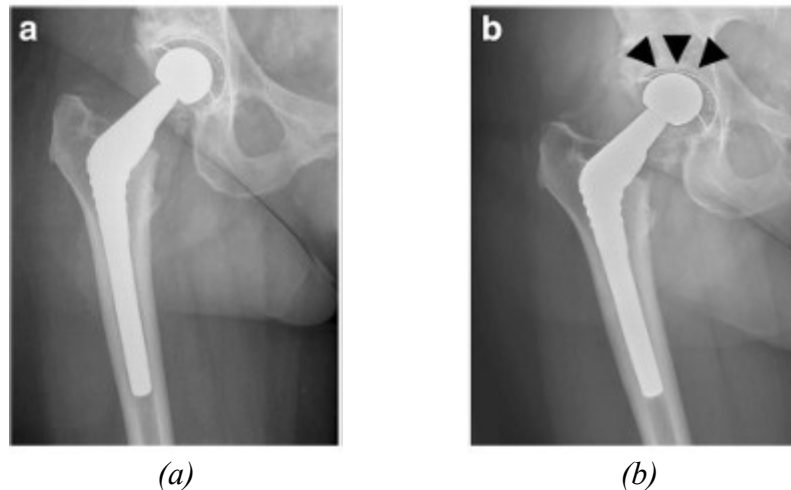


Figure 1.13: a) AP radiograph ,6months postoperatively. Cementless total hip arthroplasty. Normal postoperative findings. b) AP radiograph of the same patient, 4 years postoperatively. Cranial displacement of the femoral head in the acetabular cup (arrowheads), indicating linear wear.

- *Dislocation*: occurs in 0.5–10% of primary total hip arthroplasties, often early postoperatively; risk increases with abnormal acetabular inclination, retroversion, or malpositioned center of rotation (**Figure 1.14**).



Figure 1.14: AP radiograph. Cementless bipolar hemiarthroplasty. Lateral dislocation of head and acetabular cup.

- *Periprosthetic fractures*: more frequent around the femoral component, often at the stem tip; classified by the Vancouver system into types A, B, and C.
- *Prosthetic (stem) fracture*: metal-fatigue failure, typically in stems well-fixed distally but loose proximally.
- **Additional complications**
 - *Component migration or malalignment*: displacement or rotation of the prosthetic cup or stem, altering joint biomechanics.
 - *Adverse local tissue reaction and osteolysis*: inflammatory bone loss secondary to metal debris, ceramic fracture or polyethylene wear.
 - *Acetabular or femoral cortical perforation*: iatrogenic or stress-related cortical breach compromising stability.

Following THA, biomechanical alterations in joint kinematics and load distribution can significantly influence gait symmetry and neuromuscular coordination. Although pain relief and joint stability are generally restored, patients often exhibit residual asymmetries between the operated and contralateral limb, characterized by reduced hip extension, decreased stride

length, and altered pelvic motion. In some cases, an *antalgic gait* is observed, particularly in the early postoperative period, where patients shorten the stance-phase on the operated limb and increase reliance on the contralateral limb to minimize discomfort. This pain-avoidance strategy further accentuates asymmetrical loading, reduces walking speed, and increases energy expenditure [18].

These adaptive mechanisms reflect persistent deficits in muscle strength, particularly in the hip abductors and extensors, and delayed activation patterns that impair dynamic balance and propulsion during walking. One of the most frequently observed compensatory patterns is the *Trendelenburg gait* (**Figure 1.15**), characterized by a drop of the pelvis toward the non-operated side during stance on the operated limb. Patients commonly compensate by laterally flexing the trunk toward the operated side, thereby maintaining balance and stability. This pattern is primarily associated with deficits in the hip abductor musculature and has been consistently documented in post-THA populations [19], [20], [21].



Figure 1.15: a) Normal Gait: Gluteus Medius contracts and opposite hip is elevated. b) Trendelenburg Gait: Gluteus Medius weak and opposite hip drops.

Other prevalent gait alterations include *stiff* or *rigid gait* patterns, which manifest as reduced hip and knee range of motion on the operated side. To stabilize the joint and minimize discomfort, patients often adopt cautious, co-activated movement strategies. Such adaptations, although protective, contribute to diminished walking efficiency and altered temporal-spatial characteristics of gait [22]. Additionally, reduced propulsive force during late stance-phase is frequently observed, with patients relying more heavily on the non-

operated limb to generate forward momentum. This asymmetry can prolong double-support phases and compromise gait symmetry.

Post-THA gait is also commonly marked by asymmetric swing strategies, such as *hip hiking*, where the pelvis on the operated side is elevated during limb advancement to ensure foot clearance. Similarly, *circumduction gait* is observed when the operated limb is advanced along a semicircular trajectory rather than a straight line, compensating for limited hip flexion and enabling safe ground clearance. Both adaptations, illustrated in **Figure 1.16**, involve complex interactions of pelvic and trunk movements and reflect mechanical constraints imposed by altered joint kinematics [23].

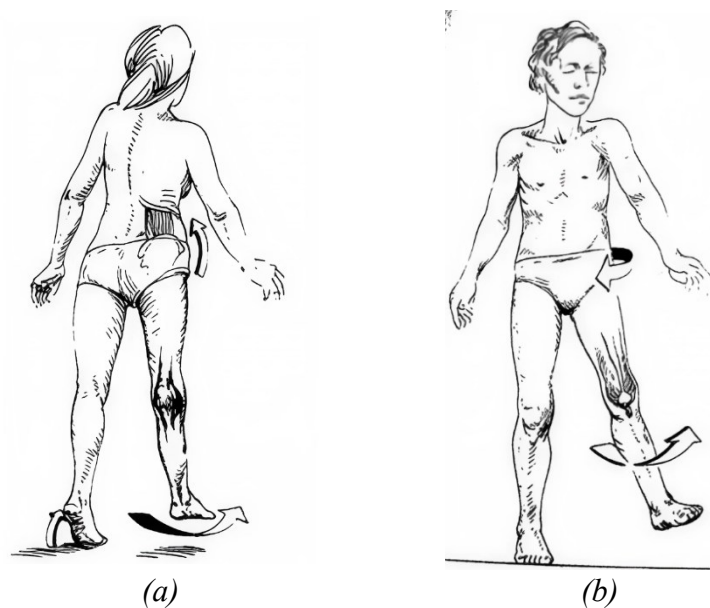


Figure 1.16: a) *Hip hiking*. b) *Circumduction Gait*.

Collectively, these compensatory patterns highlight the critical role of targeted postoperative rehabilitation in restoring gait symmetry, optimizing inter-limb coordination, and promoting long-term functional recovery and quality of life after total hip arthroplasty.

1.3 PHYSIOLOGY OF MUSCLE CONTRACTION AND MOTOR UNITS' ACTIVATION

Skeletal muscle contraction results from a complex electrophysiological and mechanical process that begins with the generation of an *action potential* in α -motoneurons of the spinal cord and culminates in the production of force at the muscle-tendon interface, namely a signal transmission defined as *neuromuscular junction (NMJ)*. Both neurons and skeletal muscle fibers are electrically excitable cells, able generating and propagating action potentials – specialized electrical signals that travel along a cell membrane as a wave – enabling rapid signal transmission over long distances. At the cellular level, all living cells maintain a membrane potential, defined as an electrical gradient across the membrane arising from the uneven distribution of positively and negatively charged ions. In neurons and muscle fibers, the intracellular potential typically ranges from -60 to -90 mV relative to the extracellular environment. These cells exploit their membrane potential to generate electrical signals by regulating ion flow through selective membrane channels [24].

The motor neuron and all the muscle fibers it innervates constitute a *motor unit (MU)*. The electrical response associated with the activation of a single MU is known as the *Motor Unit Action Potential (MUAP)*. The contractile response triggered by a single action potential varies in duration depending on the specific type of muscle fiber involved. Muscle force production is governed by several interrelated mechanisms at both the motor unit and molecular levels. Three primary factors determine force output:

1. Recruitment of motor units
2. Firing rate (discharge frequency) of active MUs
3. Synchronization of MU discharge, which increases during strong or fatiguing contractions

This hierarchical recruitment pattern reflects the classic *Henneman's size principle*, whereby low-threshold *type I* motor units - composed of slow, oxidative, fatigue-resistant fibers - are activated first, followed by higher-threshold *type II* units, which are fast, glycolytic, capable of generating greater force, but more susceptible to fatigue. Increasing the firing rate of motor units causes motor unit action potentials (MUAPs) to summate, progressively

increasing force until a fully fused tetanic contraction is achieved, representing the maximal force output. Each MUAP propagates bidirectionally along the sarcolemma, and its recorded morphology depends on several factors, including electrode position relative to the neuromuscular junction, the depth of the muscle fibers beneath the skin, and the inter-electrode distance. These mechanisms operate in conjunction with the actin-myosin cross-bridge cycling within sarcomeres, ultimately converting electrical excitation into mechanical force [25].

1.3.1 Hill-Type Muscle–Tendon Model

The Hill-type muscle–tendon unit model schematically represents the mechanical interaction between muscle fibers and tendon during force generation [26] as shown in **Figure 1.17**.

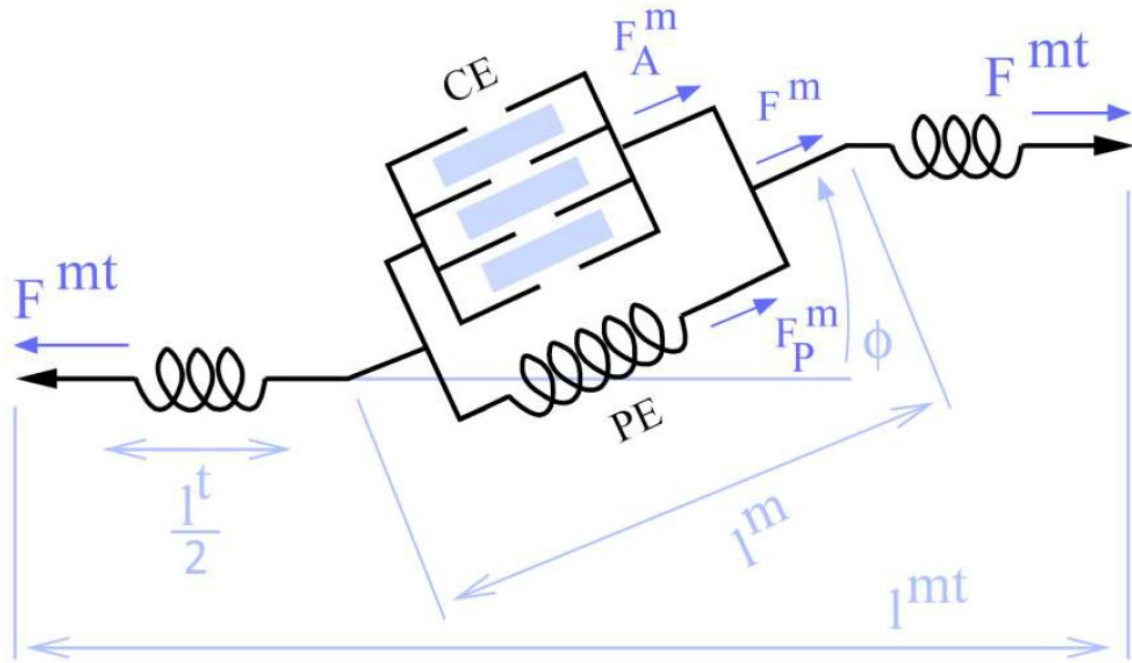


Figure 1.17: Hill-type muscle–tendon unit model illustrating the relationship between muscle fibers and tendon.

The overall musculo-tendon length l^{mt} , which varies as a function of joint kinematics, is composed of the muscle length l^m and the tendon length l^t . Within the muscle, force is generated by the contractile element, whose active contribution f_A^m depends on neural activation as well as on muscle length and contraction velocity. This active component acts in parallel with a passive elastic element, which produces a force f_P^m when the muscle is stretched beyond its resting length. The sum of these contributions defines the total muscle

force f^m . In pennate muscles, the orientation of muscle fibers with respect to the tendon, described by the pennation angle ϕ^1 , influences the effective transmission of muscle force. The muscle is connected in series to the tendon, modeled as a series elastic element, which transmits force to the skeletal system. Because of this serial arrangement, the force generated by the muscle fibers is equal to the musculotendon force f^{mt} , transmitted through the tendon, while the tendon undergoes an elongation that depends on its elastic properties. This tendon stretch contributes to the temporal delay between muscle activation and external force production. Therefore, changes in l^{mt} are distributed between muscle shortening or lengthening and tendon elongation, influencing both force transmission and movement efficiency. Within this framework, electromyographic activity reflects the neural drive that modulates force generation in the contractile element, whereas MMG signals capture the mechanical oscillations associated with muscle fiber contraction. The muscle–tendon model thus provides a coherent mechanical interpretation of the relationship between neural activation, muscle mechanical response, and the force ultimately applied at the joint level.

1.4 ELECTROMYOGRAPHY (EMG)

To understand how motor unit activation translates into measurable electrical activity, it is essential to introduce the electromyographic (EMG) signal. In particular, the surface electromyography (sEMG) provides a non-invasive window into the neural control of muscle activation. The action potentials generated by all motor units detectable by a recording electrode are electrically superimposed, resulting in a bipolar signals with a symmetric distribution of positive and negative amplitudes and a mean value equal to zero [27]. When the motoneuron discharges, it generates a train of neural impulses that can be modeled as a series of Dirac delta functions. Each MU behaves approximately as a *linear time-invariant (LTI) system*, so the EMG signal can be interpreted as the convolution of the neural impulse train with the MU impulse response. This concept is schematically illustrated

¹ The pennation angle is defined as the angle between the orientation of muscle fibers and the line of action of the tendon.

in **Figure 1.18**, which shows how the discharge patterns of multiple motor units combine to generate the surface EMG interference signal.

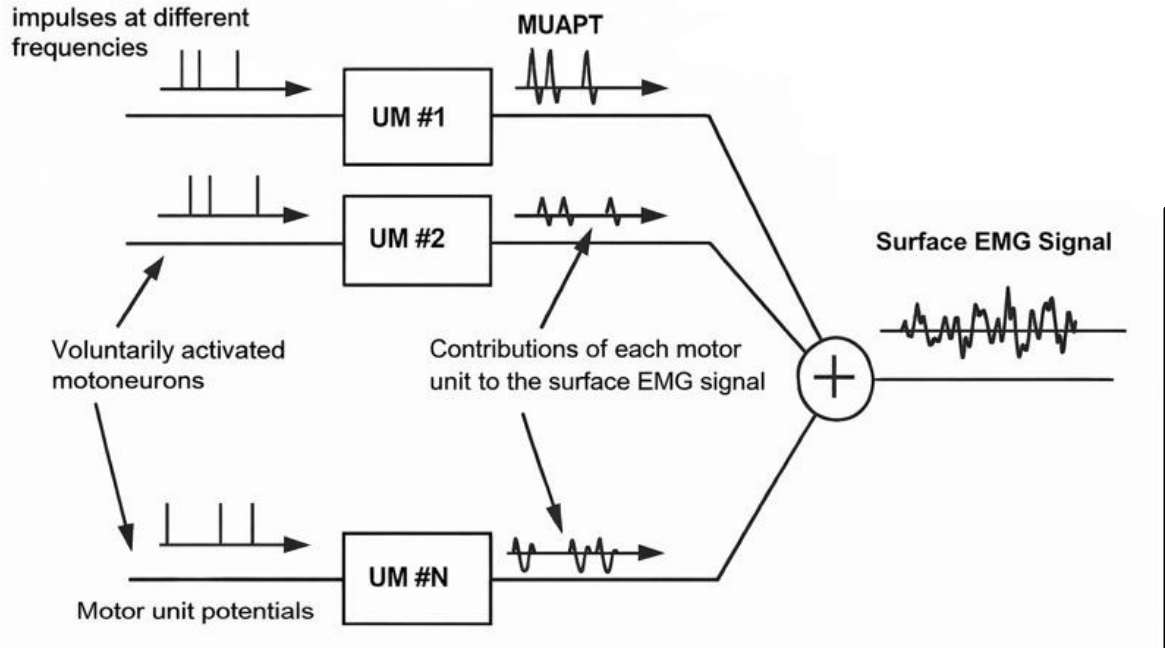


Figure 1.18: Conceptual model of surface EMG generation as the superposition of motor unit action potentials arising from multiple motor units firing at different discharge rates.

The surface EMG signal arises from the linear superposition of the MUAPTs generated by all active motor units within the detection volume of the electrodes. Due to the asynchronous firing of motor units and the variability in MUAPT shapes, the resulting EMG signal exhibits a *stochastic interference pattern* with a zero-mean bipolar distribution (**Figure 1.19**). Therefore, the interference EMG signal can be written as:

$$s(t) = \sum_{i=1}^{P(F)} F_i(t) * u_i(t)$$

where $P(F)$ is the number of active motor units at a given force level, $F_i(t)$ is the firing pattern of the i -th MU, and $u_i(t)$ is its impulse response.

Various anatomical, physiological, and technical elements influence MUAPT morphology. First of all, the muscle fiber type and the electrode location determine the initial signal characteristics, while tissue filtering further modifies the waveform. Intramuscular factors such as fiber diameter, conduction velocity, intramuscular pH, temperature, and other

membrane properties influence the propagation and amplitude of the action potential. Blood flow affects intramuscular pH by regulating the removal of hydrogen ions generated during contraction, indirectly altering the MUAPT shape. Additionally, the depolarization zone of muscle fibers and the synchronization of firing across fibers can distort the waveform. Together, these factors highlight the complexity of interpreting surface and intramuscular EMG signals.

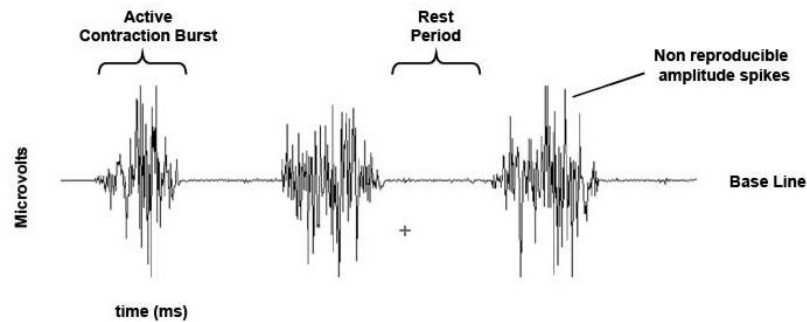


Figure 19: Raw EMG interference signal pattern.

Beyond these physiological aspects, the quality of the recorded EMG signal is also strongly affected by geometric and electrical factors. Geometric elements include:

- **Electrode placement:** the distance between the electrode and the active muscle fibers affects signal amplitude.
- **Electrode configuration:** bipolar, monopolar, or multi-electrode arrays will record different spatial summations of action potentials.
- **Inter-electrode distance:** larger distances can increase signal amplitude but may also include crosstalk phenomena from adjacent muscles.
- **Tissue properties:** subcutaneous fat, skin conductivity, and hydration level influence the propagation and attenuation of the EMG signal.

On the other hand, electrical factors includes:

- **Amplifier characteristics:** high input impedance and differential amplification are necessary to preserve low-voltage EMG signals and reject common-mode interference (CMRR).
- **Signal-to-noise ratio (SNR):** quality of electronic components and circuit design determines the level of internal noise added to the signal.

- **External noise:** power-line interference (50/60 Hz) and electromagnetic sources can contaminate the signal if not properly filtered.
- **Filtering stages:** band-pass and notch filters remove low-frequency drift, motion artifacts, and high-frequency electronic noise.
- **Electrode-skin interface stability:** movement artifacts caused by cable motion or unstable electrode contact can introduce additional noise; proper electrode attachment and cable shielding help reduce these effects.

EMG signals are typically acquired using differential amplifiers, which are specifically designed to reject common-mode noise and reduce movement or external artifacts. In a standard bipolar configuration, the voltage difference between two active electrodes placed over the muscle of interest is measured (**Figure 1.20**) [28]. To provide a stable reference, a third electrode, commonly referred to as the reference or ground electrode, is placed on a site distant from active muscle sources, often over osseous prominence. This reference electrode allows the amplifier to record potential relative to a stable baseline, improving signal fidelity and minimizing interference. Appropriate placement of all electrodes and correct amplifier settings are crucial to obtain high-quality and interpretable EMG signals.

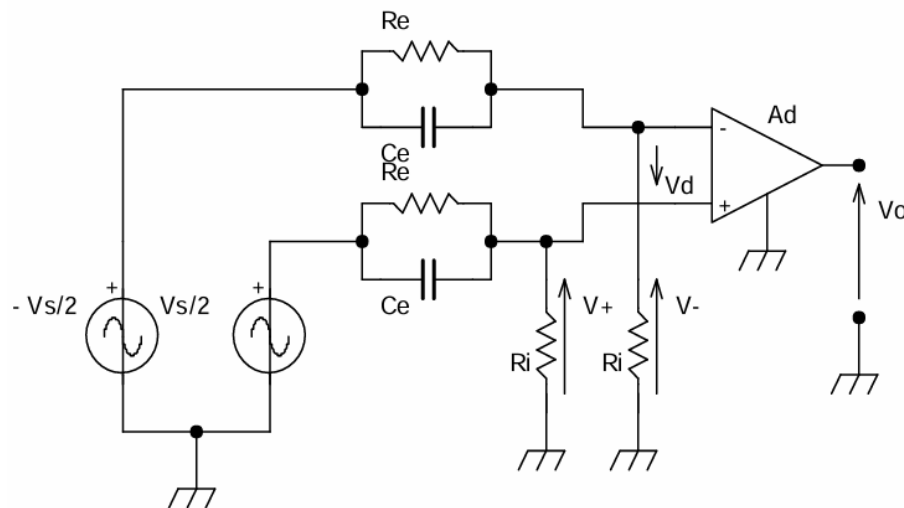


Figure 1.20: Schematic representation of a differential amplifier A_d in a bipolar EMG configuration. The voltage difference ($V_s/2$, $-V_s/2$) between two active electrodes is amplified while common-mode noise is rejected. The reference electrode sets a stable baseline. Input resistors (R_i) and the electrode-skin interface components (R_e , C_e) model impedance and intrinsic filtering.

A powerful tool to further analyze the interference EMG signal is the *Power Spectral Density (PSD)*, which describes how signal power is distributed across frequency components. The PSD provides insight into the spectral content of the MUAPs, motor unit synchronization, and recording geometry. Mathematically, the PSD of the interference EMG can be expressed as:

$$S(\omega, t, F) = R(\omega, d) \left[\sum_{i=1}^{P(F)} S_{u_i}(\omega, t) + \sum_{\substack{i,j=1 \\ i \neq j}}^{q(F)} S_{u_i u_j}(\omega, t) \right]$$

where S_{u_i} represents the auto-spectrum of the i -th motor unit, $S_{u_i u_j}$ represents the cross-spectrum between different motor units, $R(\omega, d)$ is a transfer function accounting for the inter-electrode distance d , and $q(F)$ is a factor reflecting the degree of motor unit synchronization at a given force level. This formulation highlights that the PSD is not only influenced by the individual MUAP characteristics, but also by their temporal interactions and the measurement geometry. Experimentally, it has been observed that during isometric constant-force contractions, the overall shape of the PSD remains relatively stable across different force levels, while the total power increases proportionally to the contraction intensity. This indicates that stronger contractions recruit more motor units and increase firing rates without significantly changing the frequency content of the EMG signal. Typically, surface EMG PSDs show most of their energy in the 10-250 Hz range, with peaks influenced by fiber conduction velocity, muscle fiber type composition, and electrode placement (**Figure 1.21**). PSD analysis is particularly valuable in distinguishing neuromuscular adaptations, fatigue, or pathological conditions. For instance, a shift of the EMG power toward lower frequencies may indicate muscle fatigue, due to decreased conduction velocity or altered motor unit recruitment. Similarly, changes in the high-frequency content can reflect synchronization of motor units or abnormal firing patterns in neuromuscular disorders. Consequently, the PSD provides a quantitative framework to link the physiological and anatomical properties of the muscle to the measurable electrical signals captured at the surface.

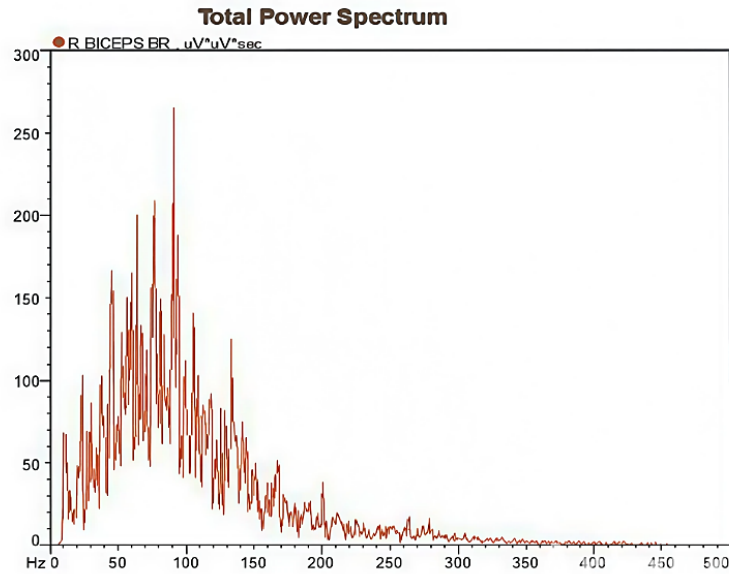


Figure 1.21: Typical Power Spectrum for an EMG acquisition.

To provide a concise overview of the fundamental characteristics of the EMG signal, **Table 1.4** summarizes the typical temporal and spectral properties of surface EMG recorded during voluntary contractions, along with their physiological interpretation [29], [30], [31].

Property	Typical value / range	Domain
Mean value	$\approx 0 \mu\text{V}$	Time
Peak-to-peak amplitude	50–500 μV (up to mV in MVC)	Time
RMS amplitude	10–300 μV	Time
Useful bandwidth	10–250 Hz	Frequency
Mean frequency	70–120 Hz	Frequency
Median frequency	60–100 Hz	Frequency
Power-line interference	50/60 Hz	Frequency
Effect of fatigue	Spectral shift to low frequencies	Physiology
Effect of force increase	Increase in total power	Physiology

Table 1.4: Temporal and spectral sEMG properties.

1.5 MECANOMYOGRAPHY (MMG)

Although surface electromyography (sEMG) remains the most established method for non-invasive assessment of muscle activation, its sensitivity to noise, electrode placement variability and variations of skin impedance have motivated interest in complementary approaches. Among them, mechanomyography (MMG) has emerged as a mechanical counterpart to sEMG, detecting low-amplitude micro-vibrations generated by muscle fibers during contraction, oscillation and transmission of mechanical waves to surrounding tissues.

During voluntary contraction, muscle fibers produce mechanical vibrations resulting from the summation of individual motor unit twitches, reflecting the mechanical response of the muscle activation. These oscillations originate from both physiological and non-physiological sources and are distributed across partially overlapping frequency bands. The lowest frequencies are typically associated with motion artifacts caused by gross limb movements, while involuntary neuromuscular oscillations, such as physiological tremors, usually remain below 10 Hz, with typical values in healthy individuals around 6-9 Hz. Vibrations arising from the contractile elements themselves are predominantly observed between approximately 10 and 40 Hz [32]. MMG signals are understood to capture the mechanical output generated by the summation of individual muscle fiber twitches, resulting from motor unit activation. For this reason, MMG can provide meaningful information even in contexts where EMG acquisition is challenging or prone to degradation, such as industrial environments or settings with high electromagnetic interference. MMG signals may be recorded using piezoelectric sensors, accelerometers, microphones, or optical displacement sensors, and they are generally less sensitive to skin impedance variations compared to sEMG, being based on mechanical rather than electrical events. Over the past decades, MMG has been employed in a wide range of applications, including muscle fiber characterization, neuromuscular monitoring, motor unit analysis, fatigue assessment, sport performance analysis, and control of prosthetic or assistive devices [33].

On the contrary, the amplitude of the MMG signal is affected by several physiological and mechanical factors, including muscle temperature, stiffness, intramuscular pressure, fluid viscosity, and motor unit firing behavior. Like EMG, MMG time- and frequency-domain

characteristics may provide insight into neuromuscular control strategies during both isometric and dynamic contractions. MMG amplitude has been associated with motor unit recruitment, whereas MMG frequency components may relate to motor unit firing rate. Therefore, analyzing both domains together can help differentiate the mechanisms used to modulate force under different contraction conditions [34].

1.6 ELECTROMECHANICAL DELAY (EMD)

When sEMG and MMG signals are examined together, an additional temporal feature of neuromuscular function can be quantified: the electromechanical delay (EMD). EMD is defined as the time interval between the onset of muscle electrical activation and the development of measurable external force or torque, and typically ranges from 30 to 100 ms. The delay reflects both electrochemical processes, involved in excitation–contraction coupling, and mechanical processes, linked to the progressive tensioning of the series elastic components before force transmission to the skeletal system [35]. Traditionally, EMD has been estimated as the time difference between EMG onset and force onset. Because MMG represents the first detectable mechanical manifestation of actine-myosin cross-bridge formation and early fiber shape changes, it allows the partitioning of EMD into two distinct components:

1. **Δ EMG-MMG**: predominantly associated with electrochemical events, including action potential propagation, Calcium release, and cross-bridge initiation.
2. **Δ MMG-Force**: primarily reflecting mechanical events, such as the stretching of tendon and aponeurosis and the transmission of tension through the muscle–tendon complex.

This combined *EMG–MMG–force* approach (**Figure 1.22**) has demonstrated that electromechanical delay is not a constant muscle property but is modulated by a variety of physiological and biomechanical factors. Significant differences in EMD have been observed according to sex, age, and physical activity level, as well as in response to muscle fatigue, temperature manipulation, stretching, and neuromuscular disorders. For instance,

women often exhibit longer ΔMMG –force compared to men, potentially due to differences in tendon stiffness and muscle–tendon architecture.

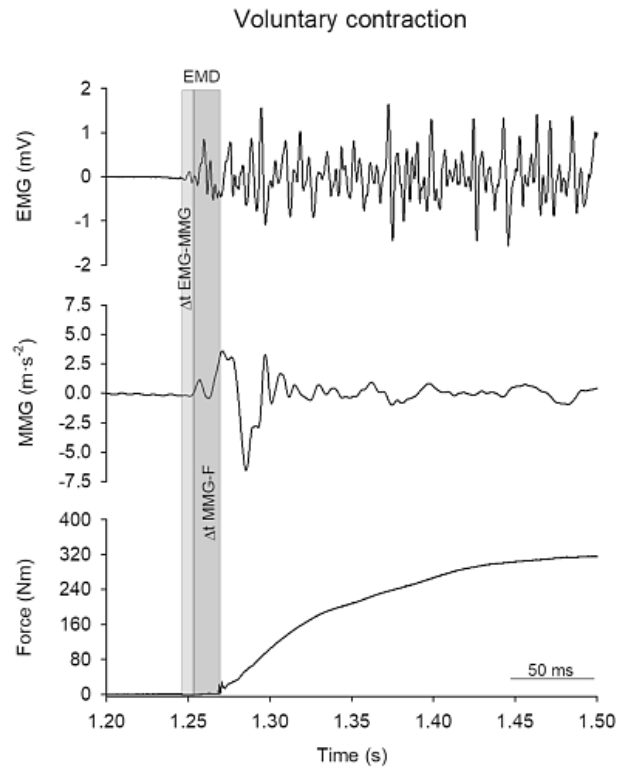


Figure 1.22: Voluntary contraction: electromyographic (EMG), mechanomyographic (MMG), force signals, and delays in a representative participant.

Age-related prolongation of EMD has been linked to slower excitation–contraction coupling and changes in connective tissue compliance, while regular physical training (particularly strength and plyometric training) appears to reduce both EMD components through adaptations in neural drive, tendon stiffness, and muscle fiber composition. Another factor influencing EMD is the contraction modality. Experimental evidence indicates that eccentric contractions generally produce longer EMD values than concentric ones, which may be attributed to differences in cross-bridge cycling rate, muscle–tendon interaction, and viscoelastic behavior of passive components. Consequently, EMD is widely regarded as a relevant indicator in performance assessment and injury prevention, particularly concerning the risk of falls in older adults, anterior cruciate ligament injury, and return-to-sport monitoring [36]. Collectively, these findings support the notion that electromechanical delay represents a sensitive biomarker of neuromuscular function. In the context of gait analysis, electromechanical delay may offer additional insights into altered neuromuscular strategies

adopted by individuals with THA. After hip replacement, patients often exhibit modifications in muscle activation timing, particularly in the gluteal, quadriceps, and calf musculature, due to altered joint mechanics, pain-related adaptation, or persistent weakness. Quantifying EMD during gait tasks could help detect delayed or prolonged muscle activation patterns that may compromise hip stability, reduce propulsion efficiency, or increase compensatory loading on the contralateral limb. Moreover, monitoring EMD may assist clinicians in differentiating between neuromuscular recovery and compensatory movement strategies across the rehabilitation timeline, supporting decisions regarding progressive loading, return to functional mobility, and fall-prevention interventions. For these reasons, the assessment of EMD may represent a promising complementary metric within instrumented gait analysis protocols for patients undergoing or recovering from THA.

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CHAPTER 2

TECHNOLOGICAL BACKGROUND AND SCIENTIFIC RATIONALE

*“Measure what can be measured,
and make measurable what cannot be measured.”*
— Galileo Galilei

Building upon the biomechanical foundations outlined in the previous chapter, this section shifts the focus from the physiological and functional mechanisms of human movement to the technological solutions that enable their quantitative assessment. Modern gait analysis increasingly relies on wearable and implantable systems that capture complex neuromuscular and kinematic information in real time. These technologies are particularly relevant in the context of hip arthroplasty, where subtle compensatory strategies and asymmetries often remain undetected through traditional clinical observation alone. In this chapter, the current landscape of sensing modalities employed in locomotion analysis is reviewed, including instrumented prosthetic components, surface electromyography, inertial units, and emerging piezoelectric-based devices. Special attention is devoted to the physical principles underlying the piezoelectric transduction mechanism and its integration with standard or complementary measurement modalities, such as EMG, MMG, and IMUs. A critical review of the existing literature highlights the strengths and limitations of current approaches and motivates the need for more robust, multimodal systems capable of capturing both mechanical and electrophysiological markers of gait. Finally, the chapter provides the scientific rationale supporting the design of the proposed framework, outlining the specific aims of the study, the expected outcomes, and its potential contributions to rehabilitation engineering and post-arthroplasty patient monitoring.

2.1 QUANTITATIVE GAIT ASSESSMENT AFTER HIP ARTHROPLASTY

Conventional gait assessment is commonly performed using optical motion capture systems, force platforms, instrumented walkways, and video-based analysis. These systems provide accurate biomechanical information and are often used as reference methods for validating wearable technologies. However, they require dedicated laboratory environments, trained personnel, time-consuming setup procedures, and limited ecological validity, since measurements are usually restricted to short walking trials under controlled conditions. Among these techniques, optical motion capture systems combined with force plates are considered the gold standard for quantitative gait analysis, enabling the estimation of joint kinematics, kinetics, and spatiotemporal parameters with high accuracy [1], [2]. Instrumented walkways provide reliable measurements of temporal and spatial gait characteristics and are widely used in clinical and rehabilitation settings [3]. Video-based assessment and observational gait analysis are also commonly adopted because of their simplicity and accessibility, although their accuracy strongly depends on the examiner's experience and they are generally limited to qualitative or semi-quantitative evaluations. Despite their established role in clinical research, these approaches present several limitations. The high cost of equipment, the need for specialized facilities and personnel, and the relatively long preparation time reduce their feasibility for routine monitoring and large-scale assessments. Moreover, laboratory-based measurements may not fully reflect patients' natural walking behavior during daily activities, limiting their ecological validity[4]. These drawbacks have stimulated increasing interest in wearable and multimodal sensing technologies, which enable continuous, unobtrusive, and potentially remote assessment of gait in more realistic environments.

2.2 CURRENT SENSING TECHNOLOGIES FOR POST-THA MONITORING

The technological monitoring of gait after hip arthroplasty has evolved along two parallel and complementary directions: instrumented prosthetic components and wearable sensor systems. These approaches differ substantially in invasiveness, measurable variables,

technological constraints, and clinical applicability, yet together outline the current landscape of quantitative gait assessment.

2.2.1 Instrumented hip prostheses

Figure 2.1 illustrates an instrumented implant, also referred to as a *smart prosthesis*, that embed sensing elements (strain or pressure sensors) within the femoral head, stem, or acetabular components to capture direct in vivo measurements of load transfer, micromotion, and implant-bone interaction. Early devices, typically based on strain gauges connected to inductive telemetry coils, provided only unidirectional or planar load estimates, primarily used to study early micromotion associated with aseptic loosening [5]. These first systems required bulky encapsulation, external powering, and had limited long-term durability.



Figure 21: Hip implant instrumented with eight temperature sensors along the neck and shaft and four strain gauges to monitor multi-axis forces at the prosthetic head and stem.

Recent developments have introduced *multidirectional load-sensing platforms*, supported by improvements in sensor miniaturization, wireless telemetry, and computational optimization as shown in **Figure 2.2**. These systems enable measurement of force vectors, bending moments, torsional loads, and implant deformation during activities such as stair ascent or sit-to-stand, providing valuable insight into joint mechanics and surgical outcomes.

Beyond load monitoring, next-generation implantable systems also explore:

- **pH and biochemical sensors** to detect early periprosthetic infection
- **pressure and strain sensors** for real-time assessment of implant fixation
- **temperature and micro-environment sensing** [6] to monitor inflammatory processes.

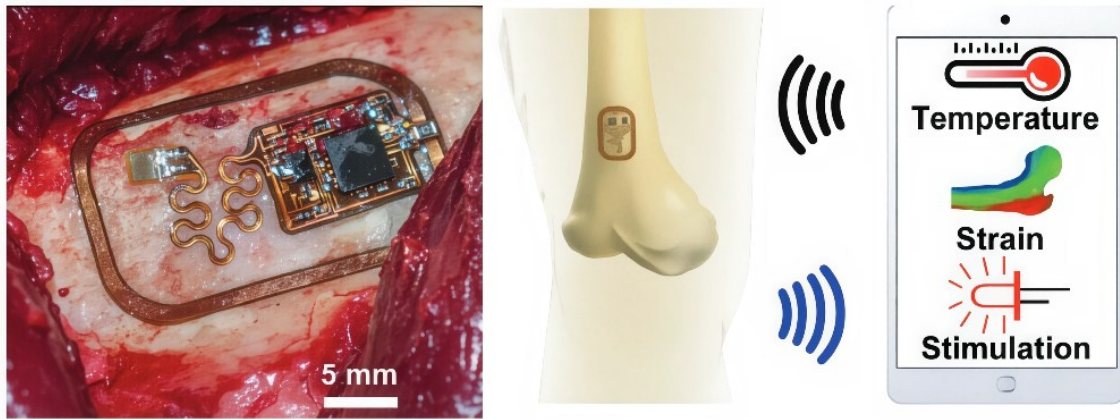


Figure 2.2: An osseousurface device with both wireless passive strain sensing capabilities and active optical stimulation, along with the equivalent circuit diagram.

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A major application remains intraoperative force sensing, where instrumented trial components quantify soft-tissue tension, joint stability, and impingement during THA. Wireless intraoperative modules provide real-time multi-axial joint forces to assist surgeons in achieving symmetric load distribution and optimal component alignment [7], [8]. Despite these advantages, the long-term deployment of instrumented prostheses remains constrained by several critical challenges. Ensuring biocompatibility and stable long-term encapsulation is essential to prevent sensor degradation and inflammatory reactions within the peri-implant environment. Additionally, current technologies still face limitations in miniaturization, as integrating multiple sensing modules without compromising the structural integrity of the implant is technically challenging. Sustained operation overtime is further hindered by powering and energy-harvesting constraints, since implantable devices must function autonomously while maintaining low power consumption. In addition to that, reliable wireless data transmission also remains a bottleneck, particularly in deep-tissue environments where signal attenuation can impair communication fidelity. Finally, these technological barriers are compounded by the regulatory complexity associated with active implantable medical devices, which require extensive safety evaluations, long-term reliability testing, and stringent approval pathways before clinical translation can be achieved [6]. For this reason, fully instrumented permanent hip implants remain mainly experimental or used intraoperatively.

2.2.2 Wearable kinematic and neuromuscular sensing

Wearable sensors represent a clinically practical alternative, enabling continuous monitoring without the need for surgical intervention. Among these, *Inertial Measurement Units (IMUs)* are the most widely adopted due to their compact size, low energy consumption, and ability to reconstruct joint kinematics via fusion of accelerometer, gyroscope, and magnetometer data [9], [10]. A representative configuration of wearable sensors, including EMG, MMG, and inertial units for lower-limb monitoring, is illustrated in **Figure 2.3**.

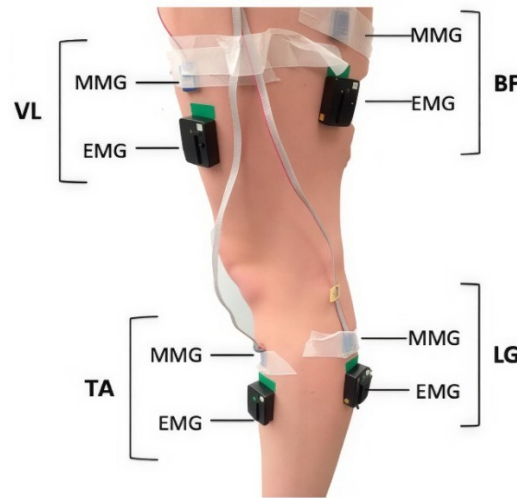


Figure 2.3: Wireless surface EMG sensors (Trigno by Delsys Inc, Boston, MA, USA) fastened with double-sided tape over muscle bellies and tri-axial accelerometers ADXL337 for MMG acquisition.

When validated against gold-standard *optoelectronic motion-capture systems*, IMUs have demonstrated sufficient accuracy to quantify several key gait parameters. Specifically, IMUs allow reliable estimation of hip flexion-extension angles throughout the gait cycle, temporal-spatial metrics such as cadence, cycle duration, and the stance-to-swing ratio, as well as sagittal-plane range of motion. They also provide robust measurements of pelvic tilt and compensatory trunk lean, together with indices of inter-limb symmetry, confirming their suitability for characterizing post-operative gait patterns in clinical populations [11], [12]. Evidence from studies involving patients after total hip arthroplasty further shows that IMUs are sensitive to the subtle kinematic deviations typically observed during recovery. These include reductions in hip extension associated with postoperative soft-tissue tightness, increased lateral trunk lean adopted to attenuate joint reaction forces, shortening or asymmetry of step length, and alterations in pelvic rotation during mid-stance. Collectively, these findings highlight the

clinical value of IMUs in detecting compensatory movement strategies that may not be evident through visual observation alone.

Wearable systems encompass a range of technologies that extend beyond IMU, providing complementary information on gait mechanics and neuromuscular function. Among these, *plantar-pressure insoles* (**Figure 2.4**) equipped with capacitive or piezoelectric sensors allow continuous monitoring of stance time, peak pressure timing, inter-limb load distribution, and heel-to-toe transition patterns. Such devices have proven particularly effective in detecting offloading strategies and asymmetries that often occur during the early postoperative phase following THA [13], [14].

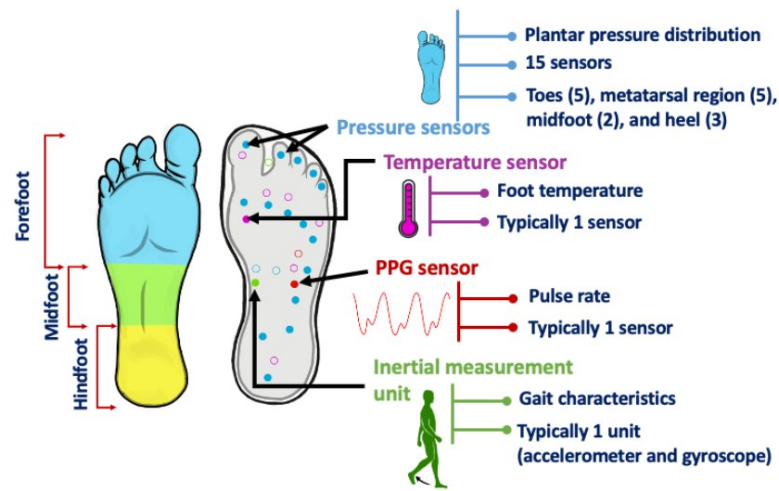


Figure 2.4: Proposed locations for sensors measuring various parameters in an insole-based monitoring system.

Recent developments have focused on *flexible and soft sensing technologies*. Thin-film piezoresistive, capacitive, and piezoelectric layers can be integrated into garments, footplates, or adhesive strips to monitor plantar pressures, joint angles, and dynamic loading patterns. Printed piezoelectric sensor arrays further enable classification of gait transitions and detection of abnormal stress distributions, making them particularly suitable for postoperative rehabilitation monitoring. In addition to their sensing capabilities, piezoelectric films can generate an electrical signal directly from mechanical deformation and may also be exploited for self-powered operation. However, complete wearable systems still require dedicated signal conditioning, data acquisition, and, in many cases, external power for readout, wireless transmission, and long-term continuous monitoring.

Instrumented implants remain the gold standard for accuracy, providing direct internal measurements of joint reaction forces, bone-implant interface stresses, and microscopic

deformation [15]. However, they are difficult to implement for daily clinical monitoring due to regulatory and technological constraints. Wearable sensors, in contrast:

- are inexpensive
- allow long-term monitoring in natural environments
- capture functional recovery and compensatory gait strategies
- are suitable for telemedicine and home rehabilitation [9], [14].

In summary, while instrumented implants provide unparalleled accuracy in measuring internal forces, wearable systems offer scalable, non-invasive solutions for continuous monitoring. The following **Table 2.1** provides a comparative overview of the main technological solutions for gait monitoring after hip arthroplasty, summarizing their key advantages and limitations.

Technology	Advantages	Disadvantages
IMUs and Instrumented Insoles	Non-invasive, technologically mature, excellent for detecting functional compensations	Cannot measure internal implant loads
Implantable Sensors in Smart Prostheses	Direct measurement of load, excellent for mechanical studies and validation	Regulatory complexity, telemetry and power supply requirements, limited long-term durability
Flexible wearable Sensors	Thin and flexible, easy integration, suitable for external modules or wearable add-ons	Challenging in long-term stability in biological environment, mechanical coupling with rigid surfaces, low-noise readout electronics

Table 2.1: Comparative overview of technological solutions for gait monitoring after hip arthroplasty.

2.3 PIEZOELECTRIC SENSING FOR BIOMECHANICAL MONITORING

A thorough understanding of piezoelectric transduction is essential for this thesis, as it constitutes the core mechanism underlying the sensors setup developed throughout the study.

2.3.1 Transduction mechanism and material properties

Since the pioneering work of Pierre and Jacques Curie, who first observed the surface charge generated on crystals such as tourmaline, quartz, and Rochelle salt under mechanical stress, piezoelectric materials have attracted increasing scientific interest due to their wide applicability [16]. This phenomenon, known as the *direct piezoelectric effect*, describes the generation of electrical charge in response to mechanical deformation. Conversely, the *inverse piezoelectric effect* refers to the mechanical deformation induced when an electric field is applied to the material. These complementary mechanisms are illustrated in **Figure 2.5**.

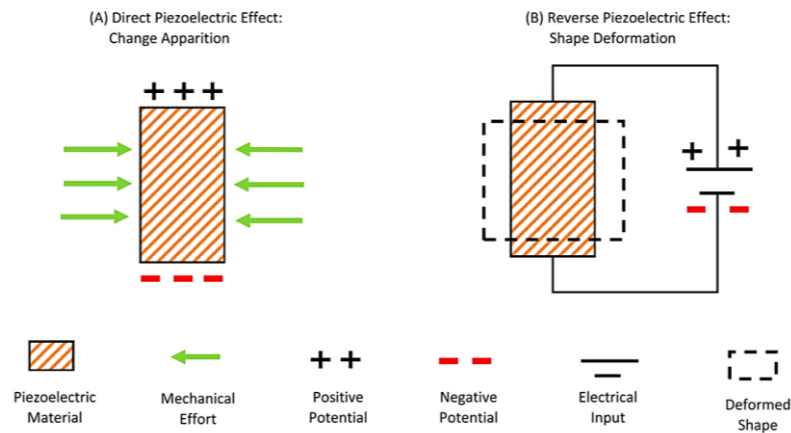


Figure 2.5: Electromechanical conversion of piezoelectric phenomena.

At the microscopic level, piezoelectricity arises from a non-centrosymmetric arrangement of electric charges within the material structure, which allows the relative displacement of positive and negative charge centers under mechanical loading and the consequent formation of a net electrical polarization [17],[18].

Although this principle is common to all piezoelectric materials, the physical origin and technological properties of the piezoelectric response differ significantly among material classes. A first important group is represented by ferroelectric ceramics, such as lead

zirconate titanate (PZT) and barium titanate (BaTiO_3). These materials usually exhibit high piezoelectric coefficients and strong electromechanical coupling. Their response is strongly influenced by the presence of ferroelectric domains, i.e., regions with locally aligned spontaneous polarization. During poling, an external electric field is applied to preferentially orient these domains, thereby producing a macroscopic piezoelectric response. However, this domain-based behavior is temperature-dependent and may be lost above the Curie temperature, where the material undergoes a transition toward a non-ferroelectric phase [19], [20]. Despite their high sensitivity, ferroelectric ceramics are generally stiff and brittle, and lead-based ceramics such as PZT also raise concerns regarding environmental and biocompatibility aspects [21].

A second class includes non-ferroelectric piezoelectric materials with a wurtzite crystal structure, such as aluminum nitride (AlN) and zinc oxide (ZnO). In these materials, the piezoelectric response is not mainly governed by switchable ferroelectric domains, but by the intrinsic polarity of the non-centrosymmetric wurtzite lattice [22], [23]. In the case of AlN thin films, piezoelectric performance strongly depends on the crystallographic quality and the preferential c-axis orientation of the deposited film, which are usually controlled by thin-film deposition techniques such as reactive sputtering. AlN is particularly attractive for biomedical and wearable sensing applications because it is lead-free, chemically stable, compatible with microfabrication processes, and suitable for thin-film integration on rigid or flexible substrates [24]. However, its piezoelectric coefficients are generally lower than those of PZT-based ceramics, making the optimization of mechanical coupling, electrode configuration, and low-noise readout electronics particularly important.

A third relevant group comprises piezoelectric polymers, among which polyvinylidene fluoride (PVDF) and its copolymers, such as P(VDF-TrFE), are the most widely investigated. In polymeric piezoelectric materials, the electromechanical response is associated with the orientation of molecular dipoles along the polymer chains [8], [9]. For PVDF, the β -phase is the most electroactive crystalline phase because its all-trans molecular conformation produces a high net dipole moment, thereby enhancing the piezoelectric response. Mechanical stretching, electrical poling, electrospinning, and the incorporation of suitable fillers are commonly used to increase the β -phase content and improve the electromechanical performance of PVDF-based materials [25], [26], [27]. Compared with ceramic materials, piezoelectric polymers generally exhibit lower piezoelectric coefficients

and reduced thermal stability, but they offer high flexibility, low density, mechanical compliance, and easier integration into wearable devices, garments, adhesive patches, and soft interfaces for human motion monitoring.

Therefore, the choice of a piezoelectric material depends strongly on the target application. Ferroelectric ceramics such as PZT are advantageous when high sensitivity and strong electromechanical coupling are required, but their rigidity and, in the case of lead-based ceramics, material-related concerns may limit their use in wearable biomedical systems. Wurtzite thin films such as AlN offer a compromise between piezoelectric functionality, miniaturization, process compatibility, chemical stability, and lead-free composition. **Table 2.2** summarizes the main characteristics of the mentioned piezoelectric materials.

Piezoelectric polymers such as PVDF, on the other hand, are particularly suitable for flexible, conformable sensors, though their lower signal amplitudes often require careful signal conditioning. In the context of gait and rehabilitation monitoring, these differences are crucial because the sensor must detect small dynamic mechanical signals while maintaining stable mechanical coupling with soft biological tissues during movement.

Piezoelectric elements can operate in *compression*, *flexural*, or *shear* modes. Compression mode provides high stiffness and is suited for high-frequency pressure and force measurements, although it is sensitive to thermal variations. Flexural mode offers compactness but has limited frequency response and reduced shock resistance. Shear mode, widely used in accelerometers, provides a favorable balance of wide frequency range, low thermal sensitivity, and low base-strain influence.

Due to their high stiffness ($\sim 10^4 \cdot 10^9 \text{ N/m}^2$), piezoelectric materials generate strong electrical outputs under minimal strain and exhibit high durability, linearity, and a dynamic range of up to 120 dB when paired with appropriate signal conditioning systems [28]. Their behavior is commonly characterized by the *piezoelectric voltage constant* g and the *piezoelectric charge constant* d . The g constant reflects material sensitivity, while the d constant correlates with the mechanical deformation produced. Notably, d relates to g through the dielectric constant $\epsilon = \epsilon_0 \epsilon_r$. Typical values include 2.3 pC/N for quartz and 140 pC/N for barium titanate [29].

Material class	Material	Main mechanism	Strengths	Limitations
Ferroelectric ceramics	PZT, BaTiO ₃	Switchable ferroelectric domains after poling	High piezoelectric coefficients, high sensitivity	Brittle, stiff, Curie-temperature effects, lead issues for PZT
Wurtzite materials	AlN, ZnO	Intrinsic polarity of non-centrosymmetric wurtzite lattice	Thin-film integration, lead-free, stable, microfabrication-compatible	Lower piezoelectric response than PZT, requires good film orientation
Piezoelectric polymers	PVDF, P(VDF-TrFE ²)	Molecular dipole orientation, especially β -phase in PVDF	Flexible, lightweight, wearable-friendly	Lower coefficients, temperature/aging effects, signal conditioning critical

Table 2.2: Comparison between the main piezoelectric materials.

2.3.2 Piezoelectric materials: PZT, PVDF, BaTiO₃ and AlN

Among the most widely used piezoelectric thin-film materials are lead zirconate titanate (PZT), Zinc oxide (ZnO), and Aluminium nitride (AlN). PZT demonstrates exceptional piezoelectric behavior due to its high piezoelectric coefficient d_{ij} and electromechanical coupling factor (k_{eff}). Nevertheless, its incorporation of lead presents a significant drawback, as it increases contamination risks during clean-room processing and raises concerns regarding its use in biomedical and body-worn applications. ZnO and AlN exhibit comparable values of k_{eff} and d_{ij} ; however, the performance of ZnO degrades markedly at elevated temperatures because of its low Curie point³. Conversely, the low-temperature deposition of AlN ensures compatibility with a broad range of materials and fabrication workflows. In addition, AlN is inherently non-ferroelectric, and thus its piezoelectric response does not rely on post-deposition poling or annealing treatments. From a structural standpoint, AlN adopts a hexagonal close-packed, non-centrosymmetric wurtzite configuration and belongs to the *III-V* semiconductor family. Each unit cell consists of an Aluminium atom tetrahedrally coordinated by four Nitrogen atoms, forming alternating Al–N layers stacked along the c-axis. The crystal system of AlN thin films is influenced by the

² Poly (vinylidene fluoride-trifluoroethylene).

polarity of the basal plane, which may be either Al-polar or N-polar (**Figure 2.6**). Al-polar films generally incorporate fewer impurities and are therefore preferred for achieving fully coalesced layers with smooth surfaces and minimal defects, whereas N-polar films typically exhibit increased surface roughness. Moreover, AlN surpasses other nitride semiconductors in several key properties, including chemical stability, mechanical strength, and thermal conductivity [30], [31]

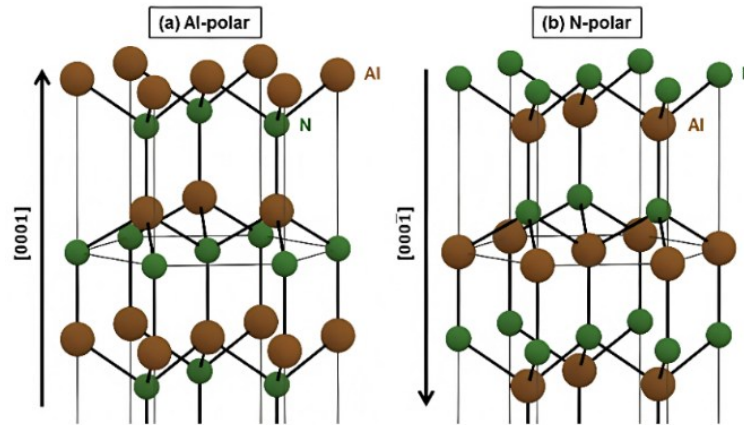


Figure 2.6: Polarity of AlN. a) Al-polar and b) N-polar.

2.3.3 State-of-the-art of piezoelectric sensors for gait and rehabilitation monitoring.

While the previous section provided insight into current technological solutions, presenting flexible and soft-sensing technologies such as thin-film piezoelectric layers, this subsection focuses on a detailed review of the literature on piezoelectric sensor design, performance, and integration in prosthetic implants or wearable systems. For instance, computational studies have evaluated the integration of piezoelectric elements into prosthetic hip stems, where the generated charge can be harvested during gait to power embedded electronics. Recent technologies involve:

- **Piezoelectric multilayer ceramics** embedded directly in femoral heads or stems, capable of converting mechanical stress into electrical signals that represent multi-axis loading [15], [32].
- **Thin-film piezoelectric disks or segmented arrays**, placed according to FEM-optimized stress maps to maximize sensitivity and minimize cross-talk between directions [33], [34].

- **Energy harvesting modules** integrated into the stem to power wireless sensing units autonomously during walking, using piezoelectric energy conversion as illustrated in **Figure 2.7** [35].

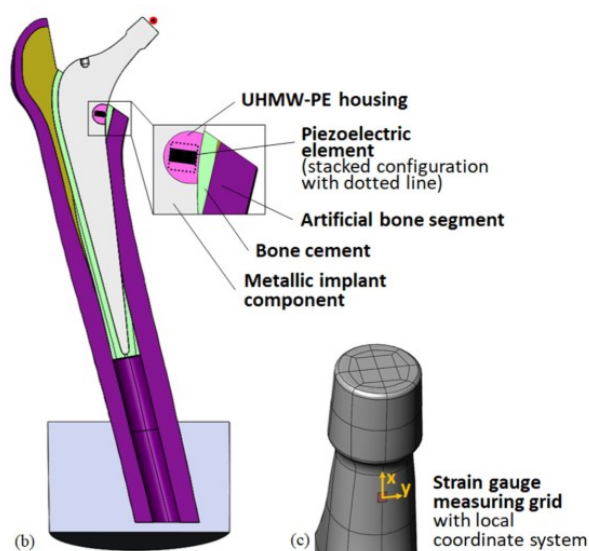


Figure 2.7: Cross-sectional view with detail of the energy harvesting system and a detail of the metallic implant component (neck) with surface patch representing the strain gauge's measuring grid.

Finite-element simulations demonstrate that piezoelectric cylinders or patches can be incorporated into uncemented revision stems without compromising mechanical safety factors, structural integrity or osteointegration (**Figure 2.8**) [36].

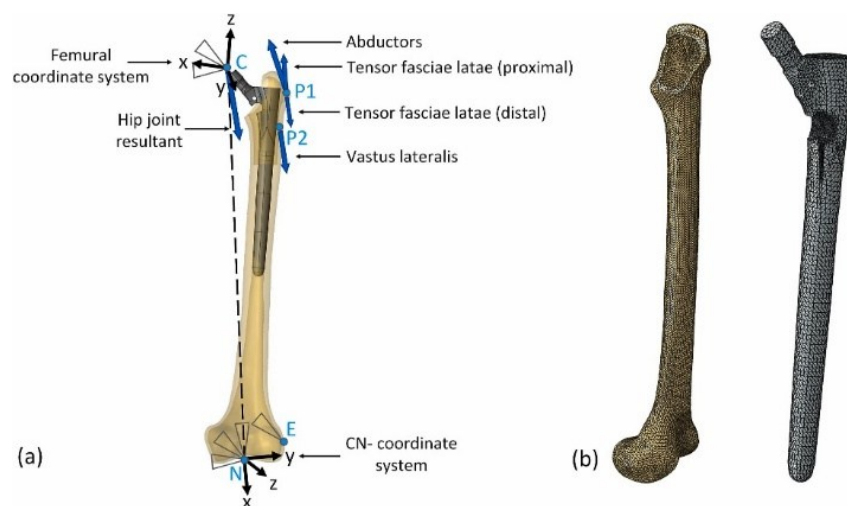


Figure 2.8: a) FE model with landmarks and physiological boundary conditions at the time point of the maximum hip joint resultant during gait. b) meshing of the geometries.

These analyses provide design guidelines regarding mechanical constraints, power output, strain and net forces distribution for future smart implants. The resulting stress distribution and

the integration of piezoelectric components for energy harvesting are illustrated in **Figure 2.9**. However, the evidence remains computational, lacking in vivo validation and clinical testing.

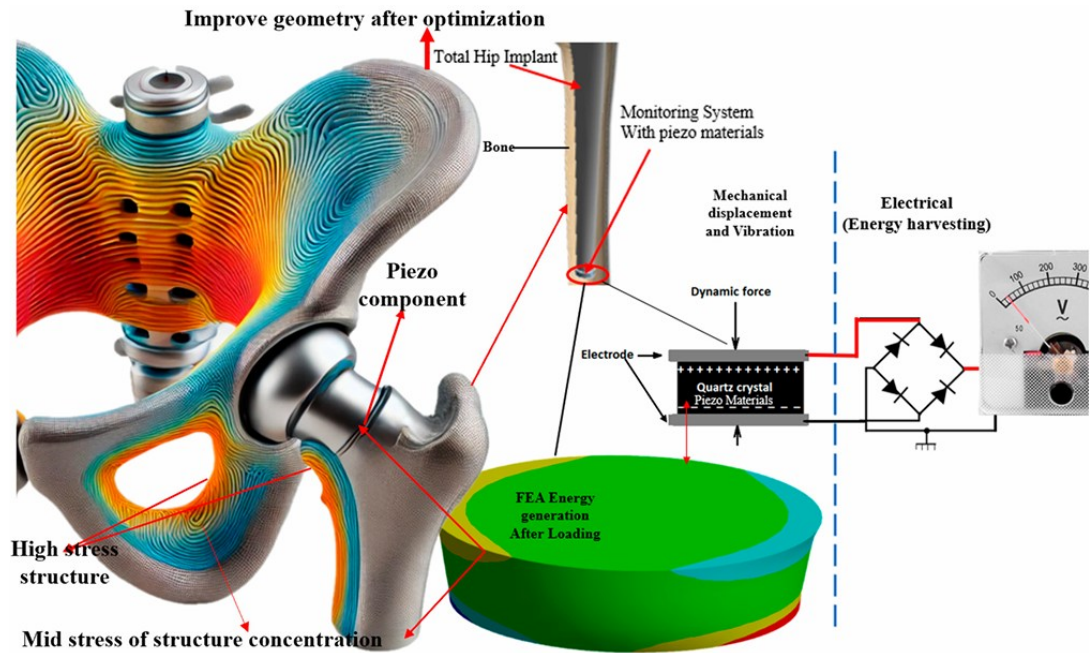


Figure 2.9: The stress distribution in optimized design and femoral bone segment with a modified hip implanted with components of a cylindrical piezoelectric element, and an electrical circuit reading generated.

As far as wearable systems are concerned, hybrid piezoelectric composites, such as *lead-zirconate-titanate* (PZT) or *microfibrillated-cellulose* structures, have been introduced to create thin and flexible plantar-pressure sensors suitable for human-motion monitoring [37]. These devices exhibit good sensitivity, bending capability, and a force-proportional electrical response, making them well-suited for measuring external load distribution during gait. However, because they are integrated into insoles rather than the implant itself, they cannot capture hip joint mechanics or deep-tissue force transmission. Their main relevance lies in demonstrating material performance, packaging strategies, and responsiveness in real-world walking scenarios.

Further developments have focused on *flexible printed piezoelectric arrays*, such as *barium-titanate*-based films arranged in multiplexed sensor grids. These systems enable spatially resolved measurements of dynamic plantar pressure during walking and have been validated in older adults for sarcopenia screening [38]. Their ability to detect load shifts and temporal gait events makes them informative for post-arthroplasty compensation analysis, especially regarding asymmetric load redistribution. Nevertheless, they remain limited to surface measurements and cannot assess internal joint forces or implant mechanics.

Complementary to plantar-pressure solutions, flexible *PVDF*-based piezoelectric strips integrated into garments or attached to the thigh, hip, or knee have been proposed for gait-recognition and posture-transition monitoring. These sensors exploit *PVDF*'s compliance and high sensitivity to dynamic deformation to classify locomotor activities with accuracies exceeding 93% [39]. Their advantages include simple attachment, broad sensing coverage, and effective tracking of walking, sitting, standing, and transitional movements. However, they do not provide information on internal loading conditions, and only indirectly infer compensatory patterns of the hip.

Overall, this technological panorama depicts a clear dichotomy: wearable piezoelectric sensors offer practical, flexible, and high-fidelity measurements of external gait parameters, while structurally integrated piezoelectric components hold promises for autonomous implant monitoring but remain at the preclinical stage. Together, these technologies form a foundation for future multimodal platforms capable of capturing both external compensatory strategies and internal biomechanical indicators relevant to post-arthroplasty rehabilitation.

2.4 IMU-BASED GAIT EVENT DETECTION

Inertial Measurement Units (IMUs) are wearable sensors increasingly adopted for human motion analysis as a cost-effective, portable alternative to traditional Optical Motion Capture (OMC) systems⁴. Modern IMUs are typically based on low-cost micro-electro-mechanical systems (MEMS) technology and integrate multiple sensing components, including:

- **Tri-axial accelerometer**
- **Tri-axial gyroscope**
- **Magnetometer**
- Onboard signal transmission units.

⁴ *Optical Motion Capture (OMC) systems refer to laboratory-based, marker-based motion analysis technologies that use multiple IR cameras to track the three-dimensional trajectories of reflective markers placed on anatomical landmarks.*

The reference coordinate system of a typical IMU, including its sensing axes and associated rotational components, is illustrated in **Figure 2.10**.

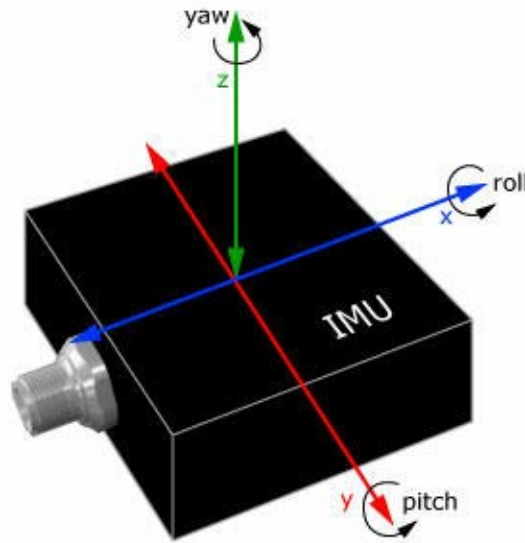


Figure 2.10: IMU reference coordinate system illustrating the sensor axes (x, y, z) and the associated roll, pitch, and yaw rotations used in gait analysis.

By measuring linear accelerations, angular velocities, and orientation relative to the Earth's magnetic field, IMUs enable the reconstruction of body segment kinematics and joint motion during dynamic tasks such as walking.

Compared to laboratory-based OMC systems, IMU-based motion capture offers several advantages, including low cost, ease of customization, flexibility in sensor placement, and enhanced comfort for the user. In rehabilitation contexts, wearable IMU systems are particularly valuable due to their portability and long battery life, enabling continuous monitoring of human movement in daily-life environments and providing complementary information to conventional laboratory assessments. This aspect is especially relevant for gait analysis, where repeated measurements across different contexts and time scales can improve the evaluation of functional performance and recovery. Despite these advantages, IMU-based motion capture systems also present inherent limitations that may affect measurement accuracy. Sensor *drift*, particularly associated with gyroscope integration, can lead to cumulative errors over time. In addition, variations in sensor placement due to soft-tissue motion or loosening of fixation can alter the relative orientation between the sensor and the underlying body segment. Magnetometers are further susceptible to disturbances from external magnetic fields, which can compromise orientation estimation. To mitigate these issues, several methodological solutions

have been proposed, including sensor fusion algorithms, drift compensation strategies, auto-calibration procedures, and integration with complementary sensing modalities.

Within rehabilitation and gait analysis applications, IMU-based systems are commonly employed for two main purposes: *assessment* and *training*. Assessment involves the quantitative evaluation of a patient's movement patterns, functional limitations, and rehabilitation progress by analyzing spatio-temporal, kinematic, and dynamic parameters. Training applications, on the other hand, focus on executing targeted motor tasks and rehabilitation exercises, often supported by real-time feedback to guide the patient toward improved motor performance. Owing to their portability, affordability, and suitability for use outside controlled laboratory environments, IMU-based systems represent a powerful tool for advancing gait analysis and personalized rehabilitation strategies [10].

Importantly, the clinical validity of IMU-based gait analysis has been supported by several studies, demonstrating good agreement with optical motion capture systems. In particular, researchers have highlighted the validity of IMUs for estimating hip range of motion during walking in patients undergoing total hip arthroplasty, using a marker-based optical motion capture system as the reference standard. Results show strong agreement between the two measurement approaches, indicating that even an inertial setup can provide reliable estimates of joint kinematics during gait. Notably, using a single wearable sensor reduces system complexity and improves feasibility in clinical environments, where time constraints and patient compliance are critical. These findings support the application of IMU-based systems for quantitative gait assessment in post-surgical populations, demonstrating their potential to monitor functional recovery and movement quality outside specialized motion analysis laboratories [11]. In gait analysis, identifying key gait events, such as *Heel Strike (HS)*⁵ and *Toe Off (TO)*⁶, is essential for segmenting the gait cycle and enabling the computation of spatio-temporal parameters. IMU-based systems have been widely investigated as alternatives to force plates and OMC for gait event detection, particularly in wearable and real-world monitoring scenarios. Several studies have demonstrated that inertial signals acquired from body-mounted sensors can be effectively exploited to identify HS and TO events by analyzing characteristic patterns in acceleration and angular velocity signals. In particular, peaks and zero-crossings in

⁵ HS is commonly identified by a peak in vertical acceleration associated with a rapid deceleration of the foot, typically observed along the local sensor axis.

⁶ TO is commonly associated with a peak in antero-posterior acceleration, often occurring together with a change in the ankle dorsiflexion–plantarflexion angle.

vertical acceleration and sagittal-plane angular velocity measured at the foot or shank level have been shown to closely correspond to the timing of foot contact and push-off events [40].

This approach enables reliable gait cycle segmentation without the need for external instrumentation, making it suitable for ambulatory gait analysis. More advanced IMU-based gait analysis frameworks have further extended event detection toward full-body motion reconstruction. For instance, IMU-based gait tracking systems can estimate three-dimensional skeletal motion while simultaneously identifying gait events, enabling continuous gait monitoring in unconstrained environments as shown in **Figure 2.11**. Such methods highlight the potential of IMU-based systems to support comprehensive gait analysis, including event detection, kinematic estimation, and temporal parameter extraction, outside specialized motion analysis laboratories [41].

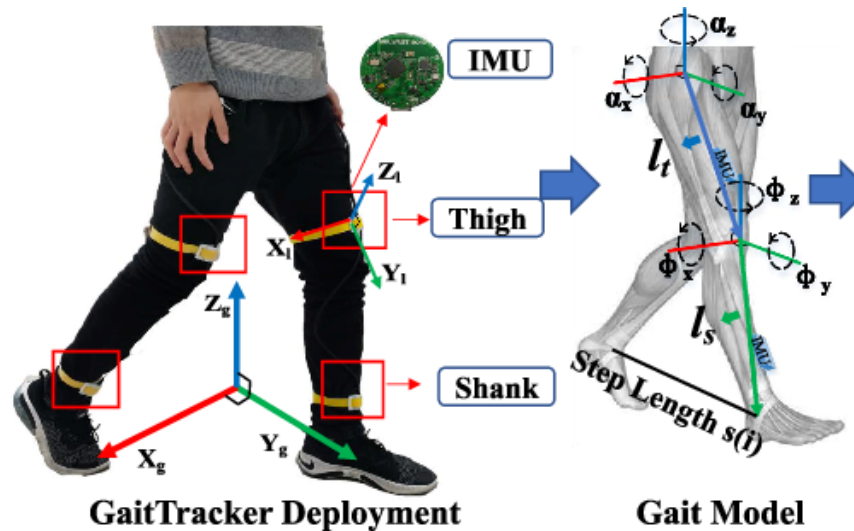


Figure 2.11: Schematic representation of IMU placement on the lower limb for gait analysis applications.

2.5 MOTIVATION FOR A MULTIMODAL APPROACH TO GAIT MONITORING

The technological overview presented in this chapter highlights the rapid evolution of sensing solutions for gait analysis, particularly in the context of orthopedic rehabilitation and post-arthroplasty monitoring. Current approaches offer distinct advantages but also present important limitations. Most of them rely on *single-modality sensing* approaches, focusing either on mechanical motion (e.g., IMU-based kinematics) or on muscular activation patterns (e.g., EMG). This separation limits the ability to fully characterize the

complex interactions between muscle activation, mechanical vibration, and segmental motion that occur during locomotion. Recent research suggests that a *multimodal sensing* strategy combining electrophysiological and mechanical signals may provide a more comprehensive representation of gait dynamics. This approach can potentially improve the detection of subtle gait alterations, enhance the interpretation of muscle function during locomotion, and provide clinically meaningful biomarkers for monitoring rehabilitation progress after orthopedic interventions. Although MMG has been widely investigated in controlled laboratory conditions, its application in dynamic locomotion tasks such as walking remains relatively underexplored in literature. For this reason, integrating MMG with EMG and inertial sensing may offer complementary information on the neuromechanical processes underlying gait, enabling a more comprehensive characterization of muscle activation and movement dynamics.

Based on these considerations, the present study proposes a wearable multimodal sensing platform integrating EMG, MMG, and IMU signals to investigate gait dynamics during walking. The main objectives of this framework are:

- to simultaneously capture electrophysiological and mechanical markers of muscle activity during gait,
- to enable reliable detection of gait events and cycle segmentation through inertial sensing,
- to investigate the temporal relationship between EMG activation, MMG mechanical response, and limb kinematics,
- and to evaluate the feasibility of such an integrated system for quantitative gait assessment in rehabilitation contexts.
- By combining complementary sensing modalities within a unified acquisition and analysis framework, the aim is to provide a physiologically informative characterization of gait, potentially supporting improved monitoring of functional recovery and patient-specific rehabilitation strategies after hip arthroplasty.

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CHAPTER 3

MULTIMODAL SENSORS SETUP AND INSTRUMENTATION

“I have not failed.

I have just found 10.000 ways

that won’t work.”

— *Thomas Edison*

This chapter presents the design and implementation of a custom multimodal sensing platform for the acquisition of neuro-mechanical signals during dynamic motor tasks. The proposed system integrates surface electromyography (sEMG), mechanomyography (MMG), and inertial measurements (IMU) within a wearable architecture specifically developed for lower-limb applications. Emphasis is placed on the design of the electronic circuitry, sensor interfacing, and system integration, as well as on the adoption of Aluminium Nitride (AlN) piezoelectric sensors for MMG acquisition. The use of AlN technology represents a key element of novelty: these piezoelectric sensors enable direct characterization of the mechanical response of muscle contraction, acting as the mechanical counterpart to conventional EMG measurements, which primarily reflect neural activation. The chapter also describes sensor placement strategies, acquisition configurations, and the data acquisition software, highlighting the rationale behind the multimodal approach and its potential for comprehensive characterization of muscle activation and movement dynamics.

3.1 AlN PIEZOELECTRIC SENSORS FOR MMG DETECTION

In the present study, piezoelectric sensors fabricated from Aluminium nitride (AlN) were employed to acquire MMG signals. This material is particularly distinguished by its ability to be deposited at relatively low temperatures while retaining its intrinsic physicochemical characteristics as a thin film. Such films offer several advantages, including low hysteresis, high sensitivity, reduced power consumption, and the ability to generate substantial mechanical deflections.

3.1.1 Aluminum Nitride – based sensor architecture and fabrication protocol

The wearable and flexible AlN-based smart sensor is currently manufactured at the IIT – *Center for Biomolecular Nanotechnologies* in Arnesano (LE). The device is composed exclusively of biocompatible and non-toxic materials, thereby minimizing the risk of allergic reactions or skin irritation. The AlN piezoelectric sensor features a multilayer architecture designed for flexible and high-performance operation, as schematically illustrated in **Figure 3.1**.

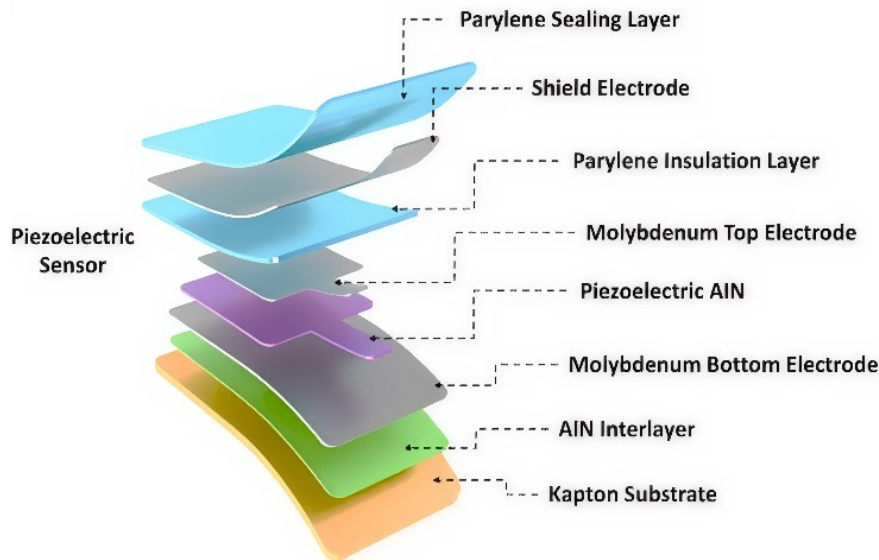


Figure 3.1: Schematic illustration of the sensor's multi-layered structure. The stack consists of an Aluminium Nitride interlayer (AlN-IL, 120 nm), a Molybdenum bottom electrode (Mo, 200–250 nm), a piezoelectric AlN film (1 μm), and a Molybdenum top electrode (Mo, 250 nm) deposited onto a 25 μm -thick Kapton substrate laminated on a 4-inch Silicon wafer (Si 545 μm thick, undoped, single-side polished) using a thin layer of polydimethylsiloxane (PDMS) as adhesive. The PDMS layer is thermally treated at 90 °C for 15 minutes to ensure optimal adhesion, while Kapton provides a thermally and mechanically stable platform compatible with the AlN deposition temperature (~170 °C) and is chosen for its excellent electrical, dielectric, thermal, and mechanical properties.

The microfabrication process begins with sputtering the AlN interlayer using a pure Al target (99.9995%) in a mixture of Ar and N₂ gases (ratio 1:1) under pulsed DC power, providing a template to reduce the amorphous polyimide surface and promote high columnar orientation of the piezoelectric AlN film, thereby ensuring robust adhesion to the polymeric substrate. The Mo bottom electrode is deposited in the same run, using a pure Mo target (99.95%) in a pure Ar atmosphere. The patterning of the Mo layer and the AlN interlayer was achieved via dry etching with ICP-RIE (Inductively Coupled Plasma – Reactive Ion Etching). Subsequently, the piezoelectric AlN film and Mo top electrode are sputtered without substrate heating and patterned under similar conditions. A thin Titanium adhesion layer (30 nm) supports the top electrode, which, along with the underlying metallic layers, functions as an electromagnetic shield. The complete stack is encapsulated between two Parylene-C coatings by chemical vapor deposition: the inner layer prevents electrical shorting to the top electrode, while the outer layer provides passivation and waterproofing. Vias for electrical connections are opened through the Parylene by oxygen plasma etching, and the device is finally cut and peeled off the rigid Si substrate, yielding a flexible sensor approximately 26 μm thick with a total area of 2 cm² (**Figure 3.2**).

The packaging and electrical connections of the sensor are crucial for ohmic-contact MEMS devices, particularly for soft and flexible ones, where electrical connectors are typically difficult to produce. The ability to produce electric pads in a sealed package that embeds the flexible piezoelectric transducer is an innovative fabrication aspect of the sensor presented in this work. **Figure 3.3** illustrates the main steps involved in fabricating the sensor package using a 3D printing system (DragonFly LD, Nano Dimensions).

This advanced printer is equipped with two independent print heads, one for nano-silver conductive ink (CI) and one for dielectric polymer ink (DI), allowing both materials to be deposited within the same printing process. The device is built directly onto the Kapton substrate through precise layer-by-layer deposition, with hundreds of nozzles accurately jetting conductive and dielectric inks according to the electrode geometry. Additional printed layers define the electrode vias and create the platform for the radiofrequency (RF)

connector. The RF connector preserves electrical performance while maintaining useful characteristics of the sensors, such as lightweight and flexibility.

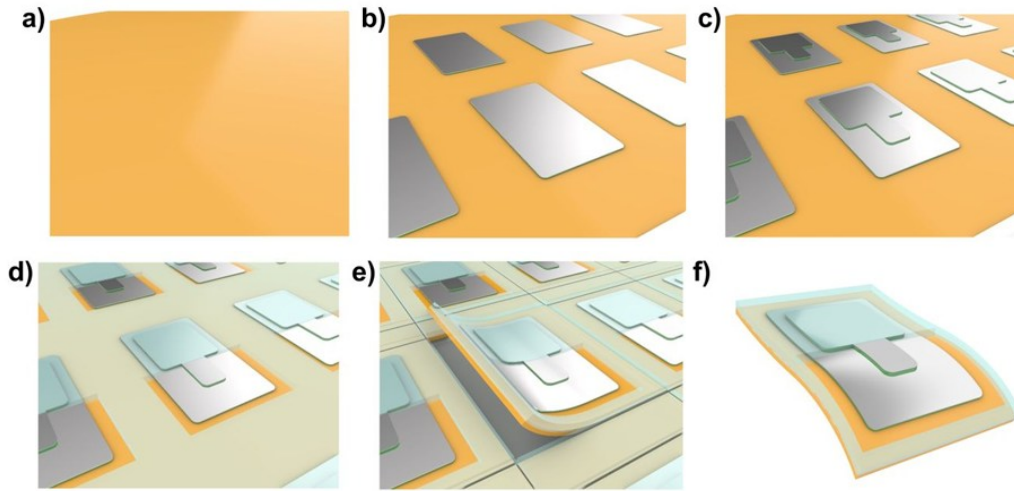


Figure 3.2: Schematic representation of the main microfabrication process steps for the production of sensors. (a). A thin-film stack composed of an AlN interlayer (120 nm) and a Mo bottom electrode (200 nm) is deposited and patterned by photolithography and dry etching (b). Deposition and modelling stages are also performed for piezoelectric AlN (1 μ m) and a Mo top electrode (200 nm) (c). An insulating 1 μ m-thick Parylene film is deposited over the entire sensor surface. Vias for electrical connection are opened by oxygen plasma (d). The sensors are cut and released (e). Sensor is ready for the electrical connections (f).

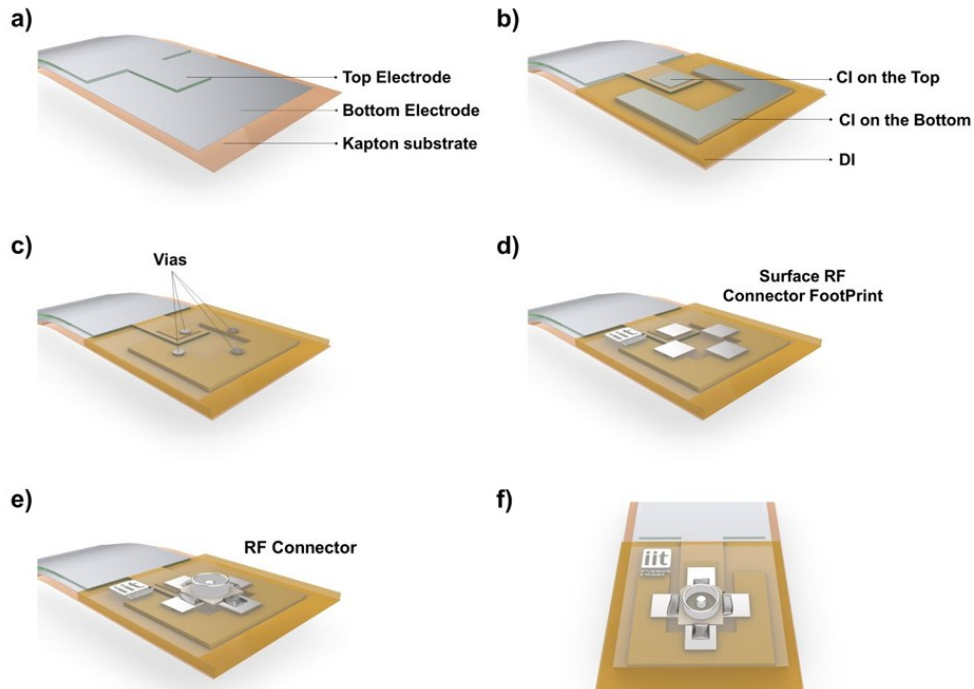


Figure 3.3: Schematic representation of the main printing steps required for package and electrical connection of the sensors. (a). A concurrent deposition of CI and DI inks is made on bottom and top electrode (b). Vias are deposited in order to connect the sensor electrical pads with the RF connection pads (c). Platforms for RF connection are printed (d). RF connector is weld on sensor (e). Sensor is ready for testing (f).

This multilayer design and fabrication approach ensures the sensor's mechanical flexibility, electrical stability, and overall suitability for integration into wearable systems for gait analysis and muscle activation monitoring. To further enhance its applicability to the human body, particular attention was devoted to the device's conformal attachment to the skin. Effective contact must be strong enough to ensure accurate signal acquisition, allow painless removal to prevent epidermal irritation, and maintain minimal interfacial mechanical stress to avoid constraining the user's natural movement. For this purpose, an additional thin layer was applied to the back of the sensor, i.e., the surface intended to interface with the skin. This layer consists of a soft, stretchable, and tacky *polydimethylsiloxane (PDMS)-based elastomer*, obtained by incorporating a small amount of *ethoxylated polyethylenimine (PEIE)* into the PDMS base and curing agent. The inclusion of this amine-based additive significantly reduces the elastic modulus of PDMS (from ~1 MPa down to ~24 kPa), improving its mechanical compliance with the skin and enhancing adhesion through increased *Van der Waals* interactions promoted by the viscous PDMS-PEIE surface adaptation [1], [2], [3].

The developed piezoelectric sensor was originally calibrated on a PDMS membrane for pharyngeal pressures in the range of 10-50 kPa [2]. In this setup, controlled pressures were applied using a solenoid-driven air flux, and the generated open-circuit voltage was measured to obtain the voltage-pressure calibration curve shown in **Figure 3.4**, demonstrating a linear response over the tested range. Although the previous calibration provides a useful reference for the expected pressure range, it cannot be considered a direct calibration for gait-related MMG measurements. The mechanical pathway from intramuscular pressure to skin-surface deformation includes tissue filtering, attenuation, sensor-skin coupling, and local anatomical variability. Therefore, the calibration curve should be used as an order-of-magnitude reference, while task-specific calibration or validation is required for quantitative pressure estimation during gait. To adapt this calibration for gait analysis, *intramuscular pressures (IMP)* reported in the literature for key lower-limb muscles were considered. For instance, quadriceps IMP during moderate contractions ranges approximately 10-20 kPa, reaching 30-50 kPa under near-maximal exertion [4], [5]. During treadmill walking, soleus IMP peaks at ~24 kPa, and tibialis anterior IMP reaches ~11 kPa [6]. These pressures are commonly reported in *mmHg* and have been converted to kPa (1 mmHg ~ 0.133 kPa) to provide a direct reference for the sensor's calibrated units. It is important to emphasize that the piezoelectric sensor captures only the

dynamic pressures conveyed through the superficial tissues, which represent an attenuated yet proportional fraction of the actual intramuscular pressure.

Therefore, while IMP values provide a useful estimate of the order of magnitude of muscular forces, the actual surface pressures detected by the sensor are typically lower, in the range of 1-20 kPa, depending on the muscle, tissue thickness, and subject-specific factors. While the sensor was not directly calibrated for locomotor applications, the voltage-pressure relationship established in the swallowing study, covering 0-50 kPa, can be empirically applied.

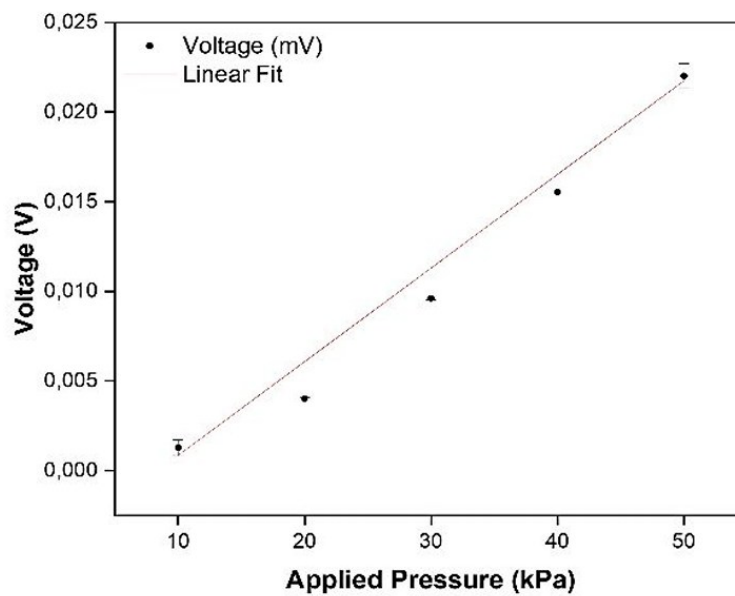


Figure 3.4: Piezoelectric sensor linear response to a pressure variation between 10kPa and 50kPa.

3.1.2 Sensor placement strategy

The placement of the piezoelectric MMG sensor is a crucial step in ensuring reliable acquisition of muscle mechanical activity during dynamic conditions, such as gait. In the present study, the Aluminium Nitride (AlN) piezoelectric sensor was positioned over the *rectus femoris* muscle belly, between the sEMG electrodes, following the same anatomical reference defined according to SENIAM guidelines (**Figure 3.5**). The rectus femoris was selected as the target muscle for the first implementation of the multimodal setup because it provides a superficial and anatomically accessible site, is suitable for standardized SENIAM-based electrode placement, and is actively involved in lower-limb advancement and knee stabilization during gait. Although hip abductors, such as the gluteus medius, are

highly relevant to post-THA compensatory patterns, the rectus femoris is a practical target for initial system validation and for assessing the temporal relationships among EMG activation, MMG response, and inertial gait segmentation.

The spatial alignment between EMG and MMG sensors enables a direct comparison of neural activation in the muscle and the resulting mechanical oscillations, reducing variability due to anatomical heterogeneity and improving the interpretation of electromechanical coupling. Furthermore, particular attention was devoted to the mechanical coupling between the sensor and the skin. The use of a compliant PDMS-based interface allowed conformal contact with the skin surface, minimizing motion artifacts while preserving natural tissue deformation. To further enhance adhesion and ensure stable contact during dynamic movements, the sensor was additionally fixed to the skin using the pressure-sensitive adhesive *Derma-tac*TM [7].

This combined approach provided a soft and compliant interface together with reliable adhesion, minimizing relative motion between the sensor and the skin and thereby improving signal stability and repeatability. This aspect is particularly important for piezoelectric sensing, as the signal amplitude and quality depend strongly on the mechanical transmission from the underlying muscle to the sensor.

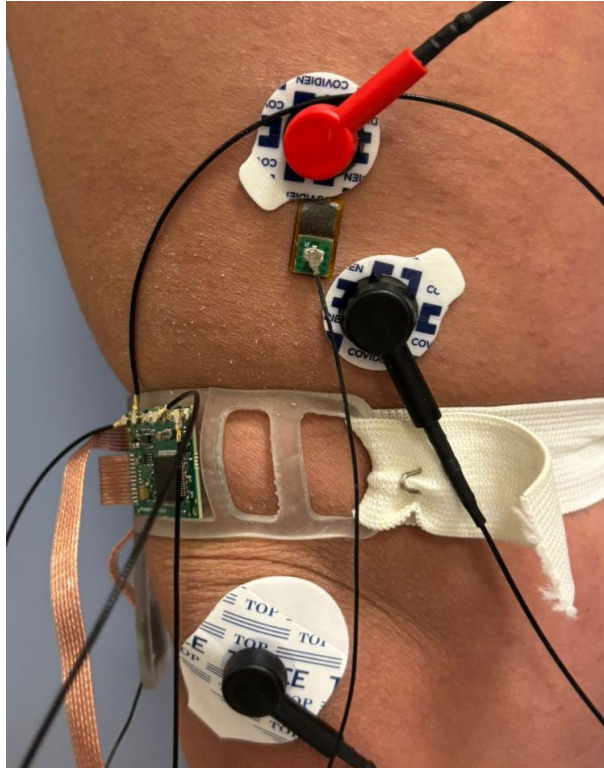


Figure 3.5: ALN piezoelectric sensor placement along rectus femoris between sEMG positive and negative electrodes. Measurement session carried out at the IIT-CBN laboratories.

3.2 ELECTRONIC ARCHITECTURE

This section presents the design of a wearable electronic system for the acquisition of bio-signals related to compensatory gait patterns characterization. The device, lightweight, elastic, and wireless, is intended for lower-limb application and it is shown in **Figure 3.6**.

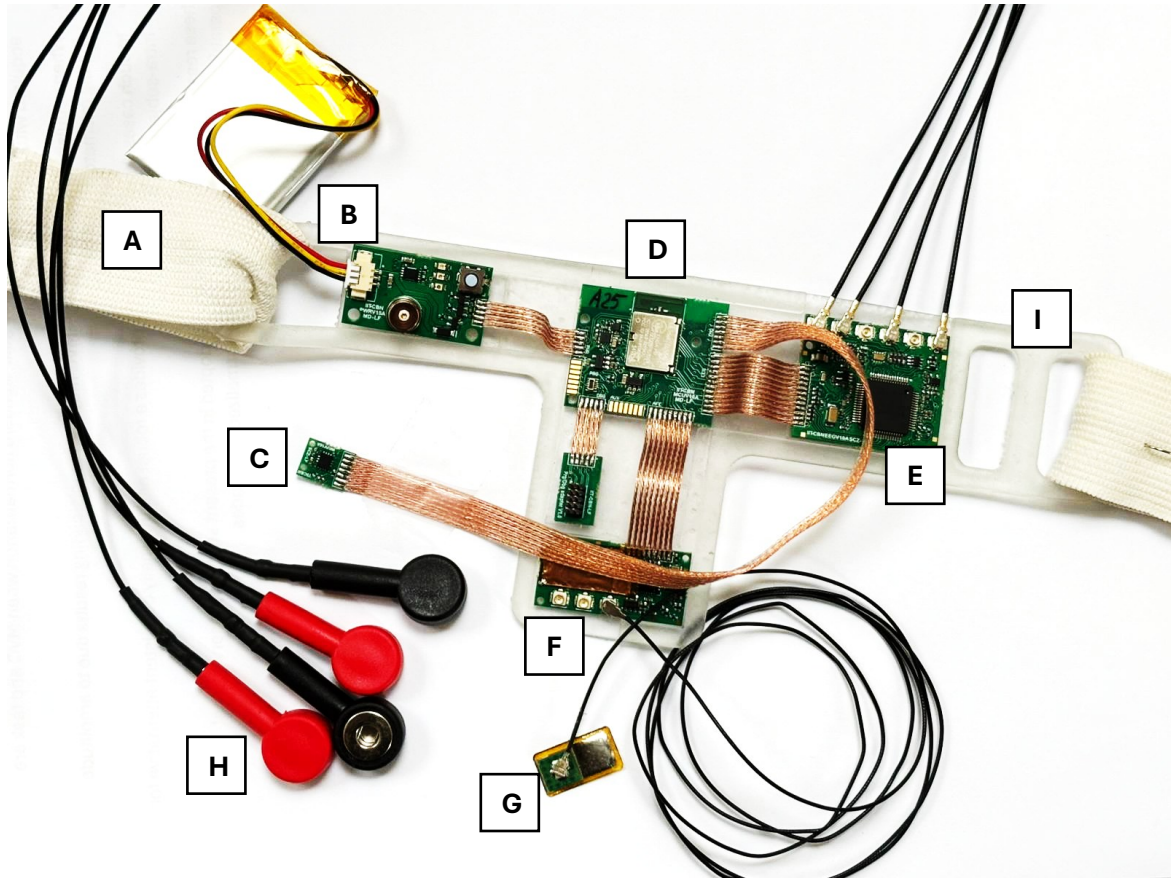


Figure 3.6: Multimodal wearable experimental setup: (A) elastic strap, (B) Power Module, (C) IMU, (D) Microcontroller Unit, (E) surface EMG module, (F) AFE piezo module, (G) AlN piezoelectric sensor, (H) U.FL connectors, (I) 3D-printed flexible case.

The circuitry is described in detail, with emphasis on the primary hardware subsystems, their functional roles, interconnections, and the underlying design rationale. The system architecture comprises multiple functional modules, each dedicated to a specific task, ranging from data acquisition and processing to information transmission. The coordinated interaction among these blocks enables the implementation of the intended device functionalities. Signal conditioning units, power circuits, and input-output modules operate in a coordinated manner, contributing to the system's overall performance and reliability.

3.2.1 Power Module

The system is powered by a compact 3.7 V Lithium-polymer (Li-Po) battery (30 mm × 35 mm), which is physically and functionally connected to the *Power Module* (**Figure 3.7**), a dedicated electronic circuit responsible for overall power management.

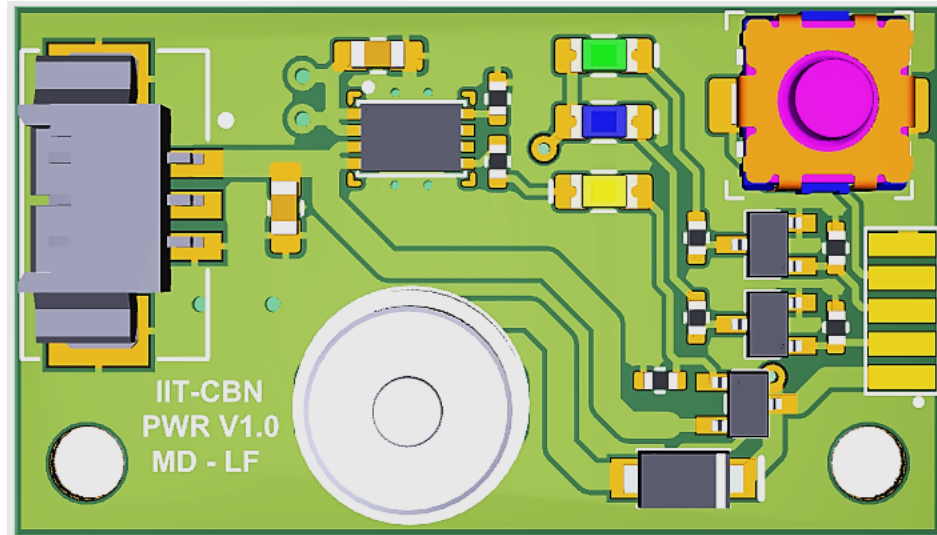


Figure 3.7: Power Module board layout (16 mm x 28 mm).

The module integrates a battery charging circuit based on the *MCP73831-2ACI/MC* [8] (U1), which efficiently regulates the charging process and provides a visual indication of charge status via LED, as presented in the schematic in **Figure 3.8**.

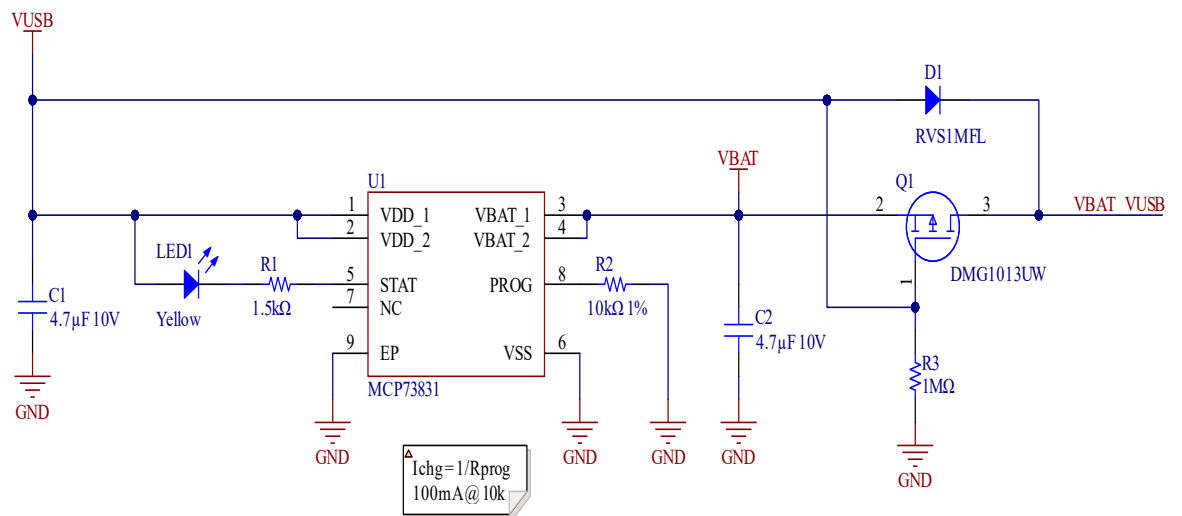


Figure 3.8: Circuit schematic for battery charging through the Microchip Technology integrated circuit "U1".

The *Power Module* delivers stabilized output voltages of 3 V and 1.8 V through two 4-pin connectors, supplying power to the microcontroller unit (MCU) and to the various sensor modules. Stable voltage regulation is ensured by two LDO (*Low Drop-Out*) regulators: the

ADP160AUJZ-3.0 (U3) for 3 V and the *ADP160AUJZ-1.8* (U4) for 1.8 V [9]. A schematic representation of the power supply architecture is described in **Figure 3.9**.

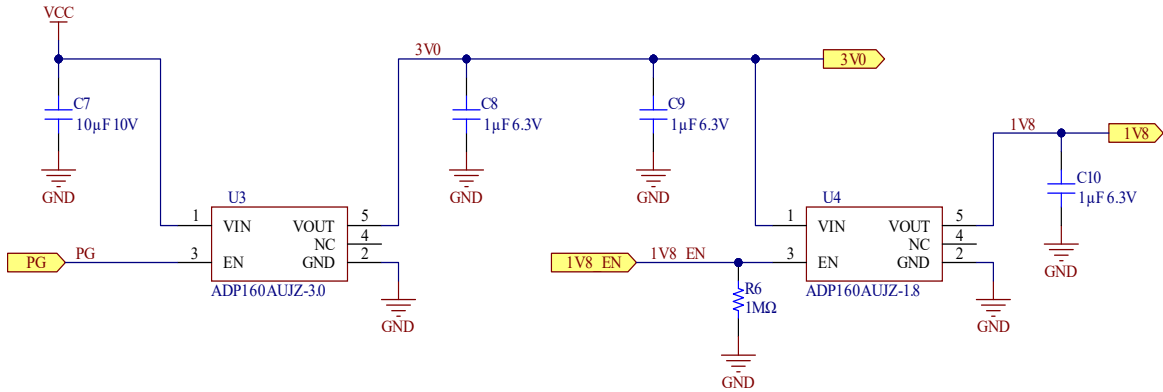


Figure 3.9: Power supply section equipped with LDO voltage regulators, where U3 provides 3 V and U4 supplies 1.8 V.

Primary power control and device on-off logic are managed by the *XC6194A* [10] (U2), an ultra-low-power load switch designed for battery-powered wearable devices. This component consumes only 1 nA in standby and provides advanced protection features, including inrush current limitation, overcurrent and short-circuit protection, and thermal shutdown. In the implemented configuration, the module applies predefined delays: 1 second for turn-on (*Turn-on Delay Time*) and 3 seconds for turn-off (*Turn-off Delay Time*), controlled via a dedicated push button. The schematic of the on-off logic is shown in **Figure 3.10**.

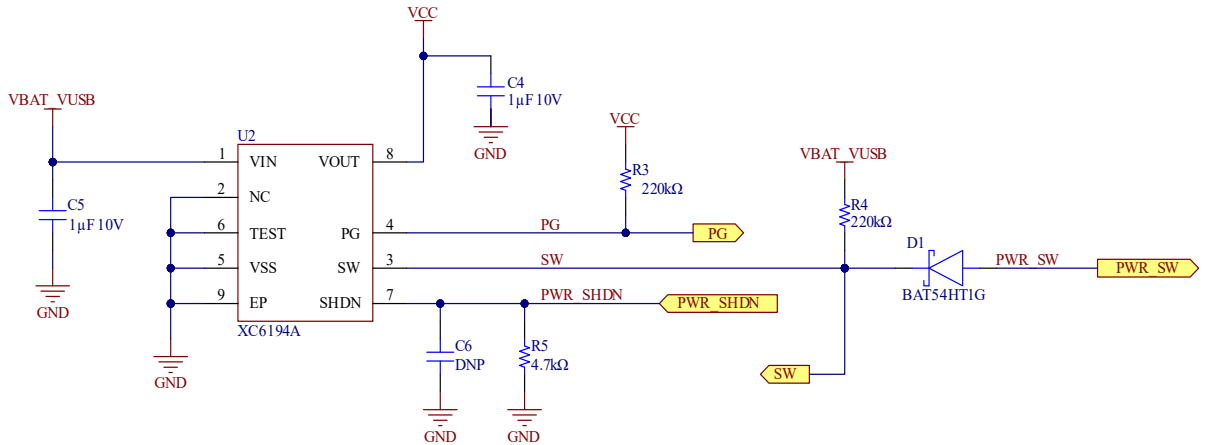


Figure 3.10: Circuit schematic enabling device on-off logic control through the integrated circuit "U2".

The charging circuitry includes three main connectors: a 3-pin *Molex header* (J2) model 53261-0371 [11] for battery connection (VBAT and GND), a magnetic *pogopin* connector [12] (J3) for convenient charging via a magnetically coupled cable, and a 5-pin *header* (J1)

providing VBAT_VUSB, GND, LED indicators, and push-button (SW) signals. The *MCP73831-2ACI/MC IC* monitors charge status, regulates charging current, and drives LEDs to indicate charging progress. The *XC6194A* load switch manages power sequencing for the MCU and other modules, enabling controlled device activation via a single push-button. The module ensures reliable, efficient power delivery while maintaining compactness and suitability for wearable applications.

3.2.2 MCU (Microcontroller Unit) and wireless communication module

The microcontroller (MCU) board in **Figure 3.11** is responsible for processing and transmitting data collected from the various sensors. It incorporates the *Kaga Fei EB5340BA1* module [13], a compact high-performance solution with integrated Bluetooth Low Energy (BLE) functionality. The module is based on the *nRF5340 System-on-Chip (SoC)* from *Nordic Semiconductor* [14], featuring a dual-core architecture with an integrated antenna.

In this project, the two cores serve complementary roles: one core processes sensor data, while the other manages the BLE transmission of the processed data to an external device. Communication is established with an *nRF52840 Dongle*, which supports multiple connections using the *Multi-NUS (Nordic UART Service)* protocol and routes messages between the MCU and the data acquisition system. This setup simplifies software interfacing by emulating a virtual serial connection, enhancing efficiency, stability, and control. Although the present study focuses on EMG acquisition, the MCU board is designed to support a variety of bio-signals, including EEG, PPG, ECG, and temperature.

The board connects the *EB5340BA1* module [8] to multiple subsystems via dedicated headers: the IMU module connects via SPI through J2 (HDR-IMU); the EMG module interfaces through J4 (HDR-EMG), which is repurposed for EMG in this implementation; the piezoelectric signal module via J5 (HDR-AFE); auxiliary inputs via J6 (HDR-AUX); programming and debugging via J7 (HDR-DBG); and an additional programming module interfaces through J8.

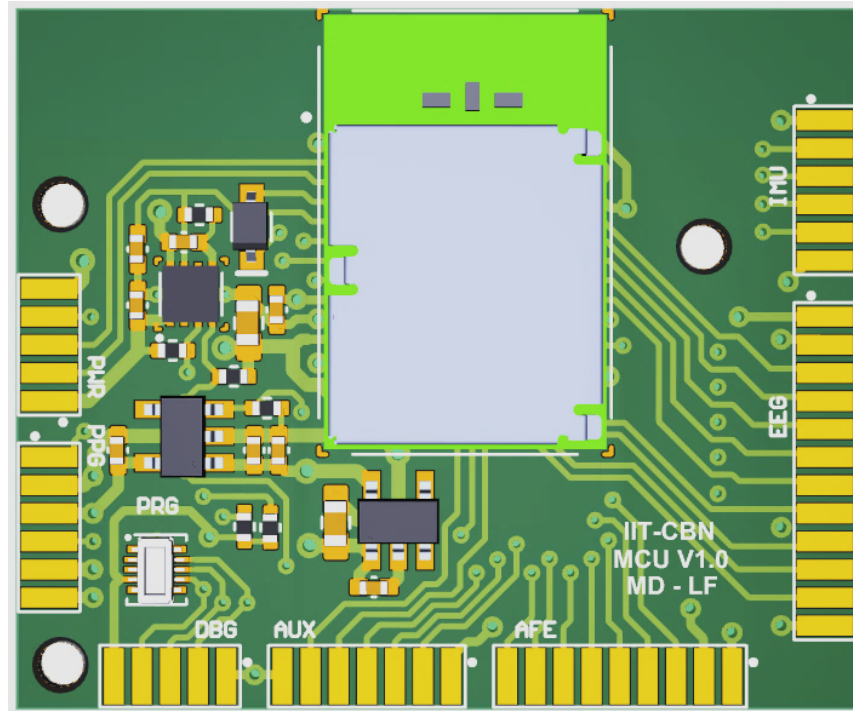


Figure 3.11: MCU board layout (25 mm x 22 mm).

3.2.3 EMG acquisition board

Surface electromyographic (sEMG) signals were acquired using a bipolar electrode configuration interfaced with a dedicated analogue front-end based on the *ADS1299* integrated circuit [15]. As shown in the circuit schematic of the *ADS1299* (**Figure 3.12**) and in the U.F.L [16] connector layout of the acquisition board, each EMG channel is implemented through a pair of differential inputs, namely a positive input ($INxP$) and a negative input ($INxN$), which are connected to the corresponding surface electrodes placed over the muscle belly along the direction of the muscle fibers.

The differential configuration allows the selective amplification of myoelectric activity while attenuating common-mode interference. In addition to the differential electrode pair, the system employs a *Reference electrode*, connected to a dedicated reference input shared among channels, which provides a stable electrical reference for the instrumentation amplifier. This electrode is positioned on an electrically inactive region, typically a bony prominence, in order to minimize contamination from myoelectric signals. Furthermore, an *active Bias electrode* is implemented and connected to the *ADS1299*'s specific bias output. This electrode is used to drive the subject's body potential via a feedback mechanism analogous to a *Driven-Right-Leg (DRL) configuration* [17], to reduce common-mode

voltage and improve the effective CMRR (*Common-Mode Rejection Ratio*), particularly in dynamic measurement conditions.

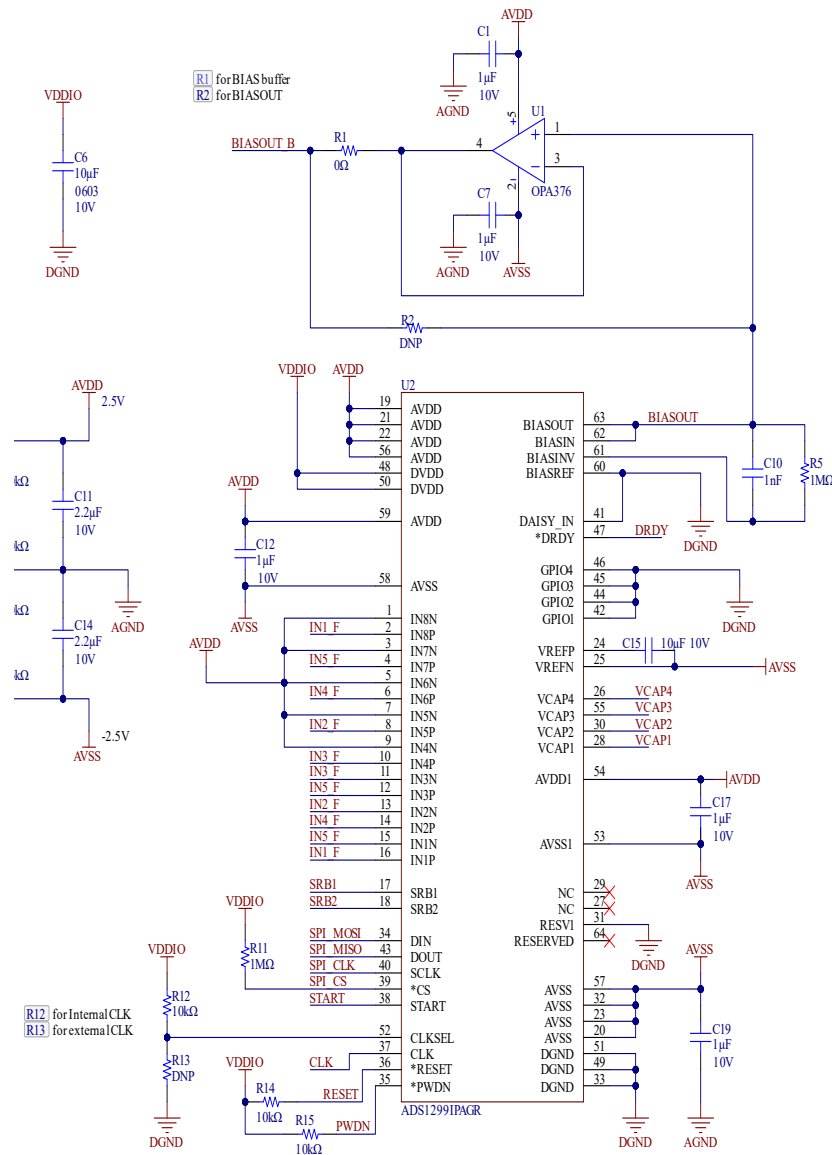


Figure 3.12: ADS1299IPAGR analog front-end schematic highlighting differential input pins (INxP, INxN), reference, and bias connections used for surface EMG acquisition.

The acquisition board exposes these signals through six U.FL *CL331* connectors [16], as illustrated in **Figure 3.13**: two connectors are assigned to the positive and negative inputs of the first EMG channel, two connectors correspond to the positive and negative inputs of a second differential channel, while the remaining connectors are dedicated to the common reference and bias electrodes. This architecture allows the system to operate either in a single-channel EMG configuration or to be straightforwardly extended to simultaneous acquisition of two independent bipolar EMG signals, sharing the same reference and bias

electrodes. Such flexibility enables multi-muscle analysis during dynamic tasks, without requiring modifications to the hardware architecture.

u.FL connectors

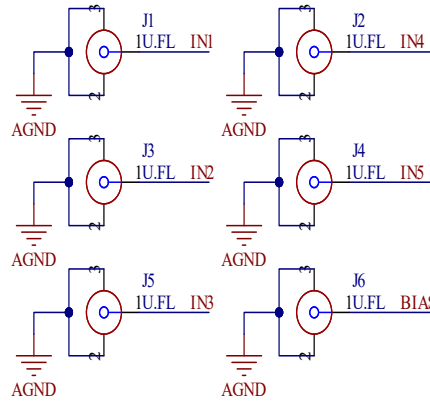


Figure 3.13: U.FL connectors layout of the acquisition board showing the allocation of differential EMG inputs.

To ensure an input bandwidth suitable for surface electromyographic signal acquisition, a passive analog filtering stage was implemented at the front-end input, as shown in **Figure 3.14**.

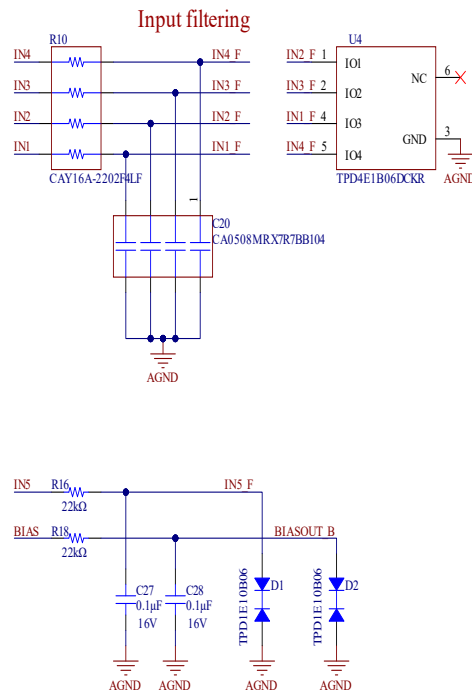


Figure 3.14: Input filtering stage for EMG channels.

Specifically, a *first-order low-pass RC filter* was employed at each differential input of the *ADSL299* to limit high-frequency noise and prevent aliasing prior to ADC conversion. The filter components were selected as $R = 3.3 \text{ k}\Omega$ and $C = 0.1 \mu\text{F}$, resulting in a cut-off frequency of approximately $f_c = 480 \text{ Hz}$, according to the standard relationship:

$$f_c = \frac{1}{2\pi RC}.$$

A first-order filter was selected for its gentle roll-off, which minimises attenuation within the frequency band of interest. Notably, at frequencies close to the cutoff, such as 500 Hz, which lies only about 20 Hz above the selected cutoff frequency, the filter's attenuation is essentially negligible. The cutoff frequency was selected to preserve the main spectral content of surface EMG while attenuating high-frequency noise and limiting aliasing. Since a first-order low-pass filter introduces gradual attenuation near the cutoff frequency, the selected cutoff must be sufficiently above the main EMG bandwidth to avoid relevant distortion of physiological components. At the same time, the filter provides effective suppression of higher-frequency noise components, representing an appropriate compromise between signal fidelity and noise reduction for dynamic measurements. By tailoring the analog front-end bandwidth to the physiological characteristics of the EMG signal, the proposed configuration improves overall signal quality while maintaining compatibility with subsequent digital processing stages. The PCB layout is reported below in **Figure 3.15** and **Figure 3.16** to provide a clear visualization of the connector arrangement and the J1-J6 identifiers used in the EMG channel wiring configuration.

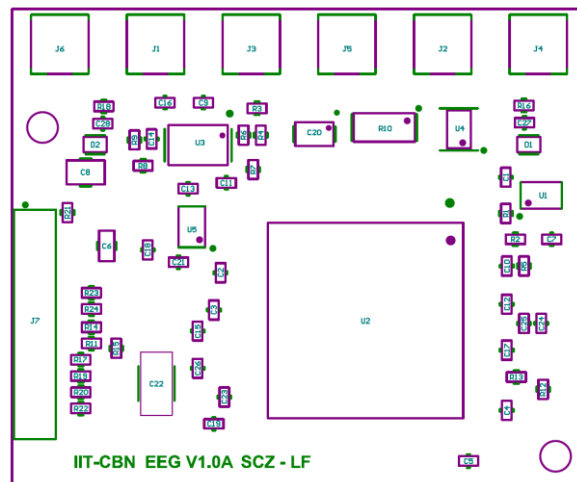


Figure 3.15: Top-layer PCB layout of the surface EMG acquisition board with connector identification (J1–J6).

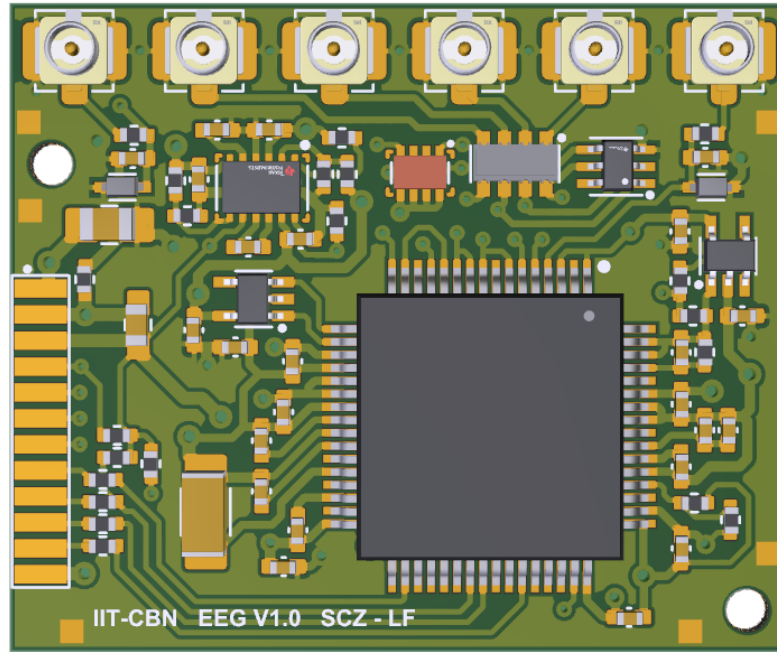


Figure 3.16: EMG acquisition board layout (30 mm x 30 mm).

3.2.4 MMG analog front-end

The AFE (*Analog Front-End*) module is shown in **Figure 3.17**. It is responsible for the acquisition and conditioning of mechanomyographic (MMG) signals produced by muscle contractions using the fabricated flexible Aluminum nitride (AlN) piezoelectric sensors. In particular, the system allows simultaneous measurement of up to three mechanical signals by connecting three piezoelectric sensors.

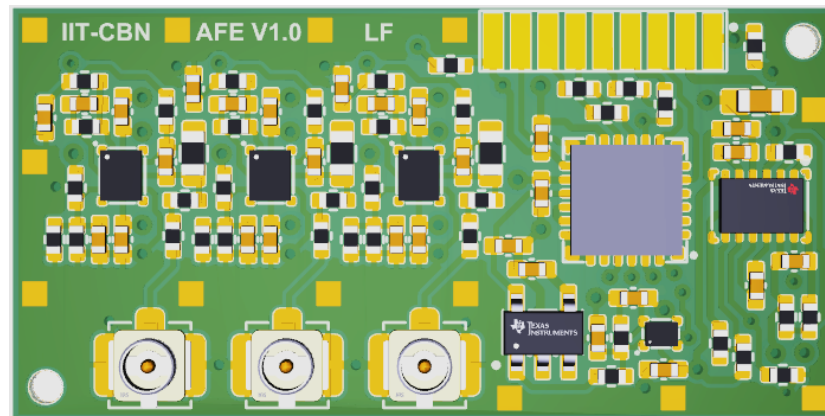


Figure 3.17: AlN AFE board layout (30 mm x 20 mm).

The acquisition circuit consists of two stages, both implemented with the *AD8506* operational amplifier (*Analog Devices*) [18]. In the first stage, the amplifier is configured as an integrator, converting the charge from the piezoelectric sensor into a proportional voltage. The second stage applies a second-order active low-pass filter, also using the *AD8506* in a

non-inverting configuration, to condition and smooth the signal. The stages are shown in **Figure 3.18**.

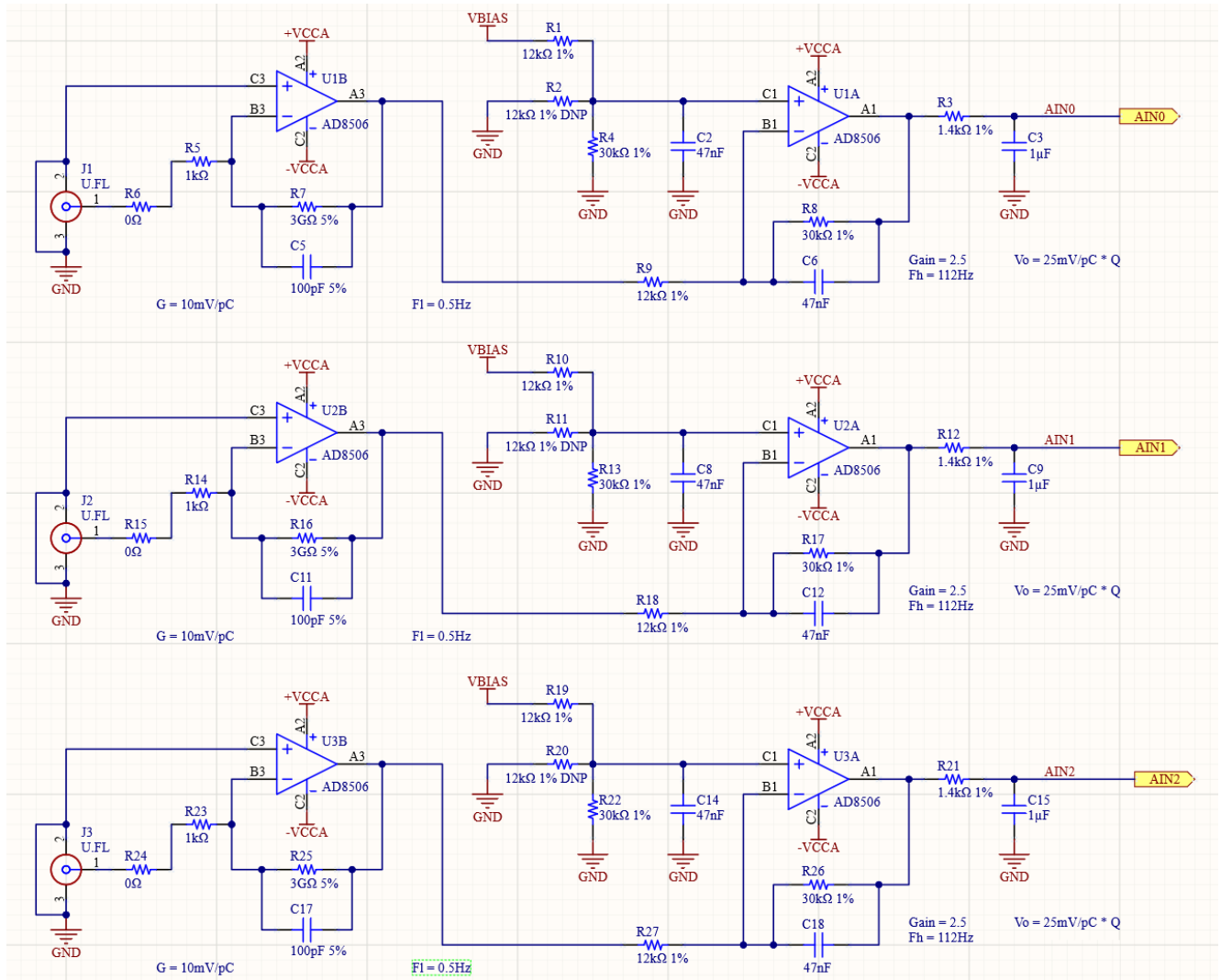


Figure 3.18: Two-stages conditioning circuit for the piezoelectric sensors.

The board includes three U.FL CL331 connectors (Hirose) [9] for connecting sensor cables (**Figure 3.19**), providing a secure and reliable electrical interface.



Figure 3.19: U.FL connector.

3.2.5 IMU (Inertial Measurement Unit) board

LSM6DS3 [12] is a 6-degree-of-freedom (6 DoF) IMU that integrates a 3-axis accelerometer and a 3-axis gyroscope within a single compact package, providing a high-performance, low-power solution for motion tracking. In this design (**Figure 3.20**), the *LSM6DS3* communicates with the microcontroller via SPI, chosen over I²C to ensure higher data throughput and minimize interference in a multi-sensor environment. The main specifications are:

- **Accelerometer ranges:** $\pm 2g$, $\pm 4g$, $\pm 8g$, $\pm 16g$
- **Gyroscope ranges:** ± 125 , ± 250 , ± 500 , ± 1000 , ± 2000 dps
- **Maximum output data rate:** 6.6 kHz for both accelerometer and gyroscope
- Low-power modes for energy-efficient operation.

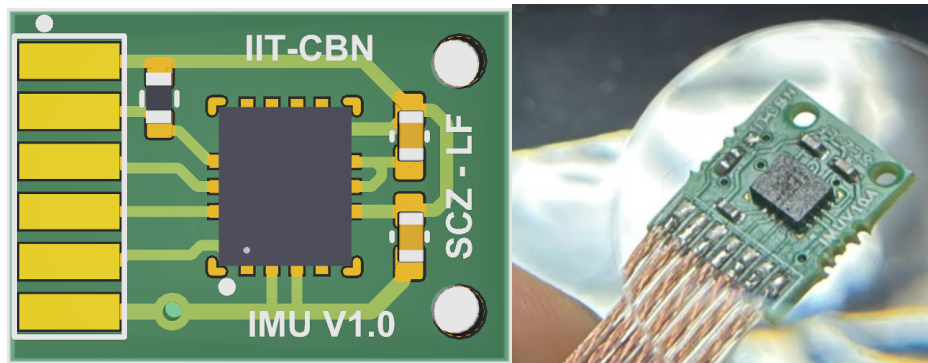


Figure 3.20: IMU board layout and its actual retail version (6 mm x 5 mm).

The supporting circuitry illustrated in **Figure 3.21** includes a 6-pin header (J1) for power and SPI connections, two 0.1 μF ceramic decoupling capacitors (C1, C2) to reduce high-frequency noise and stabilize the supply voltage, and a 1 M Ω resistor (R1) acting as a *pull-up* or *pull-down* to manage the logic of the *Chip Select* (CS) line effectively.

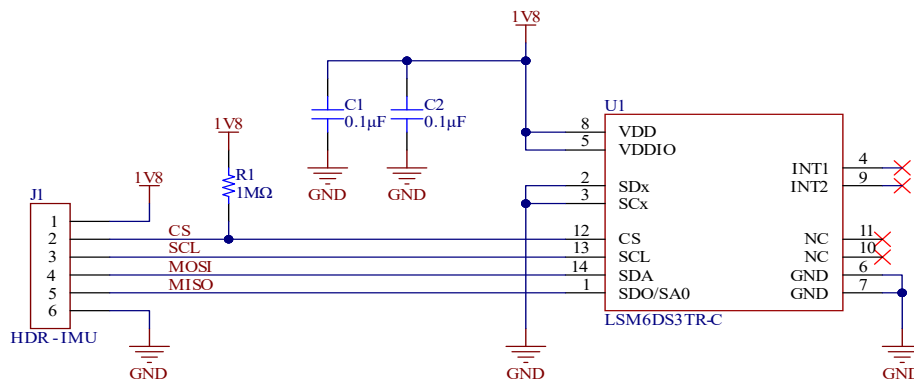


Figure 3.21: Complete schematic of the section hosting the *LSM6DS3* IMU sensor.

In general, the sensor reference coordinate system is defined according to the manufacturer's package orientation (**Figure 3.22**) and consistently aligned with the anatomical reference frame during mounting.

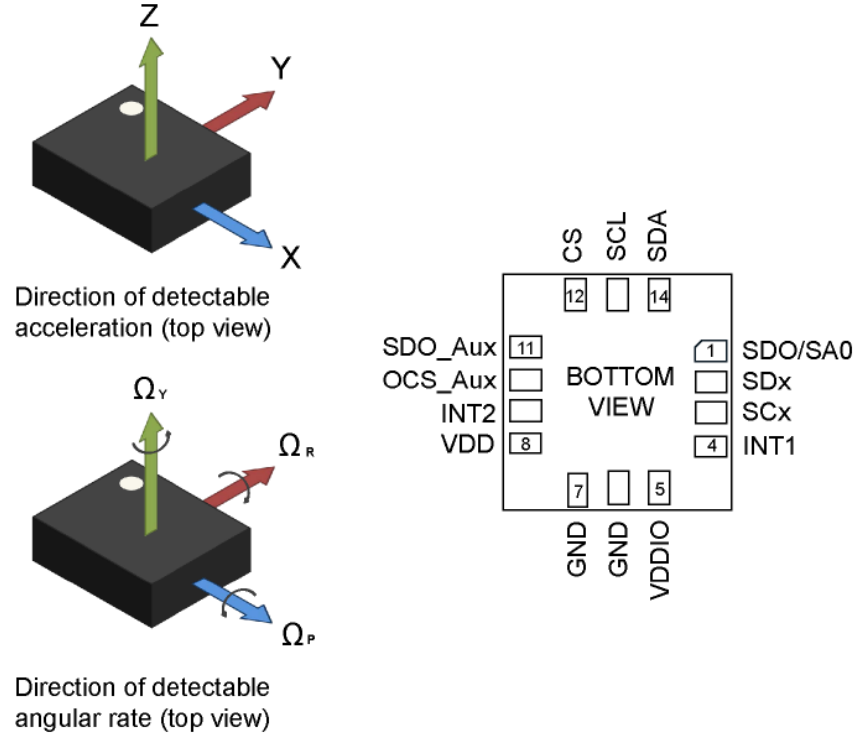


Figure 3.22: Package orientation and pin connections.

Beyond the hardware implementation, the sensor characteristics and configuration parameters play a crucial role in ensuring reliable gait events (Heel Strike and Toe Off) detection, which is the purpose of the IMU-based section. Heel Strike (HS) detection is primarily based on the identification of impulsive peaks in vertical acceleration and rapid changes in angular velocity occurring at foot-ground contact. For this reason, the selection of the sensing device and its configuration are critical to ensuring reliable event detection. The *LSM6DS3* accelerometer provides a sensitivity of 0.061 mg/LSB at ± 2 g full scale, ensuring sufficient resolution to accurately capture the impact-related acceleration peaks associated with Heel Strike events. Since HS represents a short-duration impulsive event, it is essential to discriminate true impact peaks from baseline signal noise. In high-performance mode, the accelerometer noise density is $70 \mu\text{g}/\sqrt{\text{Hz}}$, enabling reliable separation of gait-related acceleration transients from intrinsic sensor noise and therefore improving the robustness of HS detection. Similarly, TO identification relies on rapid variations in angular velocity and antero-posterior acceleration patterns. The high gyroscope sensitivity and low noise characteristics support precise detection of these rapid rotational transitions during the

push-off phase. It should also be noted that zero-g and zero-rate offsets may vary slightly due to mechanical stress during PCB mounting or environmental conditions. Therefore, a calibration procedure was performed prior to data acquisition to compensate for offset variations and ensure accurate event detection and repeatable gait cycle segmentation. From a system-level perspective, the device integrates embedded features that further support gait analysis applications, including activity/inactivity detection, step detection, a 9 KB FIFO buffer, and timestamping capability. In particular, the integrated 9 KB FIFO with timestamp support enables continuous data acquisition without loss, which is particularly advantageous for uninterrupted gait cycle segmentation and long-duration walking trials.

3.2.6 Wearable enclosure prototype

A proof-of-concept wearable electronic enclosure was designed in Autodesk Fusion 360 (**Figure 3.23**) and fabricated using *Formlabs Form 3+* 3D printer [19], employing stereolithography (SLA) technology with *Elastic 50A Resin V2* [20]. The electronic boards are interconnected through flexible flat cables connections, allowing compact integration and mechanical compliance with the wearable structure.

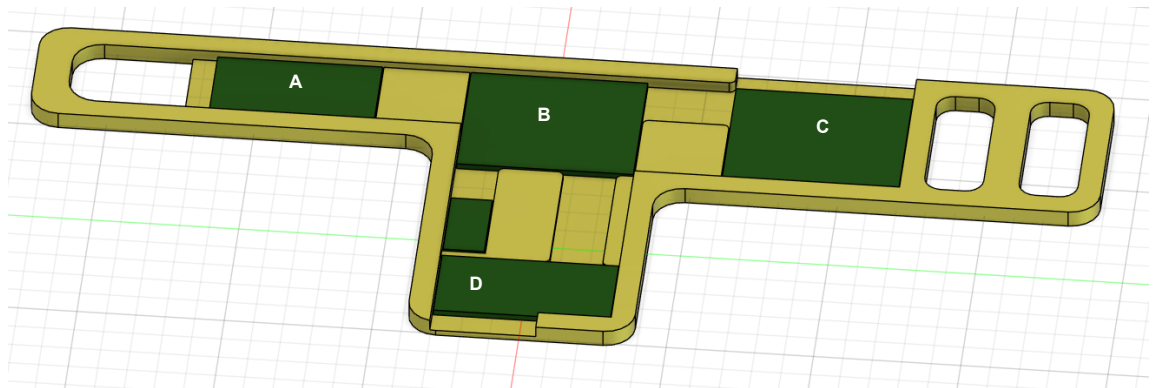


Figure 3.23: Wearable case for A) power module, B) MCU, C) EMG and D) AIN AFE boards. The IMU module allocation is not integrated within the wearable case, as it is connected via extended wiring to allow flexible placement on the anatomical site of interest.

This resin is a flexible polyurethane photopolymer with a shore hardness of 50A, comparable to soft rubber. It exhibits high elasticity, excellent deformation resistance, and good fatigue durability, making it suitable for components that must be bent, compressed, or worn in direct contact with the skin. Typical applications include flexible protective enclosures, gaskets, ergonomic components, and wearable electronics. SLA printing with this resin requires a precise UV laser, producing thin layers that allow high-resolution details and smooth surfaces, though the material remains sensitive to residual light before complete

polymerization. Following printing, the enclosures underwent a post-curing process in a *Form Cure V1* unit [21], immersed in distilled water at room temperature for two 15-minute cycles, without external heating (**Figure 3.24**).



Figure 3.24: Resin case undergoing post-curing process in *Form Cure V1* unit. Protocol conducted in the Advanced Biointerfaces Technologies Laboratory, IIT-CBN.

3.3 SURFACE EMG ACQUISITION PROTOCOL

The electronic acquisition board was designed to support both *single-ended* and *differential* EMG recordings. However, as discussed in the previous section concerning the electronic architecture, a differential acquisition configuration was selected for this study. Differential sensing significantly improves common-mode noise rejection (CMRR), enhances signal quality, and reduces susceptibility to motion artefacts and power-line interference, which are critical aspects in surface EMG recordings performed during dynamic tasks such as gait.

3.3.1 EMG channels configuration and wiring

In the *single-channel configuration*, a single muscle is monitored with a bipolar electrode setup. The positive input (IN1P) is connected to the muscle belly along the direction of the muscle fibers, while the negative input (IN1N) is placed on the same muscle at a distance of approximately 20-30 mm from the positive electrode. This inter-electrode distance ensures an adequate spatial sampling of motor unit activity while maintaining sufficient signal amplitude and minimizing cross-talk [22]. A *reference electrode* (REF) is placed over a bony prominence, such as the patella or the tibial crest, to provide a stable electrical reference with minimal muscular interference. Additionally, a *bias electrode* (BIAS) is positioned on a remote and electrically stable area, typically the gluteal region or proximal thigh, to improve common-mode rejection and stabilize the amplifier input. The corresponding hardware connections are summarized in **Table 3.1**.

U.FL connector	Signal	Electrode type	Electrode placement
J1	IN1P	EMG +	Muscle belly (along with fiber direction)
J4	IN1N	EMG –	Same muscle, 20–30 mm from EMG +
J5	REF	Reference	Bony prominence (patella / tibial crest)
J6	BIAS	Bias electrode	Remote stable area (gluteal region / proximal thigh)

Table 3.1: sEMG single-channel configuration.

In *dual-channel acquisition*, two muscles are recorded simultaneously via two independent differential inputs, each sharing a common reference and bias electrode. The first muscle is connected to IN1P and IN1N, following the same bipolar configuration described above. The second muscle is connected to IN2P and IN2N, with the positive electrode positioned over the muscle belly and the negative electrode placed 20-30 mm apart along the fiber direction. The reference (REF) and bias (BIAS) electrodes remain common to both channels, ensuring electrical stability and consistent grounding across the acquisition system. The hardware mapping in dual-channel mode is therefore illustrated in **Table 3.2**.

U.FL connector	Signal	Electrode type	Electrode placement
J1	IN1P	EMG 1 +	Muscle 1 belly (along with fiber direction)
J4	IN1N	EMG 1 –	Same muscle, 20–30 mm from EMG 1 +
J2	IN2P	EMG 2 +	Muscle 2 belly (along fiber direction)
J3	IN2N	EMG 2 –	Same muscle 2, 20–30 mm from EMG 2 +
J5	REF	Reference (common)	Bony prominence (patella / tibial crest)
J6	BIAS	Bias (common)	Remote stable area (gluteal region / proximal thigh)

Table 3.2: sEMG dual-channel acquisition.

For instance, this configuration allows simultaneous monitoring of agonist–antagonist muscle activity during gait, enabling the analysis of activation timing, co-contraction patterns, and muscle coordination across different phases of the gait cycle.

Beyond the hardware mapping described above, it is important to clarify the functional role of the *reference* and *bias electrodes* within the differential acquisition architecture. In surface electromyography (sEMG), the bioelectric signals generated by muscle activity are typically in the range of tens to hundreds of μV , making them highly susceptible to both environmental and physiological noise sources. Among these, power-line interference (50/60 Hz) represents one of the most significant contributors to signal degradation, appearing predominantly as common-mode voltage at the amplifier inputs. Since such interference is present at both differential inputs, it can severely compromise the signal-to-noise ratio if not adequately suppressed. Differential amplification with high *Common-Mode Rejection Ratio* (CMRR) is the primary strategy for attenuating shared noise components by amplifying only the voltage difference between the two electrodes. However, even high-intrinsic-CMRR instrumentation amplifiers benefit from additional active noise-reduction techniques, particularly in wearable and ambulatory systems, where the human body may act as an antenna for electromagnetic interference [23]. For this reason, many biosignal acquisition systems incorporate an active bias electrode, often implemented through a *Driven-Right-Leg* (DRL) or equivalent feedback configuration. In this approach, the common-mode voltage at the amplifier inputs is inverted and fed back into the body, effectively reducing the overall common-mode voltage. This active feedback mechanism improves the CMRR beyond that achievable with passive differential amplification alone. Experimental studies have

demonstrated that DRL-based systems achieve significantly greater attenuation of power-line interference compared to passive grounding methods [24]. The theoretical foundations and circuit implementations of such feedback techniques have been formalized in the biomedical instrumentation literature [25]. Within the present system, the bias electrode serves two primary functions:

- stabilizing the **subject's body potential** relative to the system reference
- actively reducing **common-mode interference** at the amplifier inputs.

To maximize its effectiveness, the bias electrode is positioned on an electrically stable and relatively inactive region (e.g., gluteal region or proximal thigh), minimizing the introduction of additional myoelectric activity into the feedback loop. It is important to distinguish the bias electrode from the reference electrode. While the reference electrode provides a stable potential reference for the differential measurement and is typically placed over a bony prominence, the bias electrode actively drives the body potential to suppress common-mode noise. Incorporating a bias electrode is particularly advantageous in wearable sEMG systems used during dynamic tasks such as gait, where motion artefacts and environmental interference are unavoidable.

3.3.2 Electrodes placement strategy

In the first instance, surface EMG electrodes were placed on the right lower limb using a differential configuration. Electrode positioning was performed according to standardized anatomical landmarks in **Figure 3.25** to ensure repeatability and minimize *cross-talk*⁷ from adjacent muscles. In particular, SENIAM recommendations for sensor locations in hip or upper leg muscles were followed [26]. Disposable Ag/AgCl adhesive electrodes were employed, with electrical interfacing to the acquisition board achieved through push-button connectors integrated with UFL connections.

⁷ Muscle cross-talk refers to the contamination of the EMG signal recorded from a target muscle by electrical activity originating from adjacent muscles, potentially affecting signal specificity.

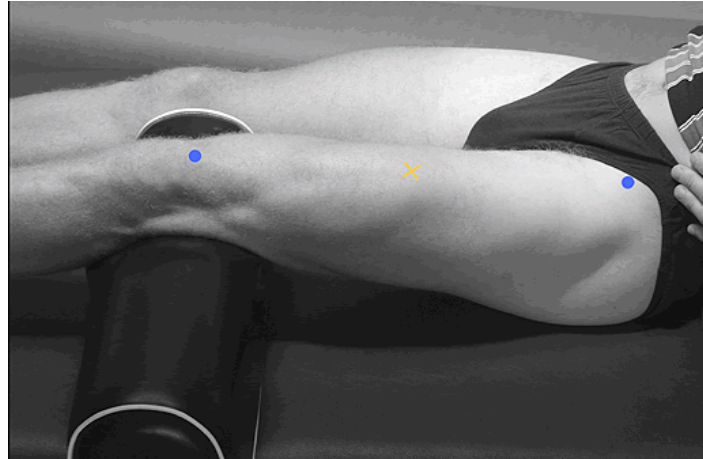


Figure 3.25: Rectus femoris muscle landmark identification prior to electrode placement, SENIAM protocol.

The bipolar electrode pair was positioned over the muscle belly of the target muscle (*rectus femoris*⁸), with the positive electrode aligned along the direction of the muscle fibers. The negative electrode was placed on the same muscle at an inter-electrode distance of approximately 20–30 mm (center-to-center), maintaining parallel orientation with respect to the fiber direction. This configuration ensures appropriate spatial selectivity while preserving signal amplitude during dynamic contractions associated with gait. Prior to electrode placement, the skin area was prepared by cleaning with alcohol to reduce skin impedance and improve electrode–skin contact. The anatomical landmarks are depicted in **Figure 3.26**, whereas electrode placement parameters are reported in **Table 3.3**.

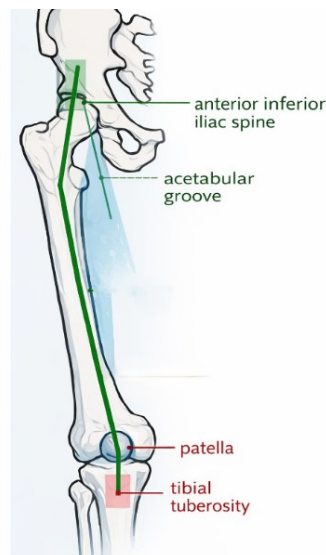


Figure 3.26: Rectus femoris anatomical landmarks illustrating the proximal origin (green) and distal insertion (red).

⁸ The Rectus Femoris is a biarticular muscle belonging to the quadriceps femoris group, involved in both knee extension and hip flexion, and is actively engaged during the swing phase of gait.

Section	Parameter	Description
Muscle Identification	Muscle	Quadriceps Femoris
	Subdivision	Rectus Femoris
Anatomy	Origin	Straight head from the anterior inferior iliac spine; reflected head from the groove above the rim of the acetabulum.
	Insertion	Proximal border of the Patella and via the patellar ligament.
	Function	Knee extension and hip flexion.
Electrode Placement (SENIAM)	Starting posture	Seated position with knees slightly flexed and trunk slightly reclined.
	Electrode size	Maximum 10 mm (in the direction of muscle fibers).
	Inter-electrode distance	20 mm (center-to-center).
	Location	At 50% of the line between the anterior superior iliac spine (ASIS) and the superior border of the patella.
	Clinical test	Knee extension without thigh rotation, applying resistance above the ankle in the direction of flexion.

Table 3.3: Anatomical parameters and SENIAM guidelines for electrode placement on the rectus femoris muscle.

The reference electrode (REF) was positioned over the *patella*, a bony prominence with minimal muscular activity, to provide a stable electrical reference. The bias electrode (BIAS) was placed over the *tibial crest* to ensure an electrically stable region with minimal contractile interference. This arrangement was chosen to maintain measurement stability during ambulatory trials while preserving the effectiveness of the previously described common-mode noise reduction. An example of the electrode placement on the right lower

limb during the measurement session is shown in **Figure 3.27**. It illustrates the bipolar electrodes (+ and -) over the *rectus femoris*, with the reference electrode (REF) on the *patella* and the bias electrode on the *tibial crest*.

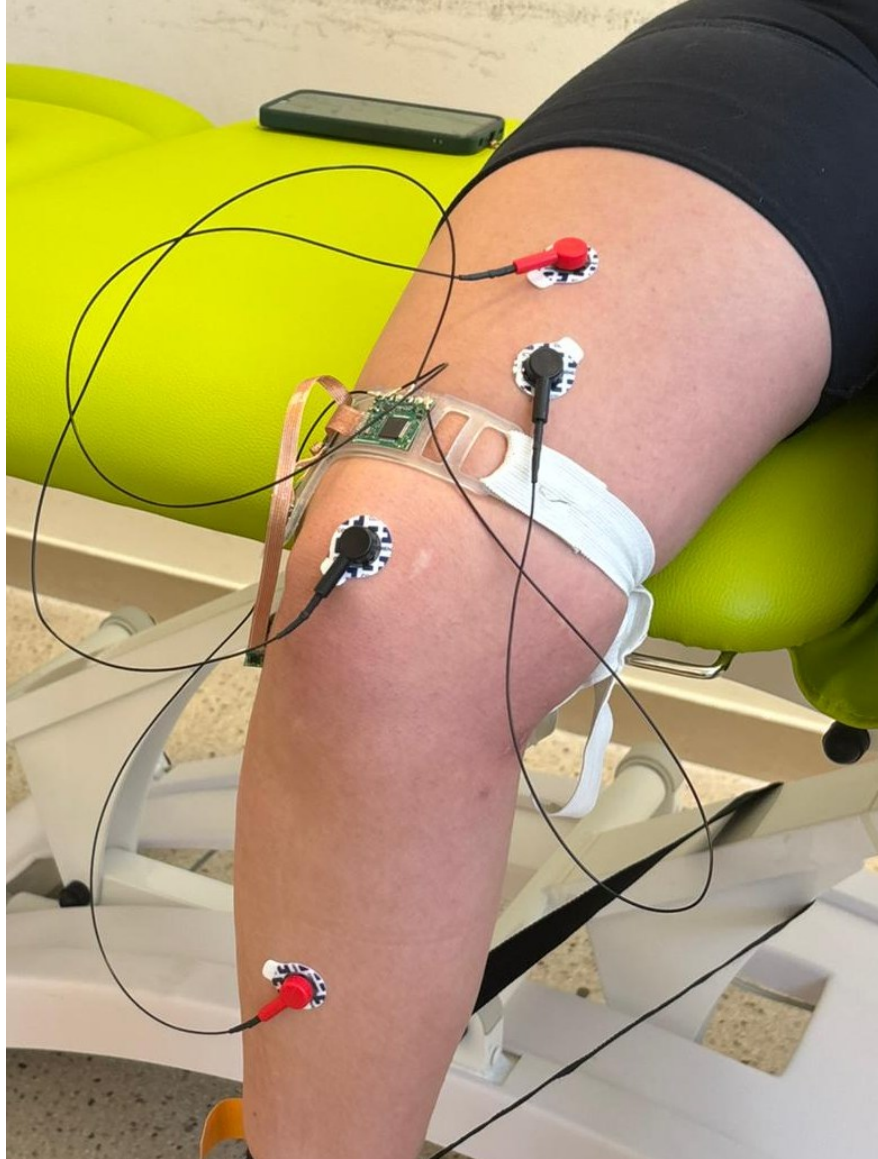


*Figure 3.27: Bipolar EMG electrodes placement.
Measurement session carried out at the IIT-CBN laboratories.*

3.4 IMU ACQUISITION PROTOCOL

The Inertial Measurement Unit (IMU) employed in this study (*LSM6DS3TR-C*) was configured to acquire both linear acceleration and angular velocity signals for the analysis of lower-limb kinematics during gait. While the hardware architecture and general

specifications of the sensing module have been described in the previous section, the present one focuses on the operational configuration, sensor positioning, and the parameters recorded during the experimental protocol. For the data acquisition phase of this project, the accelerometer and gyroscope were configured with *full-scale ranges* of ± 4 g and ± 2000 dps, respectively. These settings were selected to ensure an appropriate trade-off between sensitivity and dynamic range, allowing accurate capture of both low-amplitude steady-state motion and higher-intensity transient events occurring during gait, such as foot-ground impact and rapid limb rotations.

3.4.1 Sensor positioning and anatomical alignment

The IMU was positioned laterally on the distal portion of the right thigh, in proximity to the knee joint, as illustrated in **Figure 3.28**.

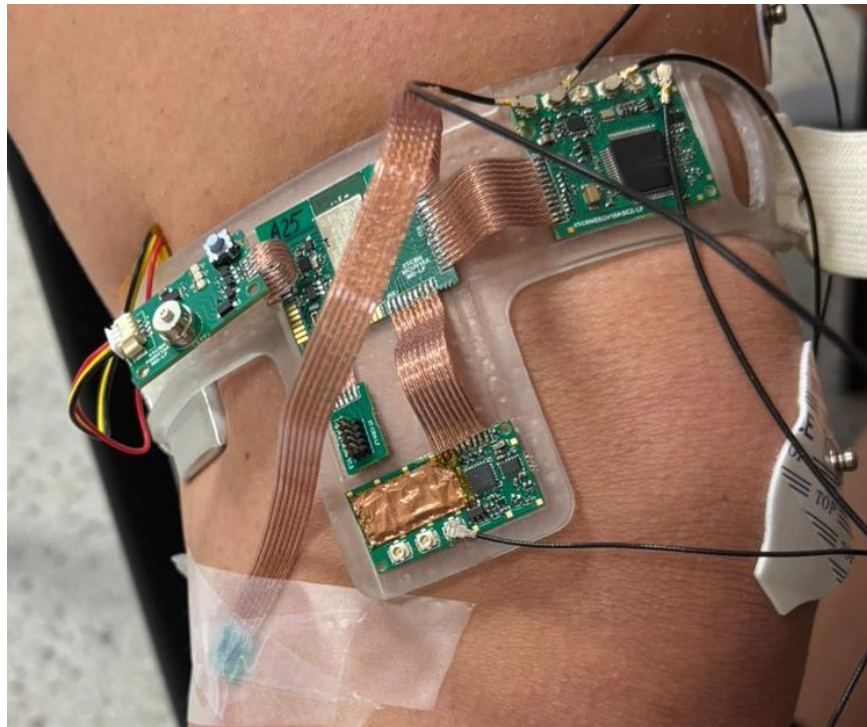


Figure 3.28: IMU positioning and attachment. The IMU was positioned on the anatomical site of interest and securely attached to the limb. The use of a flexible flat cable provided mechanical compliance, enabling independent positioning and unconstrained movement of the sensor. Measurement session carried out at the IIT-CBN laboratories.

This placement was chosen to maximize sensitivity to knee flexion–extension dynamics, which represent the dominant motion component during walking [27]. From a biomechanical perspective, this location allows the sensor to capture both rotational

kinematics associated with the swing phase and acceleration transients related to heel strike propagation along the limb.

Unlike conventional gait analysis studies, where inertial sensors are typically placed on the foot or ankle to directly capture impact dynamics, the IMU in this study was integrated within a wearable hardware platform, making distal placement not feasible. Therefore, lateral positioning at the knee level was selected as a compromise between biomechanical relevance and system integration constraints, while still ensuring the acquisition of meaningful kinematic information. Proximal sensor placements have been shown to provide reliable gait-related information, even when not directly measuring foot-ground interactions [28]. Accelerations measured at proximal segments are inherently attenuated compared to distal locations due to the damping effect of soft tissues and the progressive dissipation of impact forces along the lower limb. Nevertheless, these signals retain meaningful information about gait dynamics, as the temporal structure and relative variations associated with locomotor events are preserved [29]. Particular care was taken to maintain consistent alignment between the sensor reference frame and the limb's anatomical axes, to preserve the interpretability of the recorded signals across trials. During the experimental protocol, the IMU continuously acquired triaxial acceleration and angular velocity signals, providing a six-dimensional description of segment kinematics. These data were recorded synchronously with EMG and MMG signals within a multimodal sensing framework, enabling integrated analysis of neuromuscular activation, mechanical responses, and movement dynamics. The inertial measurements further supported gait cycle identification and temporal segmentation, facilitating the detection of key locomotor events. Since the IMU was positioned on the distal thigh rather than on the foot, gait event detection was approached as an indirect temporal segmentation problem. Acceleration and angular velocity patterns recorded at the thigh level were used to identify repeatable gait-related events, while acknowledging that foot-ground contact transients are attenuated and temporally filtered by the proximal placement. Therefore, the detected events should be validated against a reference method before being interpreted as exact heel-strike or toe-off timings.

3.5 DATA ACQUISITION SOFTWARE AND SYNCHRONIZATION

The data acquisition system is managed through a dedicated software interface developed at the IIT- *Center for Biomolecular Nanotechnologies*, designed for real-time monitoring and synchronized recording of bio-signals acquired from the integrated sensors (**Figure 3.29**).



Figure 3.29: Graphical icon of the custom-developed software for bio-signal acquisition implemented at the IIT-CBN.

Although the software was originally developed for monopolar EEG recordings, it has been specifically adapted in this work to support bipolar surface electromyography (EMG) acquisition, ensuring improved common-mode noise rejection and enhanced signal quality. The graphical user interface allows the user to select the communication ports and configure the acquisition channels prior to recording. The available configuration (**Figure 3.30**) includes bipolar EMG, three ADC channels dedicated to MMG signal acquisition and the Inertial Measurement Unit (IMU) channels, that are simultaneously enabled, allowing for multimodal analysis of muscle activity and movement.

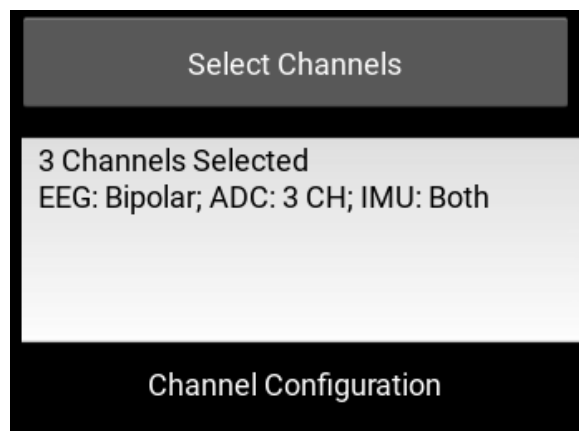


Figure 3.30: Software configuration adapted for EMG signal acquisition.

Once the connection with the device is successfully established, the software provides real-time visualization of the acquired signals, displayed in separate panels for each channel, with

adjustable scaling and zoom parameters to facilitate signal interpretation. Data transmission is handled via a wireless communication protocol based on Bluetooth Low Energy (BLE), leveraging a serial emulation service that enables efficient, continuous data streaming. Each data packet contains information regarding the sensor type, number of active channels, and a high-resolution timestamp, ensuring accurate temporal synchronization across all acquired signals. The system is designed to support concurrent multi-sensor acquisition without data loss or desynchronization, as confirmed by functional tests demonstrating stable streaming, correct channel mapping, and absence of framing errors or channel mixing when multiple acquisition modules are active. Finally, the software enables automatic data storage in structured directories identified by session timestamps, facilitating subsequent offline analysis. This architecture makes the system particularly suitable for experimental studies requiring reliable and synchronized acquisition of physiological and kinematic data.

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CHAPTER 4

EXPERIMENTAL DESIGN AND DATA ACQUISITION PROTOCOLS

*“A scientist in his laboratory is not merely a technician:
he is also a child placed before natural phenomena
which impress him like a fairy tale.”*
— Marie Curie

Chapter 4 presents the experimental design and data-acquisition protocols used to assess the technical feasibility and physiological consistency of a custom multimodal sensing system that integrates standard EMG acquired with Ag/AgCl bipolar electrodes, MMG acquired with piezoelectric sensors, and IMU measurements. The study was structured into two complementary phases: preliminary static recordings of the upper-limb *brachioradialis* and dynamic walking trials targeting the lower-limb *rectus femoris* under functional conditions. The preliminary static phase was intended to provide a controlled reference condition for verifying signal quality, sensor functionality, and the temporal consistency between EMG and MMG during voluntary contractions, rather than a clinical or population-level physiological baseline. The experimental setup, acquisition environment, and safety considerations are also described, providing the methodological framework for the subsequent biosignals processing and neuromechanical analysis.

4.1 CONCEPTUAL FRAMEWORK AND STUDY DESIGN

The experimental activity was structured according to a progressive, hierarchical approach, aimed at ensuring methodological consistency and robustness of signal acquisition and processing in a feasibility-oriented experimental framework. In particular, the study was divided into two main phases:

- preliminary **static recordings** on an upper-limb muscle (*brachioradialis*)
- **dynamic acquisitions** during locomotion on a lower-limb muscle (*rectus femoris*).

The objective of this experimental activity is strictly limited to the assessment of the technical feasibility and physiological plausibility of the proposed multimodal sensing system. The study is not intended as clinical validation, nor does it involve any form of diagnostic evaluation, patient stratification, or clinically validated outcome assessment.

The initial static phase was designed to establish a controlled experimental condition in which the relationship between electrical (EMG) and mechanical (MMG) muscle activity could be investigated without the confounding effects of whole-body movement. This step enabled assessment of the acquisition chain performance, optimization of signal processing strategies, and identification of physiologically meaningful features.

Subsequently, the experimental protocol was extended to dynamic conditions to evaluate the performance of the multimodal sensing system during walking and assess the consistency of EMG–MMG coupling during a functional locomotor task. The experimental evaluation of the proposed multimodal sensing system in controlled laboratory conditions was conducted on a healthy subject to characterize EMG and MMG signals as physiological reference signals in a controlled experimental setting. Since the activity was conducted as a preliminary technical feasibility test on a healthy volunteer within the laboratory setting, no clinical intervention or patient recruitment was performed. It is important to emphasize that the entire acquisition setup was developed from the ground up as a custom multimodal platform, integrating EMG, MMG, and IMU sensing within a unified wearable architecture. In this context, even the EMG acquisition chain, although considered a gold standard for muscle activation assessment, was implemented using a custom-designed solution rather than relying on established commercial systems (e.g. *Cometa* EMG Software or similar).

Therefore, this feasibility-oriented experimental phase was essential not only to characterize the physiological signals but also to assess the reliability, consistency, and overall performance of the complete experimental setup. Accordingly, the present work should be interpreted as a technical feasibility and physiological consistency study rather than a clinical validation study, since no reference commercial systems or clinically validated measurement standards were employed. Overall, the two-stage strategy ensured a gradual transition from controlled conditions to ecologically valid scenarios, improving both the reliability and interpretability of the results.

4.2 PRELIMINARY STATIC RECORDINGS

Preliminary measurements were conducted on the *brachioradialis* muscle (**Figure 4.1**), selected for its superficial location and ease of access, which facilitates reliable sensor placement and minimises anatomical and experimental variability.



Figure 4.1: Anatomical representation of the brachioradialis muscle [1].

The primary aim of this phase was to gain familiarity with the AIN piezoelectric sensor and to characterize the fundamental properties of EMG and MMG signals under controlled conditions. This step allowed:

- verification of signal quality and sensor functionality
- development and optimization of the signal processing pipeline
- identification of relevant physiological features (e.g., activation bursts, envelope dynamics, peak detection)
- preliminary assessment of the temporal relationship between electrical and mechanical muscle activity

As shown in the experimental setup (**Figure 4.2**), EMG signals were acquired using Ag/AgCl bipolar electrodes, while MMG signals were recorded using an AlN piezoelectric sensor fixed to the skin with *Derma-tac* adhesive and aligned with the muscle fiber direction. At this stage, the full multimodal wearable system was not yet employed; instead, a simplified laboratory setup was adopted to facilitate controlled signal acquisition. This configuration allowed precise control of the acquisition conditions and facilitated the initial characterization and quality assessment of both EMG and MMG signals prior to their integration into the wearable multimodal platform used in the dynamic trials.

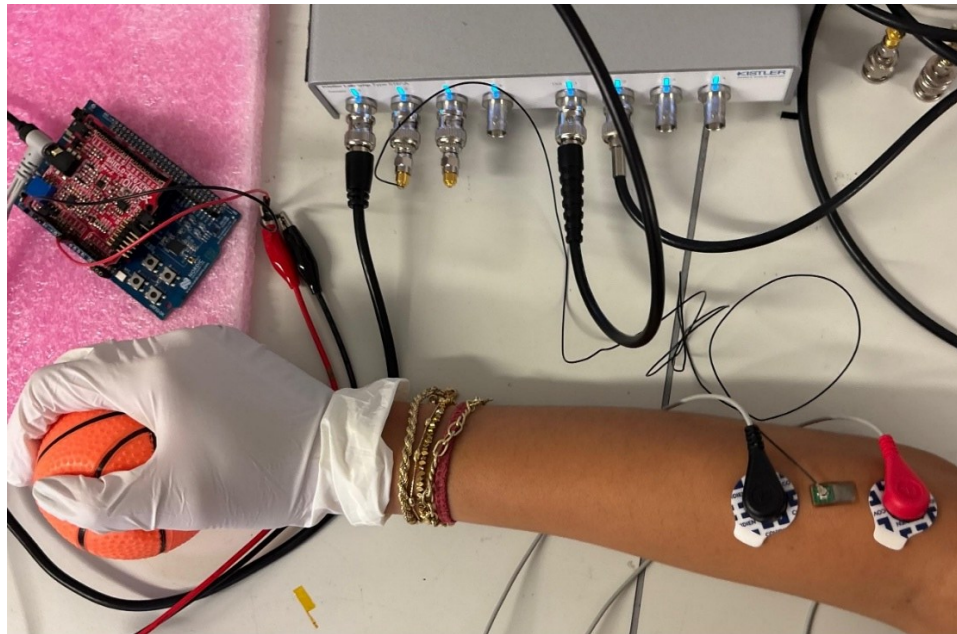


Figure 4.2: Experimental setup for EMG and MMG signal acquisition on the brachioradialis muscle. Measurement session carried out at the IIT-CBN laboratories.

EMG signals were acquired using a SHIELD-EKG-EMG prototype board from Olimex [2] in a bipolar configuration, with the reference electrode positioned at the elbow. The acquisition chain also included a Kistler LabAmp system [3], where preliminary analog filtering stages were applied to both EMG and MMG signals, and an oscilloscope (Tektronix

MDO4104-3) used for real-time signal visualization and verification. The experimental task consisted of repeated voluntary contractions elicited by a grasping action (ball squeezing) over approximately 60 seconds. This simple and repeatable motor task ensured a clear alternation between activation and rest phases, enabling robust identification of contraction bursts and facilitating comparison between EMG and MMG signals.

4.3 DYNAMIC WALKING TRIALS

Following the validation phase, the experimental protocol was extended to dynamic conditions involving lower-limb muscles during walking. Data acquisition was performed using a multimodal wearable system integrating EMG, MMG, and IMU sensors positioned on the right thigh, targeting the quadriceps muscle group, particularly the *rectus femoris* muscle as shown in **Figure 4.3**.

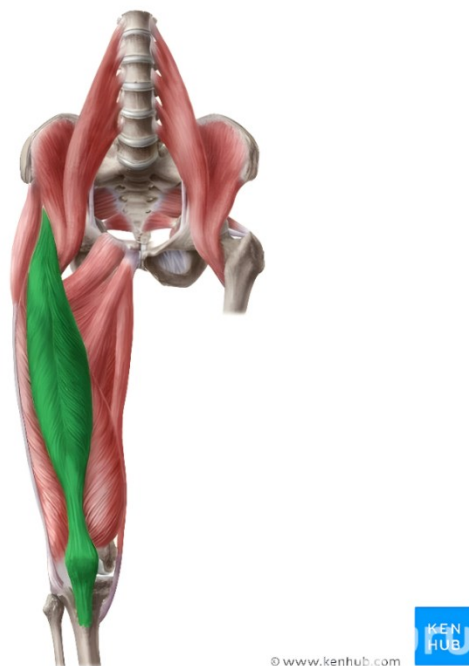


Figure 4.3: Anatomical representation of the rectus femoris muscle [4]

The rectus femoris was selected as the target muscle for the dynamic trials because it is superficial, easily accessible for both sEMG and AIN-MMG placement, and functionally involved in hip flexion, knee extension, limb advancement, and load control during gait. Although hip abductors are central to several post-THA compensatory patterns, rectus

femoris monitoring represents a practical first target for assessing the technical feasibility and physiological consistency of the proposed multimodal setup under dynamic lower-limb conditions. The experimental protocol was designed as a *multi-intensity neuromechanical probing paradigm*, consisting of a shuttle walking task, including

- **forward** walking
- controlled **turnaround**
- **return** walking

Each segment included a limited number of steps (approximately four per limb per direction), allowing the acquisition of multiple gait cycles within a compact, controlled environment. Specifically, the forward path consisted of four steps with the right limb and four with the left, with an analogous structure adopted during the return phase. The right limb was instrumented with the wearable sensing system (**Figure 4.4**) and was therefore considered the reference side for multimodal measurements.

This configuration was intentionally selected to introduce physiologically meaningful variations in neuromuscular demand within a single continuous trial, thereby enabling the system to be tested across different activation regimes. In particular, the protocol encompasses distinct dynamic phases, each associated with different levels of motor control and mechanical loading:

- **gait initiation** (acceleration)
- **steady-state walking**
- **deceleration**
- **directional changes**

From a methodological perspective, steady-state walking segments were used for quantitative gait analysis and EMG–MMG comparison, ensuring consistency with established gait analysis practices that typically rely on quasi-stationary locomotion. Conversely, transient phases such as acceleration, deceleration, and turning were used as a qualitative stress-test of the sensing platform, allowing assessment of whether EMG, MMG, and IMU signals remained interpretable under changing mechanical and neuromuscular demands. However, quantitative gait analysis was restricted to the most stationary walking

segments. The presence of varying mechanical and neuromuscular demands allows verification that EMG activity, MMG mechanical oscillations, and inertial signals co-vary in a physiologically coherent manner, thereby supporting the reliability and dynamic range of the multimodal acquisition setup.

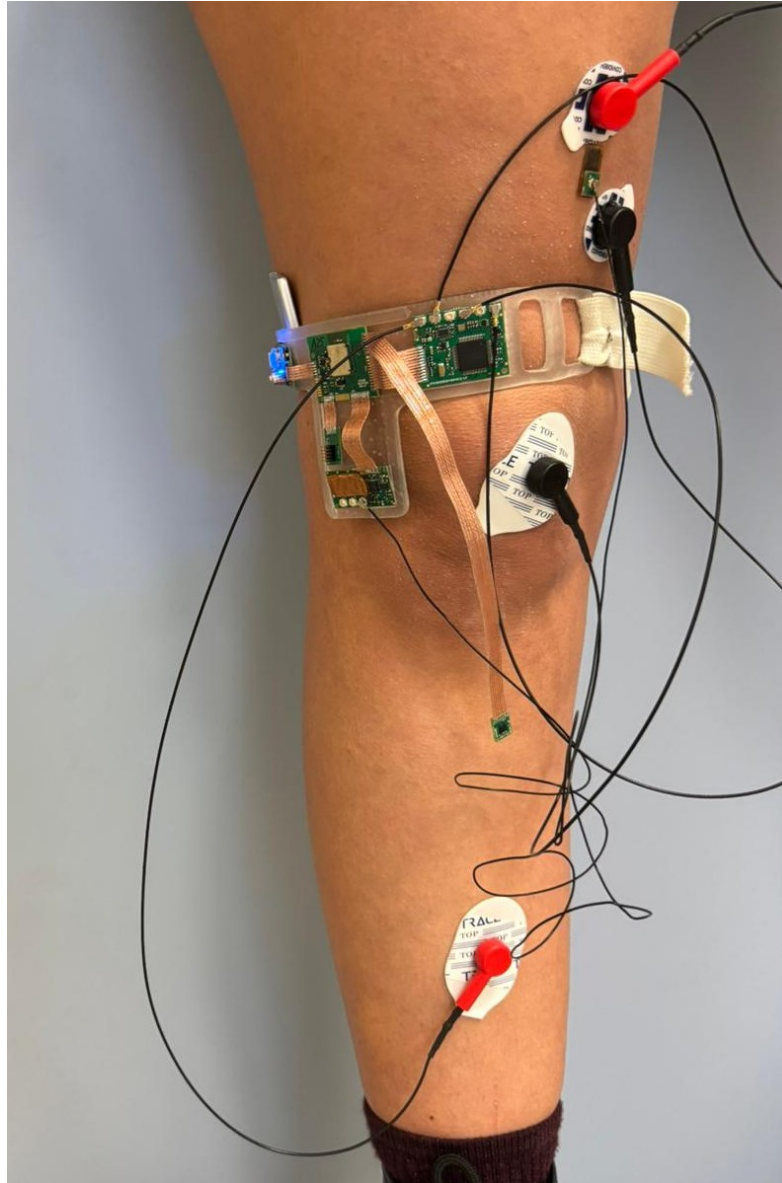


Figure 4.4: Experimental setup for EMG and MMG signal acquisition on the rectus femoris muscle. Measurement session carried out at the IIT-CBN laboratories.

The adoption of a shuttle walking configuration is further supported by ecological and clinical considerations. Corridor-based protocols with repeated direction changes are widely used in functional walking assessments, such as the *Six-Minute Walk Test (6MWT)* [5], as outlined in the *American Thoracic Society guidelines*. In this context, the inclusion of controlled turnarounds enhances the ecological validity of the protocol while maintaining

experimental control. Although the present protocol was not intended to reproduce the Six-Minute Walk Test, it shares with corridor-based functional walking assessments the use of straight walking segments and direction changes in a controlled environment. This makes the task more ecologically relevant than isolated laboratory contractions while preserving sufficient experimental control. Overall, this approach combines methodological rigor with ecological relevance: steady-state segments enable direct comparison with conventional gait analysis, while transient phases enhance the evaluation of sensor performance, signal quality, and multimodal synchronization under heterogeneous loading conditions. This integrated framework provides a comprehensive neuromechanical characterization [6] of gait, allowing simultaneous assessment of neuromuscular activation (EMG), mechanical muscle response (MMG) [7], and segment kinematics (IMU) [8].

4.4 EXPERIMENTAL SETUP AND ACQUISITION CONDITIONS

All experiments, including both preliminary static recordings and dynamic walking trials, were conducted at the laboratories of the IIT – *Center for Biomolecular Nanotechnologies*, ensuring controlled and reproducible experimental conditions. The laboratory environment provided:

- minimal electromagnetic interference
- stable temperature conditions
- sufficient space for repeated walking trials

These conditions were essential to guarantee high-quality signal acquisition and to minimize external disturbances that could affect both electrical and mechanical measurements in dynamic tasks. From a safety perspective, the experimental protocol was non-invasive and involved only voluntary movements performed at a self-selected walking speed. The subject was continuously monitored during data acquisition to ensure proper task execution and prevent fatigue or discomfort, thereby maintaining data reliability and participant safety throughout the experimental sessions.

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CHAPTER 5

MULTIMODAL SIGNAL PROCESSING AND ANALYSIS METHODS

*“Without the love of research,
mere knowledge and intelligence
cannot make a scientist.”*

— Irène Joliot-Curie

Chapter 5 describes the signal processing and data preparation pipeline applied to the biosignals acquired in this study, focusing specifically on the methodological treatment of the signals. The processing framework includes three complementary signal modalities: surface electromyography (EMG), mechanomyography (MMG), and inertial measurement unit (IMU) data. EMG was used to assess neuromuscular electrical activation, whereas MMG provided information on the mechanical response of muscle tissue during contraction. IMU data were instead used as a kinematic reference to characterize body segment motion, identify gait events, and support gait cycle segmentation. Two experimental conditions were considered: static recordings from the brachioradialis muscle, used to validate the EMG-MMG processing pipeline and assess electromechanical coupling, and dynamic gait trials on the quadriceps muscle, where EMG-MMG processing was integrated with IMU-based gait event detection for cycle-by-cycle analysis. Overall, this chapter presents the methodological steps required to clean, filter, normalize, segment, and organize the acquired signals. The processed data provide the basis for subsequent analysis of neuromuscular activation, mechanical muscle responses, and gait-related temporal patterns.

5.1 SIGNAL PROCESSING OVERVIEW

The signal processing pipeline adopted in this study jointly handles surface electromyography (EMG) and mechanomyography (MMG) signals, while integrating inertial measurement unit (IMU) data to support the temporal interpretation of locomotor activity. Although EMG and MMG signals originate from different physiological mechanisms, respectively reflecting neural activation and the mechanical response of muscle contraction [1], EMG preprocessing was designed according to established recommendations for surface electromyography, including SENIAM-based principles⁹ [2] for electrode placement and signal treatment. MMG processing followed an analogous conceptual structure, but its parameters were independently adapted to the lower frequency and mechanical sensitivity of mechanomyographic signals. This unified strategy, applied to both signals, facilitates the comparison between electrophysiological and mechanical indicators of muscle activity and supports the investigation of their relationship during motor tasks. Nevertheless, specific adaptations were introduced to account for the distinct spectral and mechanical characteristics of MMG signals. EMG signals typically exhibit a physiological bandwidth of approximately 20–450 Hz, whereas MMG signals are dominated by lower-frequency components, typically 5–100 Hz. These tuning choices mainly concern parameter selection within the processing stages, ensuring that the framework remains suitable for both electrophysiological and vibration-based measurements. While the same general analytical structure was maintained across both conditions, certain parameters were adjusted to accommodate the different signal characteristics associated with static and dynamic measurements.

In parallel, IMU data were processed as a kinematic reference rather than as a direct indicator of muscle activity. The inertial signals, including accelerometer and gyroscope measurements, were used to identify locomotor phases, separate forward and return walking segments, and detect the main gait events, namely Heel Strike (HS) and Toe-Off (TO). The gyroscope signal provided information on the angular motion of the lower limb, while the accelerometer signal supported the identification of impact-related events associated with foot-ground contact. Using this approach, IMU-derived events enabled the temporal

⁹ The SENIAM project (Surface ElectroMyoGraphy for the Non-Invasive Assessment of Muscles) is a European concerted action in the Biomedical Health and Research Program (BIOMED II) of the European Union.

alignment of EMG and MMG signals with biomechanically meaningful phases of the gait cycle. While the same general analytical structure was maintained across both static and dynamic conditions, specific parameters were adjusted to accommodate the different signal characteristics and experimental objectives. In the static condition, acquired from the brachioradialis muscle, the processing pipeline was mainly aimed at signal characterization and the evaluation of electromechanical coupling. In the dynamic condition, acquired during gait trials, the pipeline was extended by incorporating IMU-based gait event detection, HS-HS cycle segmentation, and temporal normalization to a 0-100% gait cycle scale. This organization enabled cycle-by-cycle comparison of EMG and MMG activity and provided a consistent framework for investigating the relationship between neural activation, mechanical muscle response, and lower-limb kinematics during walking.

5.2 PREPROCESSING OF EMG AND MMG SIGNALS

The preprocessing pipeline for EMG and MMG signals was designed to follow a common conceptual structure across all experimental conditions. This choice was made to ensure methodological consistency between static and dynamic acquisitions, while allowing specific processing parameters to be adjusted according to the different characteristics of each task. In particular, static recordings required smoother signal profiles and greater robustness against baseline fluctuations, whereas dynamic gait recordings required greater temporal responsiveness to preserve step-related variations. Although EMG and MMG signals originate from different physiological mechanisms, their processing followed a comparable sequence of operations, including signal conditioning, artifact attenuation, filtering, rectification, envelope extraction, smoothing, and RMS estimation. This unified approach allows the electrophysiological activity measured by EMG and the mechanical muscle response measured by MMG to be compared within a coherent analytical framework.

5.2.1 Signal conditioning and artifact handling

Before signal-specific processing, both EMG and MMG signals were subjected to a preliminary conditioning stage to improve numerical stability and reduce the influence of non-physiological artifacts. First, invalid samples, including NaN and Inf values, were

removed to prevent computational errors during subsequent filtering operations. This step was particularly important because zero-phase forward-backward filtering procedures are sensitive to discontinuities and corrupted samples.

After removal of invalid data, the signals were centered by subtracting a robust estimate of the baseline. Specifically, the median value of each signal was removed according to:

$$x_0(t) = x(t) - \text{median}(x(t))$$

where $x(t)$ represents the raw signal and $x_0(t)$ represents the centered signal. *Median subtraction* was preferred over mean subtraction because it is less sensitive to outliers and impulsive disturbances. This operation removes the DC offset and slow baseline shifts while preserving the temporal structure of the physiological signal. As a result, the subsequent filtering stages are applied to a signal centered around zero, improving numerical stability and reducing the risk of baseline-related distortions.

To further reduce the influence of transient artifacts, a *winsorization procedure* based on the *Median Absolute Deviation (MAD)* was applied. Since winsorization can attenuate both artifacts and true high-amplitude physiological transients, the selected threshold was kept conservative and visually verified to ensure that contraction-related bursts were preserved. The threshold coefficient used in the implementation should be explicitly reported to ensure reproducibility. The MAD was computed from the centered signal as:

$$MAD = \text{median}(|x_0(t) - \text{median}(x_0(t))|)$$

Since, after median centering, $\text{median}(x_0(t))$ is approximately zero, the MAD provides a robust estimate of the variability of the centered signal. The standard deviation was then obtained as:

$$\sigma = 1.4826 \cdot MAD$$

A conservative threshold was defined as:

$$L = 6 \cdot \sigma$$

Signal samples exceeding this threshold were clipped, according to:

$$x_w(t) = \begin{cases} -L, & x_0(t) < -L \\ x_0(t), & -L \leq x_0(t) \leq L \\ L, & x_0(t) > L \end{cases}$$

where $x_w(t)$ represents the winsorized signal. This procedure limits extreme amplitude excursions while preserving the temporal continuity of the recording. The use of MAD makes the estimation of signal variability less affected by impulsive artifacts compared with the classical standard deviation. Therefore, the winsorization step attenuates transient disturbances related to motion artifacts, electrode or sensor shifts, mechanical shocks, and abrupt variations in sensor-skin coupling, without altering the overall physiological dynamics of the signal.

This artifact-handling strategy was particularly relevant for MMG signals, which are more sensitive to mechanical coupling, tissue motion, and low-frequency drift. However, applying the same robust conditioning strategy to both EMG and MMG ensured that the two signals were treated within a consistent preprocessing framework. As a result, the conditioned signals were more stable and suitable for band-pass filtering, envelope extraction, RMS computation, and subsequent comparison between electrical and mechanical muscle activity.

In addition to sample-level artifact handling, a protocol-level segmentation strategy was applied to retain only the portions of the recordings that were relevant for the subsequent analysis. For the dynamic gait trials, only the forward and return walking segments were included in the processing pipeline. The initial calibration phase, gait initiation and stopping transients, and the turnaround phase were excluded because their signal content was not representative of steady locomotor activity. The forward and return segments were processed as separate blocks. A NaN gap was inserted between them to preserve their temporal separation and avoid artificial continuity across the pause and turnaround phase. This approach allowed the two walking conditions to be visualized within the same time sequence while preventing edge effects and spurious transitions from affecting envelope extraction, RMS computation, and subsequent gait-cycle segmentation.

A similar exclusion criterion was applied to the static recordings. In this case, the first 1.5 s of the signal were cropped before further processing because this initial portion showed

irregular behavior and sporadic peaks that could not be clearly attributed either to weak voluntary contractions or to noise. Trimming this segment ensured a cleaner and more reliable signal for activation detection, peak identification, and electromechanical delay estimation.

5.2.2 EMG signal processing

After signal conditioning, the EMG signal was processed to isolate the frequency components associated with surface myoelectric activity and to obtain time-domain descriptors of muscle activation. Under ideal conditions, surface EMG is typically analyzed over a frequency range of approximately 20-450 Hz. When required by the acquisition conditions, *IIR notch filtering* at 50 Hz and its harmonics was used to reduce power-line interference.

However, when the effective sampling frequency limited the usable spectral range, the upper cut-off frequency was automatically adjusted according to the Nyquist criterion. This was necessary to avoid numerical instability and prevent the filter from operating too close to the Nyquist frequency. The upper cut-off frequency was therefore defined as:

$$f_H = \min(450, 0.45 \cdot f_s) \text{ Hz}$$

where f_s is the effective sampling frequency of the signal. In the gait dataset, the measured sampling frequency was 250 Hz, corresponding to a Nyquist frequency of 125 Hz. Because the effective sampling frequency of the gait recordings was 250 Hz, the dynamic EMG analysis was restricted to the lower portion of the conventional sEMG bandwidth. Consequently, the recorded signals should not be regarded as a complete representation of surface EMG spectral content. Instead, they were considered suitable mainly for the analysis of activation timing, low-frequency envelope modulation, RMS estimation, and overall muscle activation patterns during gait, whereas detailed spectral analysis and fatigue-related frequency metrics were beyond the scope of the present study. Accordingly, the upper cut-off frequency was set to:

$$f_H = 0.45 \cdot 250 = 112.5 \text{ Hz}$$

resulting in an effective EMG band-pass range of 20-112.5 Hz. The choice to use $0.45 \cdot f_s$, rather than approaching the Nyquist frequency directly, introduced a safety margin that

reduced the filter sensitivity to components close to Nyquist and limited the risk of filtering artifacts. Finally, filtering was applied in zero-phase mode using `filtfilt`¹⁰ to avoid phase delays and preserve the correct timing of muscle activations, which is essential for subsequent analyses based on temporal alignment and gait-cycle segmentation. Moreover, in dynamic recordings sampled at 250 Hz, notch filtering was limited to narrow-band components below the Nyquist frequency, mainly 50 Hz and, when necessary, 100 Hz. The use of notch filters was kept conservative to avoid excessive distortion of the already limited EMG spectral bandwidth.

The filtered EMG signal was a *full-wave rectification* to obtain a unipolar representation suitable for amplitude analysis. The EMG *envelope*¹¹ was extracted from the rectified signal using a low-pass filter with task-specific cut-off frequencies: 2 Hz for static recordings and 6 Hz for dynamic gait recordings. The lower cut-off frequency used in the static condition provided a smoother activation profile, whereas the higher cut-off frequency used during gait preserved faster modulation related to the locomotor cycle. A *moving average smoothing* step was subsequently applied, using a 300 ms window for static recordings and a 200 ms window for dynamic recordings. Finally, the *RMS*¹² was computed using a 50 ms moving window to quantify signal energy and capture short-term variations in muscle activation.

5.2.3 MMG signal processing

The MMG signal was processed using an analogous sequence of operations to that adopted for EMG, but with parameters adapted to its lower frequency and mechanical sensitivity. This choice is consistent with previous studies describing MMG as a low-frequency mechanical manifestation of muscle contraction [3,4]. For this reason, the MMG preprocessing stage was specifically designed to attenuate low-frequency drift, high-frequency noise, and non-informative mechanical disturbances while preserving the frequency components related to muscle mechanical activity.

¹⁰ *filtfilt* is a MATLAB function that performs zero-phase digital filtering by applying the filter forward and backward, avoiding phase delay.

¹¹ The envelope represents the slow temporal modulation of the rectified EMG signal and provides an estimate of the overall activation pattern of the muscle over time.

¹² The RMS provides a measure of the signal energy within a short moving window and is particularly useful for capturing rapid variations in contraction intensity.

After the initial conditioning stage, the MMG signal was filtered using a *fourth-order Butterworth band-pass filter* with a nominal frequency range of 5-100 Hz. The lower cut-off frequency was used to remove drift by attenuating slow baseline variations due to posture, global limb motion, changes in sensor-skin contact pressure, and intrinsic piezoelectric baseline fluctuations. These low-frequency components are not directly associated with active fiber oscillations and may compromise envelope extraction and RMS estimation if not removed. The upper cut-off frequency was instead used to attenuate high-frequency noise and non-informative vibrations. As for EMG, the upper cut-off frequency was adjusted as needed to match the effective sampling frequency. In dynamic gait recordings, the MMG band-pass range was therefore defined as:

$$BP_{MMG} = 5 - \min(100, 0.45 \cdot f_s) \text{ Hz}$$

where f_s is the effective sampling frequency of the signal. Thus, when the sampling frequency did not allow the full nominal range to be used, the upper cut-off frequency was automatically reduced while preserving the physiologically relevant MMG band as much as possible.

Notch filtering was not considered a mandatory processing step for MMG, since the signal is mechanical rather than electrical and is therefore less directly affected by power-line interference. However, it was retained as an optional step when specific noise conditions required additional attenuation of narrow-band interference.

Following band-pass filtering, the MMG signal was *full-wave* rectified. The MMG envelope was then extracted from the rectified signal using task-specific low-pass cut-off frequencies. A 5 Hz low-pass filter was used for static recordings to obtain a stable representation of the mechanical response during controlled contractions, whereas a 10 Hz low-pass filter was adopted for dynamic gait recordings to preserve faster mechanical modulations associated with walking.

Temporal smoothing was then performed using a moving average window of 400 ms in static condition and 200 ms in dynamic condition. The longer smoothing window used in static recordings improved the stability of the mechanical response profile, whereas the shorter window used during gait maintained sufficient temporal resolution for cycle-based analysis.

As for EMG, the *RMS* was computed using a 50 ms moving window to estimate the local energy of the mechanical oscillations over time.

5.2.4 Task-specific tuning parameters

The distinction between static and dynamic processing was mainly reflected in the envelope extraction and smoothing stages. Static recordings were acquired under controlled conditions and, therefore, processed with parameters aimed at producing stable, smooth activation profiles. This was particularly important for activation interval detection, peak localization, and electromechanical delay estimation. In contrast, dynamic gait recordings required a more responsive processing configuration. Since muscle activity during walking is cyclic and phase-dependent, envelope cut-off frequencies were increased, and smoothing windows were shortened to preserve the timing of step-related variations. This allowed EMG and MMG envelopes to retain sufficient temporal detail for alignment with gait events and for subsequent cycle-by-cycle analysis. The adopted parameter selection is summarized in **Table 5.1**.

Processing Stage	Signal	Static Condition	Dynamic Condition	Rationale
Signal Conditioning	Both	Median centering + baseline correction	Median centering + baseline correction	Removes DC offset and improves numerical stability
Artifact Handling	Both	MAD-based winsorization	MAD-based winsorization	Limits impulsive artifacts while preserving signal continuity
Power-line Interference Removal	EMG	Notch filter at 50 Hz and harmonics	Notch filter at 50 Hz and harmonics	EMG is sensitive to electrical noise
	MMG	Optional notch filtering	Not applied	MMG is less affected by power-line interference
Band-pass Filtering	EMG	20 – 450 Hz	20 - min (450, 0.45*fs) Hz	Captures MUAP frequency content while respecting the Nyquist constraint in dynamic recordings

	MMG	5 – 100 Hz	5 – min (100, 0.45*fs) Hz	Captures low-frequency mechanical vibrations while respecting the Nyquist constraint in dynamic recordings
Drift Removal	MMG only	Achieved through the 5 Hz high-pass cut-off	Achieved through the 5 Hz high-pass cut-off	Removes slow baseline variations due to posture, sensor–skin coupling, and piezoelectric drift
Rectification	EMG	Full-wave	Full-wave	Converts bipolar signal to unipolar for envelope extraction
	MMG	Full-wave	Full-wave	Converts bipolar mechanical signal to unipolar
Envelope Extraction	EMG	2 Hz low-pass	6 Hz low-pass	<u>Static</u> → smoother activation profile; <u>Dynamic</u> → preservation of faster gait-related variations
	MMG	5 Hz low-pass	10 Hz low-pass	<u>Static</u> → stable profile; <u>Dynamic</u> → preservation of faster mechanical modulation
Temporal Smoothing	EMG	300 ms moving average	200 ms moving average	<u>Static</u> → smoother profile; <u>Dynamic</u> → higher temporal responsiveness
	MMG	400 ms moving average	200 ms moving average	Stronger smoothing in static recordings; higher responsiveness during gait
RMS Calculation	Both	50 ms moving window	50 ms moving window	Quantifies local signal energy and short-term amplitude variations

Table 5.1: Tuning parameters for each processing stage.

5.3 STATIC CONDITION ANALYSIS

The static analysis was performed to evaluate the behavior of the processed EMG and MMG signals under controlled contraction conditions before applying the same processing framework to dynamic gait trials. This stage aimed to verify that the pipeline could produce stable EMG and MMG envelopes suitable for activation detection, extract comparable amplitude- and frequency-related features from both signals, and assess the temporal relationship between electrical muscle activation and mechanical response. Therefore, this section was not intended to provide a complete physiological interpretation of brachioradialis function, but rather to validate the reliability of the processing pipeline and establish a methodological basis for the subsequent dynamic analysis.

5.3.1 Activation detection algorithm

Activation detection was performed on the smoothed EMG and MMG envelopes obtained after filtering, rectification, envelope extraction, and moving average smoothing. The envelope was selected as the reference signal for activation detection because it represents the slow-varying amplitude modulation of muscle activity and provides a robust representation of contraction timing. For each signal, a baseline interval was first identified in the early portion of the recording and used to estimate the resting activity level. The baseline mean and standard deviation were computed as:

$$\mu_{base} = mean(x_{env,base})$$

$$\sigma_{base} = std(x_{env,base})$$

where $x_{env,base}$ represents the envelope values within the baseline interval. An adaptive activation threshold was then defined as:

$$T = \mu_{base} + k \cdot \sigma_{base}$$

where k is a threshold factor selected according to the signal type. In the implemented MATLAB algorithm, a higher threshold factor was used for EMG, while a lower threshold factor was used for MMG, reflecting the different amplitude characteristics and variability of the two signals.

An activation interval was detected when the envelope exceeded the corresponding threshold. Consecutive active samples were grouped into candidate activation windows. To reduce false detections, activation intervals shorter than a predefined minimum duration were discarded. This step allowed brief spurious bursts, potentially related to electrode movement or mechanical disturbances, to be excluded from the analysis. In addition, activation intervals separated by a temporal gap shorter than a predefined maximum value were merged, avoiding the artificial splitting of single contraction events into multiple activations. A final peak-ratio criterion was also introduced: if the peak amplitude of an activation was lower than a fixed fraction of the previous activation peak, the event was considered insufficiently independent and merged with the previous activation. This step reduced the probability of interpreting small residual oscillations as separate voluntary contractions. Using this procedure, activation intervals were identified in both EMG and MMG signals and subsequently used for feature extraction and electromechanical delay estimation.

5.3.2 Peak identification and features extraction

After activation intervals had been identified, peak detection and feature extraction were performed within each valid activation window. For each activation, the maximum value of the envelope was identified, and its temporal position was stored. Peak identification was used to locate the time of maximum electrical activation in the EMG signal and the time of maximum mechanical response in the MMG signal. Within each valid activation, the peak envelope value and its timing were computed to characterize maximum muscle output or activation intensity.

For each activation segment, several time-domain features were extracted from the envelope signal x_{env} . The *mean value* was computed to quantify the average activation level during the contraction:

$$Mean = \frac{1}{N} \sum_{i=1}^N x_{env}(i)$$

The *RMS value* is an estimate of signal energy:

$$RMS = \sqrt{\frac{1}{N} \sum_{i=1}^N x_{env}^2(i)}$$

The *peak value* was defined as:

$$Peak = \max(x_{env})$$

The *area under the curve* (AUC) was computed as:

$$AUC = \frac{1}{f_s} \sum_{i=1}^N x_{env}(i)$$

where f_s is the sampling frequency. Finally, the standard deviation is useful to quantify the intra-activation variability:

$$STD = \sqrt{\frac{1}{N-1} \sum_{i=1}^N (x_{env}(i) - \overline{x_{env}})^2}$$

In addition to time-domain parameters, the *median frequency* was obtained from the band-pass filtered signal using Welch's power spectral density method. The median frequency is defined as the frequency that divides the power spectrum into two regions with equal power:

$$\sum_{f=0}^{f_{med}} P(f) = \frac{1}{2} \sum_{f=0}^{f_{max}} P(f)$$

These features were selected to characterize different aspects of muscle activity. Mean and RMS describe the average activation level and signal energy, peak amplitude identifies the maximum activation intensity, AUC represents the total activity over the contraction interval, STD describes the variability within the activation, and median frequency provides information on the spectral distribution of the signal. In the analyzed static recording, every activation interval was characterized using these parameters. This comparison was useful to verify whether MMG followed the same activation structure identified in EMG, while preserving its mechanically specific amplitude and frequency characteristics.

5.3.3 Electromechanical delay estimation

Electromechanical delay was estimated to quantify the temporal relationship between the electrical activation detected by EMG and the mechanical response detected by MMG. The delay estimated in this section is the time lag between the EMG envelope peak and the MMG envelope peak. Therefore, it should be interpreted as an EMG–MMG peak-to-peak delay rather than a classical electromechanical delay, which is usually defined as the time from activation onset to force or mechanical response onset. For each activation, the time of the EMG envelope peak and the time of the corresponding MMG envelope peak were identified. The delay was then calculated as:

$$EMD_k = (t_{peak,EMG,k} - t_{peak,MMG,k}) \cdot 1000$$

where EMD_k is the electromechanical delay of the k -th activation expressed in milliseconds, $t_{peak,EMG,k}$ is the time of the EMG peak, and $t_{peak,MMG,k}$ is the time of the corresponding MMG peak. The *mean delay* across all valid activations was then computed as:

$$\overline{EMD} = \frac{1}{N} \sum_{k=1}^N EMD_k$$

with the corresponding standard deviation:

$$STD_{EMD} = \sqrt{\frac{1}{N} \sum_{k=1}^N (EMD_k - \overline{EMD})^2}$$

This procedure allowed the time lag between the electrical and mechanical components of muscle activity to be quantified for each activation and summarized across the entire static recording.

5.4 DYNAMIC CONDITION ANALYSIS

The aim of the dynamic analysis was to apply the EMG–MMG processing pipeline to walking trials and prepare the signals for cycle-by-cycle investigation. The dynamic analysis had three main methodological objectives. First, EMG and MMG signals were

processed using the dynamic-specific parameters defined in Section 5.2, allowing the extraction of envelopes and RMS profiles suitable for locomotor analysis. Second, the EMG signal was normalized to enable amplitude comparison within the walking session. Third, the processed EMG and MMG signals were temporally aligned with IMU-derived gait events, which were then used to segment the gait cycle.

5.4.1 EMG normalization during gait

Surface EMG amplitude is strongly influenced by non-physiological factors such as electrode placement, skin-electrode impedance, inter-electrode distance, amplifier gain, cable orientation, and motion artifacts [5, 6]. For this reason, amplitude normalization is required when comparing EMG activity across trials or conditions. Normalization to a *Maximal Voluntary Contraction (MVC)*, usually expressed as %MVC, is commonly considered the reference approach because it expresses muscle activation relative to maximal voluntary capacity [7].

In the present study, five MVC trials were recorded using a standardized contraction structure composed of three phases: a *ramp* phase, during which the subject progressively increased the contraction level; a *plateau* phase, during which maximal effort was maintained; and a *release* phase, during which the contraction was gradually reduced. Each MVC trial was processed using the same EMG pipeline adopted for the gait recordings, including signal conditioning, filtering, rectification, envelope extraction, and RMS computation. This ensured that the MVC reference and the walking EMG signals were treated consistently in processing. To avoid subjectively selecting the MVC reference, an *automatic ranking procedure* was implemented. First, the ramp-plateau-release structure of each trial was identified, and the central plateau portion was extracted because it corresponds to the phase during which maximal activation is most stable. Within this plateau window, three quantitative criteria were computed. The first was the *mean RMS amplitude*, which quantified the average level of neuromuscular activation during the sustained maximal contraction. Higher RMS values were considered more representative of maximal voluntary effort. The second criterion was the *coefficient of variation*, calculated as the ratio between the standard deviation and the mean RMS within the plateau. This parameter was used to assess contraction stability, with lower values indicating a more constant and reproducible plateau. The third criterion was the *baseline RMS activity*, computed during the initial resting

portion of the trial, to verify the absence of pre-activation, motion artifacts, or elevated noise before contraction onset.

These criteria were combined into a composite *ranking score* to identify the most representative MVC trial. The ranking score was based on the combination of high plateau RMS amplitude, low plateau variability, and low baseline activity. Trials showing an unstable baseline, unclear contraction onset, or a plateau not consistent with the expected ramp-plateau-release structure were excluded from the selection procedure. This approach allowed the MVC reference to be selected based on objective amplitude and stability criteria rather than solely on visual inspection.

The theoretical MVC normalization can be expressed as:

$$\% MVC = \frac{EMG_{task}}{EMG_{MVC}} \cdot 100$$

where EMG_{task} is the EMG amplitude measured during the walking task and EMG_{MVC} is the reference amplitude obtained from the selected MVC trial. However, in the present study, MVC and walking trials were acquired in separate experimental sessions. This represented a methodological limitation because surface EMG amplitude is strongly affected by electrode placement, skin-electrode impedance, inter-electrode distance, amplifier gain, cable orientation, and motion artifacts. Therefore, when MVC and gait recordings are not acquired under the same experimental conditions, the MVC reference may not reflect the amplitude scaling of the walking session.

For this reason, MVC normalization was not adopted as the final normalization strategy for gait EMG. Instead, a within-session percentile-based normalization has been proposed as a robust alternative [8, 9]. Specifically, the reference value was computed as the *95th percentile of the RMS signal* extracted from the useful walking segments, including both forward and return walking portions. The adopted normalization was defined as:

$$\% P95 = \frac{EMG_{task}}{P95_{walk}} \cdot 100$$

where $P95_{walk}$ is the 95th percentile of the RMS signal across forward and returning walking segments. For consistency, the same $P95_{walk}$ reference was used to normalize both the RMS

and envelope signals. This allowed the EMG features to be expressed on a common amplitude scale within the same walking session. The %P95 strategy does not provide a direct physiological interpretation as a percentage of maximal voluntary capacity. Therefore, it cannot be interpreted as %MVC and is not intended for inter-subject comparison. Nevertheless, it provides a robust and internally consistent normalization approach for intra-subject and intra-session comparison, particularly when MVC and walking trials are not acquired under identical experimental conditions. Accordingly, %P95 normalization was selected in this work to avoid artificial amplitude inflation and preserve comparability between forward and return walking segments.

After preprocessing and EMG normalization, the dynamic EMG and MMG signals were prepared for integration with the IMU-based gait segmentation procedure. This preparation step ensured that the muscle signals were suitable for the following analysis stages: identification of gait events, HS-HS cycle segmentation, temporal normalization to the 0-100% gait cycle, and extraction of cycle-averaged EMG and MMG profiles.

5.5 IMU SIGNAL PROCESSING

In the dynamic condition, the IMU was used as a kinematic reference: its main role was to characterize lower-limb segment motion during walking and to support the identification of locomotor phases and gait events. In this way, IMU data provided the temporal framework needed to align the processed EMG and MMG signals with the functional phases of the gait cycle, rather than treating them solely as continuous time series.

5.5.1 Robust estimation of sampling frequency

Unlike EMG and MMG signals, which were acquired as continuous biosignals through a relatively stable acquisition chain, IMU data may be more affected by *timestamp jitter* due to digital communication, buffering, and sensor data handling. For this reason, instead of assuming a nominal sampling rate, the sampling interval was computed from the temporal difference between consecutive samples:

$$\Delta t_i = t_{i+1} - t_i$$

This approach provides a robust estimate of the effective sampling interval, reducing the influence of occasional irregular timestamps and ensuring reliable filter design, window definition, and gait event detection. A robust estimate of the sampling interval was then obtained using the median value:

$$\Delta t_{IMU} = median(\Delta t_i)$$

The effective sampling frequency was calculated as:

$$f_{s,IMU} = \frac{1}{\Delta t_{IMU}}$$

Using the median rather than the mean made the estimate less sensitive to occasional timestamp irregularities or jitter. This ensured that the subsequent filtering operations were based on the actual temporal resolution of the acquired IMU data. The same sampling frequency was then used to define filter cut-off frequencies and moving window lengths in samples.

5.5.2 Conversion of IMU data into physical units

The raw IMU outputs were converted from digital *counts* into physical units before biomechanical processing. This conversion was necessary to make the inertial signals interpretable and comparable with expected ranges of human movement. Although some event-detection procedures can operate on relative signal variations, expressing the data in physical units improves transparency, reproducibility, and consistency with sensor specifications.

For the *LSM6DS3* IMU used in this study, the accelerometer was configured with a full-scale range of ± 4 g, while the gyroscope was configured with a full-scale range of ± 2000 dps [10]. According to the corresponding sensor sensitivity settings, the accelerometer sensitivity is:

$$S_{acc} = 0.122 \text{ mg/LSB}$$

whereas the gyroscope sensitivity is:

$$S_{gyro} = 70 \text{ mdps/LSB}$$

Accelerometer samples were first converted from raw digital counts to gravitational acceleration units:

$$a_g = a_{raw} \cdot S_{acc} \cdot 10^{-3}$$

where a_{raw} is the raw accelerometer value expressed in LSB and S_{acc} is expressed in mg/LSB. The factor 10^{-3} converts milligravity units into g. When required, acceleration was then converted into SI units:

$$a_{m/s^2} = a_g \cdot 9.81$$

Similarly, gyroscope samples were converted from raw digital counts to angular velocity in degrees per second:

$$\omega_{deg/s} = \omega_{raw} \cdot S_{gyro} \cdot 10^{-3}$$

where ω_{raw} is the raw gyroscope value expressed in LSB and S_{gyro} is expressed in mdps/LSB. The factor 10^{-3} converts millidegrees per second into degrees per second. Angular velocity was then converted into radians per second as:

$$\omega_{rad/s} = \omega_{deg/s} \cdot \frac{\pi}{180}$$

After conversion, accelerometer and gyroscope signals were available in physical units suitable for filtering, axis selection, movement-energy computation, and gait event detection. This step ensured that the IMU data could be interpreted within biomechanical ranges and sensor specifications, while maintaining consistency across subsequent processing stages.

5.5.3 Gyroscope filtering

The gyroscope signals were filtered to isolate the angular motion components associated with gait and to attenuate high-frequency noise. A *fourth-order low-pass Butterworth filter* was applied with a cut-off frequency of approximately 6 Hz:

$$\omega_{LP}(t) = LPF_{6Hz}\{\omega(t)\}$$

This cut-off was selected because the dominant components of normal walking are concentrated at low frequencies [11], while higher-frequency components are more likely to reflect noise, vibration, or non-informative mechanical disturbances. The filtered gyroscope signal was therefore used to describe the main rotational pattern of the lower limb during walking. Zero-phase filtering was applied when appropriate to avoid temporal shifts in the gyroscope waveform. Preserving timing was essential because the gyroscope signal was later used as a temporal reference for identifying gait-related events and for separating locomotor phases.

5.5.4 Accelerometer filtering and dynamic acceleration calculation

The accelerometer signal contains both dynamic acceleration due to movement and the quasi-static acceleration due to gravity [12]. For this reason, accelerometer preprocessing was designed to emphasize movement-related components while reducing slow baseline variations and high-frequency noise [13]. First, a high-pass filtering step was applied to attenuate the gravitational component and slow drift:

$$a_{HP}(t) = HPF_{0.5Hz}\{a(t)\}$$

A low-pass filter was then applied to reduce high-frequency noise while preserving acceleration transients associated with gait:

$$a_{dyn,axis}(t) = LPF_{20Hz}\{a_{HP}(t)\}$$

After filtering the three accelerometer axes, the dynamic acceleration magnitude was computed as:

$$A_{dyn}(t) = \sqrt{a_x^2(t) + a_y^2(t) + a_z^2(t)}$$

This magnitude-based representation was adopted to reduce dependence on the sensor's exact orientation [14]. Since the IMU was mounted on the body segment rather than on the foot, impact-related acceleration components could be attenuated and distributed across axes. The use of the dynamic acceleration magnitude, therefore, provided a more robust signal for detecting acceleration peaks associated with foot-ground contact.

5.5.5 Automatic selection of the main gyroscope axis

Because the orientation of the IMU relative to anatomical axes may vary slightly between acquisitions, the principal gyroscope axis was selected automatically rather than assumed a priori. This approach is consistent with studies showing that IMU placement and walking task can influence gait event detection accuracy [15]. After low-pass filtering, the variance of each gyroscope axis was computed over the walking signal:

$$a_x^2 = \text{var}(\omega_x)$$

$$a_y^2 = \text{var}(\omega_y)$$

$$a_z^2 = \text{var}(\omega_z)$$

The axis with the highest variance was selected as the main gyroscope axis:

$$\omega_{main}(t) = \omega_j(t), \quad j = \arg \max_{j \in \{x,y,z\}} \text{var}(\omega_j)$$

This criterion assumed that the axis with the largest variance contains the strongest rotational component associated with the locomotor task. In gait analysis, this axis is expected to be closely related to the dominant flexion-extension motion of the lower limb. The data-driven selection of the main gyroscope axis reduced dependence on exact sensor placement and improved the generalizability of the processing pipeline.

5.5.6 Automatic identification of walking segments

After selection of the main gyroscope axis, walking segments were identified using a movement-energy approach. The absolute value of the filtered main gyroscope signal was first computed, and a moving average was applied to obtain a smooth estimate of movement intensity:

$$E_{gyro} = \text{movmean}(|\omega_{main}(t)|, W)$$

where W represents the time window used for smoothing, expressed in samples. A short window was selected to reduce rapid fluctuations while preserving the temporal structure of walking activity.

An adaptive threshold was then defined using robust statistics:

$$T_{walk} = \text{median}(E_{gyro}) + \alpha \cdot \text{MAD}(E_{gyro})$$

where α is a tuning coefficient and MAD is the Median Absolute Deviation. Samples with gyroscope energy above this threshold were classified as movement-related:

$$E_{gyro}(t) > T_{walk}$$

Consecutive supra-threshold samples were grouped into candidate walking segments. To avoid retaining brief movements or isolated artifacts, segments shorter than a minimum duration were discarded. This step allowed the algorithm to remove short non-informative portions and retain only sustained locomotor blocks.

The resulting walking segments were used to separate the forward and return portions of the gait trial. These segments were then passed to the subsequent gait event detection stage, where Heel Strike and Toe Off events were identified within each walking block. This organization prevented the pause and turnaround phase from introducing artificial gaps or misleading temporal intervals into the gait-cycle analysis.

5.6 DETECTION OF GAIT EVENTS USING IMU

Following IMU preprocessing and automatic walking segment identification, the next step was to detect the main gait events required for temporal segmentation of the locomotor cycle. In particular, Heel Strike (HS) and Toe Off (TO) events were identified within each walking segment using a combined gyroscope-accelerometer strategy. The detection algorithm was designed to exploit the complementary information provided by the two inertial signals. This approach was particularly suitable for the present setup, in which the IMU was positioned at knee level rather than directly on the foot. The detection was performed separately for the forward and return walking segments. This ensured that

spatiotemporal parameters and event consistency were evaluated only during continuous walking.

5.6.1 Toe Off identification

Toe-Off events were identified from the filtered main gyroscope signal [16, 17]. First, the absolute value of the selected gyroscope axis was analyzed to identify prominent angular velocity peaks associated with the swing-related motion of the lower limb. These peaks were detected using a minimum temporal distance between consecutive peaks, corresponding to the minimum expected step duration:

$$d_{min} = 0.4 \cdot f_{s,IMU}$$

where $f_{s,IMU}$ is the effective IMU sampling frequency. This constraint was introduced to prevent multiple peaks from being detected within the same step cycle. A signal-dependent threshold was also used for peak selection:

$$T_{peak} = median(|\omega_{main}|) + 1.2 \cdot std(|\omega_{main}|)$$

Peaks above this threshold were used as temporal references for the gait cycle. For each gyroscope reference peak, TO was identified as the local minimum of the gyroscope signal occurring before the swing-related peak. The search was restricted to a predefined temporal window preceding the reference peak:

$$[t_{peak} - 0.30 \text{ s}, t_{peak} - 0.05 \text{ s}]$$

This interval was selected to restrict the search to the temporal region immediately preceding the swing-related angular velocity peak, where the transition from stance to swing is expected to occur. The lower bound prevents the algorithm from selecting minima belonging to the previous gait cycle, while the upper bound avoids selecting points too close to the swing peak itself, where the signal is already dominated by limb acceleration during swing. Within this interval, the TO event was selected as:

$$TO = \arg \min_{t \in [t_{peak}-0.30s, t_{peak}-0.05s]} \omega_{main}(t)$$

This choice assumed that TO occurs before the main swing phase and corresponds to a transition in the angular velocity pattern of the lower limb. Importantly, TO was not defined as a global minimum of the entire gyroscope signal, but as a local minimum within a physiologically constrained window. This reduced the probability of false detections and improved the biomechanical plausibility of the event sequence.

5.6.2 Heel Strike identification

Heel Strike events were identified using the dynamic acceleration magnitude. For each gyroscope reference peak, a search window was defined after the peak:

$$[t_{peak} + 0.05 \text{ s}, t_{peak} + 0.25 \text{ s}]$$

In this gap, the HS event was evaluated as the local maximum of the dynamic acceleration magnitude:

$$HS = \arg \max_{t \in [t_{peak} + 0.05 \text{ s}, t_{peak} + 0.25 \text{ s}]} A_{dyn}(t)$$

where $A_{dyn}(t)$ is the magnitude of the filtered dynamic acceleration vector. This criterion was adopted because HS is associated with the impact of the foot with the ground, which produces a transient increase in acceleration. Since the IMU was positioned proximally at knee level, the impact peak was expected to be attenuated compared with foot-mounted sensors [18, 19]. For this reason, HS detection was constrained by the gyroscope reference peak and performed within a short physiologically plausible window rather than by searching for the absolute maximum of the acceleration signal. This strategy allowed the acceleration signal to provide information on impact timing, while the gyroscope signal constrained the search to the appropriate phase of the gait cycle. The combined use of gyroscope and accelerometer signals, therefore, improved the reliability of event detection compared with a single-signal approach.

5.6.3 Temporal validation of HS and TO events

After detecting HS and TO events, a temporal validation procedure was applied separately to each walking segment. This was necessary because using the full sequence of detected events without separating forward and return walking would include the temporal gap

associated with pause and turnaround, artificially distorting step-time and cadence estimates [13]. The validation was therefore performed independently for each continuous walking block. For each segment, the algorithm first verified the number and temporal consistency of HS and TO events. The difference between the number of detected HS and TO events was required to remain within a limited tolerance, since a large mismatch would suggest extra detections or missed events. The sequence of events was also checked to ensure that TO and HS appeared in a physiologically plausible temporal order.

Step time was calculated from consecutive HS events within the same segment:

$$T_{step,k} = t_{HS,k+1} - t_{HS,k}$$

Only step times within a predefined physiological range (0.30 s-1.50 s) were retained for validation.

The *median step* time was then computed as:

$$\widetilde{T_{step}} = median(T_{step})$$

and step-to-step variability was estimated using the robust *Median Absolute Deviation*:

$$MAD_{step} = 1.4826 \cdot MAD(T_{step})$$

Cadence was calculated from the median step time as:

$$Cadence = \frac{60}{\widetilde{T_{step}}}$$

On the other hand, *stance time* was estimated by pairing each HS with the first subsequent TO within the same walking segment:

$$T_{stance,k} = t_{TO,k} - t_{HS,k}$$

Only values within 0.20 s-1.20 s were retained. The median stance time and its variability were then computed in the same way as for step time. Finally, the *stance fraction* was calculated as:

$$SF = \frac{\widetilde{T_{stance}}}{\widetilde{T_{step}}}$$

This parameter expresses the proportion of the gait cycle spent in stance and was used as an additional check of biomechanical plausibility.

5.6.4 Spatiotemporal parameters and Quality Score

To provide an objective summary of the reliability of event detection, a quality score was computed for each walking segment. The score was designed as an internal methodological validation index, not as a clinical outcome measure. It combined several criteria related to event count consistency, temporal plausibility, step regularity, stance plausibility, stance variability, and stance fraction. For each walking segment, the score was initialized at 100 and progressively reduced when one or more validation criteria were not satisfied:

$$Score = 100 - \sum_i P_i$$

where P_i represents the penalty associated with each validation criterion. The final score was constrained between 0 and 100. The main components of the score were:

- consistency between the number of HS and TO events
- sufficient number of HS events for step-time estimation
- plausibility of median step time
- step-time variability assessed through MAD
- plausibility of median stance time
- stance-time variability assessed through MAD
- plausibility of stance fraction.

The quality score can therefore be interpreted as a compact indicator of the internal consistency of the IMU-based event detection algorithm. High scores indicate that the detected events are temporally regular, physiologically plausible, and consistent across the walking segment.

5.7 GAIT CYCLE SEGMENTATION AND TIME NORMALIZATION

After IMU-based identification of HS and TO events, the processed EMG and MMG signals were segmented into individual gait cycles. This step was necessary to transform the continuous walking recordings into comparable cycle-based units and to allow subsequent phase-aligned analysis of neuromuscular and mechanical activity. The segmentation procedure was based on consecutive HS events, which served as temporal boundaries for each gait cycle. Each accepted cycle was then normalized to a common 0-100% gait cycle scale. This approach allowed cycles with different absolute durations to be compared within the same normalized phase domain and enabled point-by-point computation of representative curves across repeated cycles. Time normalization to a 0-100% scale is commonly used in gait analysis because stride duration naturally varies across repetitions, even under steady walking conditions. Without normalization, direct comparison in absolute time would introduce temporal misalignment between cycles.

5.7.1 Definition of the HS-HS cycle

Each *gait cycle* was defined as the interval between two consecutive HS events of the same limb. Therefore, the k -th gait cycle was represented as:

$$HS_k \rightarrow HS_{k+1}$$

This choice provides a repeatable biomechanical reference because HS corresponds to initial contact and marks the beginning of the stance phase [20]. For each cycle, the corresponding time interval is:

$$T_{cycle,k} = t_{HS,k+1} - t_{HS,k}$$

where $T_{cycle,k}$ is the duration of the k -th gait cycle, $t_{HS,k}$ is the time of the initial HS, and $t_{HS,k+1}$ is the time of the following HS. In the normalized representation, 0% corresponds to the first HS and 100% corresponds to the following one.

5.7.2 Inclusion Criteria for valid cycles

Not all HS-HS intervals were automatically retained for further analysis. Each candidate's gait cycle was evaluated against predefined inclusion criteria to avoid partial cycles, mis-detected events, or low-resolution segments. A cycle was considered valid only if it satisfied the following conditions:

- the cycle was bound by two consecutive HS events within the same walking segment;
- exactly one TO event was present within the HS-HS interval;
- the EMG and MMG signals contained enough samples within the cycle;
- the temporal alignment between IMU, EMG, and MMG streams was preserved;
- the cycle did not include pause, turnaround, gait initiation, stopping, or other non-stationary portions of the protocol.

The presence of one TO event within each HS-HS interval was required to ensure physiological consistency of the stance-to-swing transition. Cycles without TO or with more than one TO were excluded because they could indicate missing events, extra detections, or incorrect temporal pairing. A minimum sampling density criterion was also applied to ensure that each cycle contained enough EMG-MMG samples for reliable interpolation and feature extraction. In the implemented pipeline, cycles with insufficient EMG sample density were discarded before time normalization. This prevented low-resolution or incomplete segments from biasing the computation of ensemble statistics

5.7.3 Temporal normalization to 0-100%

After selection of valid HS–HS cycles, each cycle was temporally normalized to a 0-100% gait cycle scale. This transformation converted the absolute time axis of each cycle into a dimensionless phase axis, allowing comparison between cycles of different durations.

For each cycle, a normalized phase variable was defined as:

$$\varphi_k(t) = \frac{t - t_{HS,k}}{t_{HS,k+1} - t_{HS,k}} \cdot 100$$

where $\phi_k(t)$ represents the percentage of the gait cycle for the k -th cycle. According to this definition $\phi = 0\%$ at $t = t_{HS,k}$ and $\phi = 100\%$ at $t = t_{HS,k+1}$. Each accepted cycle was then interpolated onto a common normalized grid. In the implemented procedure, 101 equally spaced points were used. For a generic processed signal $x_k(t)$, such as the EMG envelope, EMG RMS, MMG envelope, or MMG RMS, the signal expressed over the normalized gait cycle is:

$$x_k^{norm}(\phi) = \text{interp1}(t_k, x_t(t), \phi)$$

This procedure allowed all cycles to be stacked into matrices in which each row represented one gait cycle and each column represented the same percentage of the normalized gait cycle. Pointwise *descriptive statistics* could then be computed across cycles:

$$\bar{x}(\phi) = \frac{1}{N} \sum_{K=1}^N x_k^{norm}(\phi)$$

and

$$SD_x(\phi) = \sqrt{\frac{1}{N-1} \sum_{K=1}^N (x_k^{norm}(\phi) - \bar{x}(\phi))^2}$$

where N is the number of valid cycles included in the condition. The resulting mean and standard deviation curves provide a phase-aligned description of signal behavior across the normalized gait cycle. The report describes this normalization procedure to enable inter-cycle comparison independent of absolute stride duration and to support phase-aligned averaging. From a biomechanical perspective, the normalized cycle can be interpreted according to standard gait phase subdivisions: 0% corresponds to HS, approximately 0-60% represents the stance phase, TO is expected around the stance-to-swing transition, and 60-100% corresponds to the swing phase.

For each walking condition (forward and return), valid cycles were normalized independently to the 0-100% scale and then organized into condition-specific matrices. This allowed forward and return walking to be compared later using the same methodological framework while preserving their separation as distinct locomotor conditions.

5.8 PREPARATION OF EMG-MMG SIGNALS FOR STATISTICAL COMPARISON

After gait-cycle segmentation and temporal normalization, the processed EMG and MMG signals were further prepared for quantitative comparison. This step was introduced to evaluate the temporal relationship between the electrical activation of the muscle, as measured by EMG, and the corresponding mechanical response, as measured by MMG. Because of EMG and MMG different genesis and amplitude scales, direct comparison of their raw amplitudes is not appropriate. Therefore, the analysis was focused on temporal association, waveform similarity, and the occurrence of activation patterns within comparable portions of the gait cycle, rather than on absolute amplitude values. For this purpose, EMG and MMG envelopes were normalized, temporally aligned, and compared using correlation and error-based metrics. Two complementary levels of analysis were prepared: a *block-level comparison*, performed separately for forward and return walking segments, and a *gait-cycle-level comparison*, performed after HS-HS segmentation and normalization to the 0–100% gait-cycle scale.

5.8.1 Envelope normalization

Before statistical comparison, EMG and MMG envelopes were normalized to a common dimensionless scale. Without normalization, statistical comparison would be dominated by scale differences rather than by similarities or differences in temporal behavior [3]. For each signal, min-max normalization was applied to rescale the envelope within the interval [0,1]:

$$x_{norm}(t) = \frac{x(t) - x_{min}}{x_{max} - x_{min}}$$

where $x(t)$ represents the processed envelope signal, x_{min} and x_{max} are respectively the minimum and maximum values of the signal within the considered analysis window, and $x_{norm}(t)$ is the normalized signal. Applied to the EMG envelope, the normalization can be expressed as:

$$EMG_{norm}(t) = \frac{EMG_{env}(t) - \min(EMG_{env})}{\max(EMG_{env}) - \min(EMG_{env})}$$

Similarly, for MMG:

$$MMG_{norm}(t) = \frac{MMG_{env}(t) - \min(MMG_{env})}{\max(MMG_{env}) - \min(MMG_{env})}$$

This transformation preserves the temporal structure and relative shape of each envelope while removing differences in absolute amplitude. It is important to note that this normalization was used only for EMG-MMG statistical comparison. It is distinct from the %P95 normalization adopted for gait EMG amplitude scaling.

5.8.2 Temporal alignment and interpolation

After envelope normalization, EMG and MMG signals were temporally aligned to allow point-by-point comparison. Since the two signals may be acquired or processed on slightly different time bases, direct sample-by-sample comparison requires that both signals be expressed over a common temporal axis.

In the implemented procedure, the EMG time vector was used as the reference time base. The MMG envelope was then interpolated onto the EMG time vector using *linear interpolation*:

$$MMG_{interp}(t_{EMG}) = \text{interp1}(t_{MMG}, MMG_{norm}(t_{MMG}), t_{EMG})$$

where t_{MMG} is the original MMG time vector, $MMG_{norm}(t_{MMG})$ is the normalized MMG envelope, and $MMG_{interp}(t_{EMG})$ is the MMG signal resampled on the EMG time base. After interpolation, the two signals were represented as paired samples:

$$[EMG_{norm}(t_i), MMG_{interp}(t_i)], \quad i = 1, 2, \dots, N$$

where N is the number of samples included in the considered analysis window. This common time base allowed the computation of correlation and error metrics between EMG and MMG envelopes. Linear interpolation was selected because the comparison was performed on smoothed envelope signals rather than on raw high-frequency waveforms. Therefore, the objective was to preserve the slow temporal modulation of muscle activity while ensuring temporal correspondence between the two modalities.

5.8.3 Block-Level and Cycle-Level Comparison

Two complementary comparison levels were prepared: *block-level* analysis and *gait-cycle-level* analysis. At the block level, EMG and MMG envelopes were compared separately within forward and return walking trials. This prevented non-continuous portions of the protocol from affecting the temporal comparison.

For each walking block, the normalized EMG envelope and the interpolated normalized MMG envelope were compared over the same time interval:

$$EMG_{block}(t), \quad MMG_{block}(t)$$

where t belongs to the selected forward or return walking segment. This analysis provided a measure of the overall temporal association between EMG and MMG during each continuous walking block.

At the gait-cycle level, the comparison was performed after HS-HS segmentation and temporal normalization to the 0-100% gait-cycle scale. Each valid cycle was represented on the same normalized phase domain $\varphi = 0, 1, 2, \dots, 100\%$. For each cycle k , the normalized EMG and MMG profiles were defined as:

$$EMG_k^{norm}(\varphi), \quad MMG_k^{norm}(\varphi)$$

For the k -th cycle, the cycle-by-cycle comparison was performed between these profiles. Second, mean waveform comparison was used to evaluate the similarity between the average EMG and MMG profiles across all valid cycles of the same walking condition. The mean waveforms were defined as:

$$\overline{EMG}(\varphi) = \frac{1}{N} \sum_{k=1}^N EMG_k^{norm}(\varphi)$$

$$\overline{MMG}(\varphi) = \frac{1}{N} \sum_{k=1}^N MMG_k^{norm}(\varphi)$$

where N is the number of valid gait cycles in the considered condition.

This dual-level approach allowed the EMG-MMG relationship to be assessed both over the entire walking block and within the normalized gait-cycle structure. The block-level comparison captured the global temporal association, whereas the cycle-level comparison allowed the relationship between electrical and mechanical muscle activity to be evaluated relative to gait phase.

5.8.4 Correlation coefficients and Error metrics

The temporal association and waveform similarity between EMG and MMG were quantified using three statistical metrics: Pearson correlation coefficient, Spearman rank correlation coefficient, and Root Mean Square Error.

The *Pearson correlation coefficient* was used to quantify the strength of the linear relationship between the normalized EMG and MMG envelopes. Given two paired signals x_i and y_i , with $i = 1, 2, \dots, N$, the Pearson coefficient was computed as:

$$r = \frac{\sum_{i=1}^N (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^N (x_i - \bar{x})^2} \sqrt{\sum_{i=1}^N (y_i - \bar{y})^2}}$$

where x_i and y_i represent the paired normalized EMG and MMG samples, and $\bar{x}$ and $\bar{y}$ are their mean values. Pearson correlation was used to assess whether the two signals increased and decreased in a linearly related manner over time. The Pearson coefficient ranges between $-1 < r < 1$, where:

- $r = 1$: perfect positive correlation
- $r = 0$: no linear relationship
- $r = -1$: perfect negative correlation

The *Spearman rank correlation coefficient* was used to evaluate the monotonic association between EMG and MMG. Unlike Pearson correlation, Spearman correlation is computed on the ranked values of the signals and is therefore less sensitive to non-linear relationships and amplitude distribution differences. It was defined as:

$$\rho = r(\text{rank}(x), \text{rank}(y))$$

where $rank(x)$ and $rank(y)$ are the ranked versions of the two signals, and r is the Pearson correlation applied to the ranks. When no tied ranks are present, Spearman correlation can also be expressed as:

$$\rho = 1 - \frac{6 \sum_{i=1}^N d_i^2}{N(N^2 - 1)}$$

where d_i is the difference between the ranks of the two paired observations:

$$d_i = rank(x_i) - rank(y_i)$$

Finally, the *Root Mean Square Error* was computed to quantify the point-by-point difference between the normalized EMG and MMG waveforms:

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (x_i - y_i)^2}$$

where x_i and y_i are the paired normalized signal values. While correlation coefficients describe the degree of temporal association between signals, RMSE provides complementary information about waveform similarity by measuring the average distance between the two normalized curves. Therefore,

- $RMSE = 0$: identical signals
- *Higher RMSE*: greater waveform difference

Together, these metrics allowed the EMG–MMG relationship to be described from complementary perspectives: Pearson correlation quantified linear temporal association; Spearman correlation quantified monotonic association; RMSE quantified pointwise waveform differences.

5.9 MMG-IMU-BASED GAIT CYCLE RECONSTRUCTION METHOD

Following the EMG-MMG statistical comparison, an additional methodological step was introduced to prepare the MMG signal for gait-cycle reconstruction using IMU-derived events. This step represents one of the central methodological outcomes of the thesis, as it explores combining IMU data with MMG signals from a piezoelectric sensor rather than relying exclusively on the conventional EMG-IMU approach. Since MMG-based gait-cycle reconstruction remains less extensively explored than EMG-based approaches, the MMG signal was organized within an IMU-defined gait-cycle structure to evaluate its potential for wearable gait analysis. In this framework, EMG was not used for gait segmentation; instead, HS and TO events were obtained from the IMU signal, while MMG was mapped onto the resulting gait-cycle structure. The mathematical framework for HS-HS segmentation, temporal normalization, interpolation, and extraction of mean and standard deviation curves was already described in the previous sections, therefore this section focuses only on its application to MMG-only gait-cycle reconstruction.

5.9.1 IMU-guided segmentation of MMG signals

The MMG envelope was segmented using the IMU-derived HS events previously identified in Section 5.6. Consecutive HS events defined the boundaries of each MMG gait cycle, while TO events were retained as internal markers of the transition between stance and swing. The same inclusion criteria described in Section 5.7 were applied: only complete HS-HS intervals within the same walking segment, containing one valid TO event and sufficient MMG samples, were retained. Forward and return walking conditions were processed separately to avoid artificial cycles across the pause and turnaround phase.

5.9.2 Temporal normalization of MMG cycles

Each valid MMG cycle was temporally normalized to the same 0-100% gait-cycle scale described in Section 5.7. Linear interpolation was used to represent all MMG cycles on a common phase grid, allowing cycles with different absolute durations to be compared within the same normalized domain. This step generated condition-specific MMG cycle matrices,

where each row represented one normalized MMG cycle and each column represented the same percentage of the gait cycle.

5.9.3 Phase-based organization of the gait cycle

After temporal normalization, the MMG cycles were organized according to standard gait-cycle phases:

- 0% - 10%: Loading response
- 10% - 30%: Mid stance
- 30% - 50%: Terminal stance
- 50% - 60%: Pre-swing
- 60% - 73%: Initial swing
- 73% - 87%: Mid swing
- 87% - 100%: Terminal swing

HS represented the beginning of the cycle, while TO identified the transition from stance to swing. The normalized cycle was therefore divided into conventional functional regions, including loading response, mid stance, terminal stance, pre-swing, initial swing, mid swing, and terminal swing.

In this chapter, this phase-based organization was used only as a methodological framework for arranging the MMG data. The actual distribution of MMG activity across these phases is reported and interpreted in the Results chapter.

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CHAPTER 6

RESULTS AND DISCUSSION

“Our greatest weakness lies in giving up.

*The most certain way to succeed is always
to try just one more time.”*

— Thomas A. Edison

Chapter 6 presents the results obtained from the multimodal EMG-MMG-IMU pipeline described in Chapter 5. The chapter follows the same methodological order, starting with a preliminary static feasibility assessment on the brachioradialis muscle, in which repeated voluntary activations and the temporal relationship between EMG and MMG were assessed. It then focuses on the dynamic gait trials on the quadriceps muscle, including MVC ranking, EMG normalization, processed EMG and MMG signals, and IMU-based detection of walking segments and gait events. Finally, the chapter presents the integrated gait-cycle analysis, including 0-100% normalization, EMG-MMG statistical comparison, and MMG-IMU-based gait-cycle reconstruction. This final analysis represents the main outcome of the thesis, highlighting the potential of piezoelectric MMG combined with IMU data as a wearable approach for gait analysis. This final analysis can be interpreted as a methodological proof of concept rather than as a clinical validation of compensatory gait detection.

6.1 STATIC CONDITION RESULTS

6.1.1 Activation detection results

The static condition was used as a controlled validation step for the EMG-MMG processing pipeline. **Figure 6.1** illustrates the raw signals obtained during the brachioradialis acquisitions. The red line shows the EMG signal recorded with standard electrodes, whereas the blue line shows the MMG signal recorded by the piezoelectric sensor.

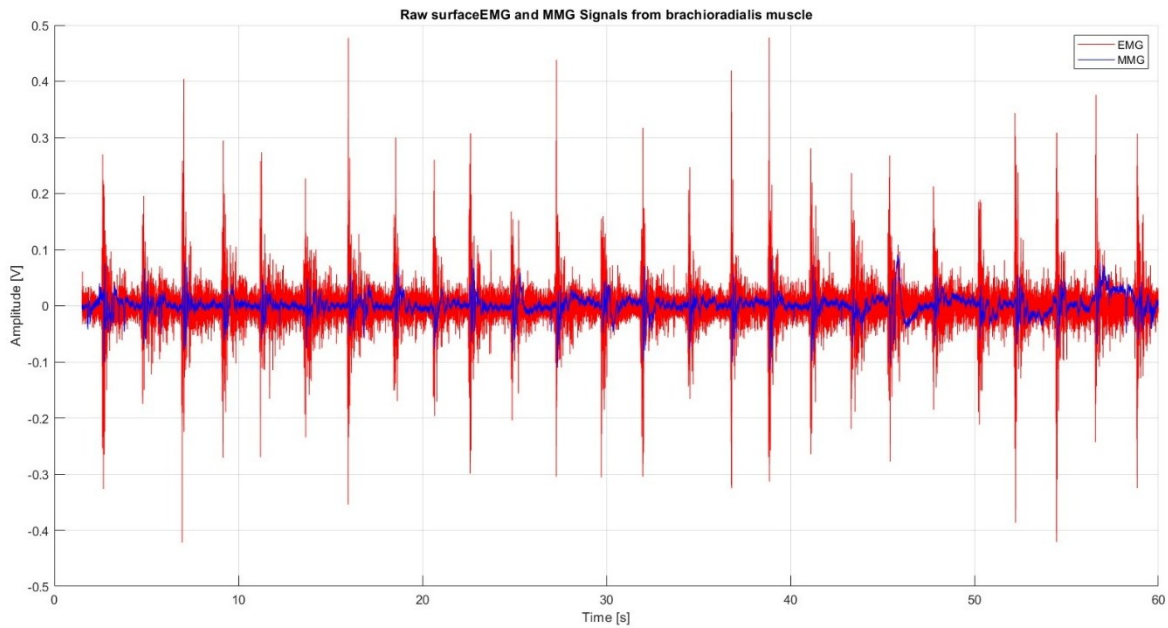


Figure 6.1: Raw sEMG and MMG signals from the brachioradialis muscle.

After removal of the initial unstable portion of the recording and application of the preprocessing chain described in Chapter 5, the EMG and MMG envelopes were analyzed to identify repeated voluntary activations of the brachioradialis muscle. A total of 26 *activation intervals* were detected in both EMG and MMG signals. These intervals correspond to voluntary muscle contractions at the sensor locations and provide a suitable basis for extracting time-domain and frequency-domain descriptors. The successful identification of the same number of activation intervals in both modalities indicates that the processed envelopes preserved the temporal structure of the contraction sequence and that MMG responses were consistently detectable in temporal correspondence with the EMG activation sequence. The detected activation intervals are highlighted on the processed EMG and MMG envelopes in **Figure 6.2**. The repeated occurrence of corresponding activation

windows confirms that both signals preserve the temporal structure of the voluntary contraction protocol.

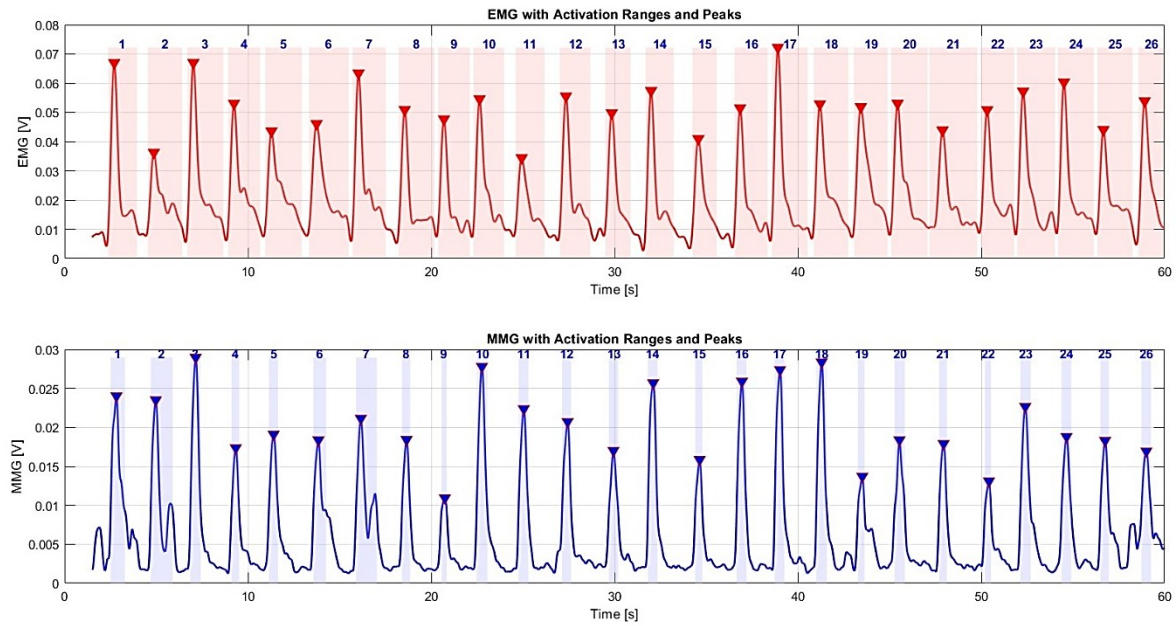


Figure 6.2: EMG and MMG envelopes with detected activation windows and peak markers.

6.1.2 EMG and MMG feature extraction results

For each detected activation interval, the main features extracted from the EMG and MMG envelopes include mean amplitude, RMS, peak amplitude, area under the curve, standard deviation, and median frequency. The values obtained across the 26 activations are summarized in **Table 6.1**.

Feature	EMG mean $\pm$ SD	MMG mean $\pm$ SD	Interpretation
Mean amplitude	0.02 $\pm$ 0.002 V	0.01 $\pm$ 0.003 V	Average envelope amplitude
RMS	0.03 $\pm$ 0.003 V	0.02 $\pm$ 0.003 V	Local energy/intensity of activation
Peak amplitude	0.05 $\pm$ 0.009 V	0.02 $\pm$ 0.005 V	Maximum activation within each interval
AUC	0.04 $\pm$ 0.006 V·s	0.01 $\pm$ 0.003 V·s	Integrated activation over time

STD	0.01± 0.003 V	0.004 ± 0.002 V	Within-activation amplitude variability
Median frequency	50.52 ± 7.51 Hz	9.96 ± 0.89 Hz	Spectral distribution of signal power

Table 6.1: Summary of EMG and MMG features extracted from the static brachioradialis condition.

The EMG features were systematically higher in numbers than the corresponding MMG features in terms of mean amplitude, RMS, peak amplitude, AUC, and standard deviation. This difference is consistent with the different physical nature of the two signals: EMG reflects the electrical activity generated by motor unit action potentials, whereas MMG represents the mechanical oscillations associated with muscle contraction. The median frequency values also confirmed the expected spectral distinction between the two modalities. EMG showed a higher median frequency (approximately 50.5 Hz), whereas MMG was concentrated at lower frequencies (approximately 10 Hz). This supports the frequency-domain assumptions used in the preprocessing stage, where EMG and MMG were treated with different band-pass ranges. Overall, the feature analysis confirms that static acquisition yielded stable, distinguishable EMG and MMG descriptors. The EMG signal captured rapid electrical activation patterns, while the MMG signal provided a lower-frequency and smoother mechanical representation of the same contraction sequence.

6.1.3 Electromechanical Delay Results

The temporal relationship between EMG and MMG was quantified using an EMG–MMG peak-to-peak delay, defined as the time difference between the EMG and MMG envelope peaks within each activation interval. This metric should be interpreted as the peak latency between the electrical and mechanical signal envelopes, rather than as a classical electromechanical delay based on activation and force onsets. Across the 26 detected activations, the MMG peak occurred after the EMG peak in the majority of cases, confirming the expected temporal sequence between electrical excitation and mechanical muscle response [1] as shown in **Figure 6.3**. The average EMG–MMG peak-to-peak delay was 102.4 ± 21.4 ms. This value indicates that, on average, the mechanical response captured by the MMG sensor followed the electrical activation measured by EMG by approximately 102 ms. The positive delay supports the physiological plausibility of the acquired signals, since

muscle depolarization precedes force development and the resulting mechanical oscillations [2]. The variability observed across activations may be related to differences in contraction intensity, mechanical coupling between the sensor and the skin, and the intrinsic variability of voluntary contractions. Nevertheless, the consistent positive delay indicates that the static acquisition was able to capture a coherent electromechanical relationship between EMG and MMG.

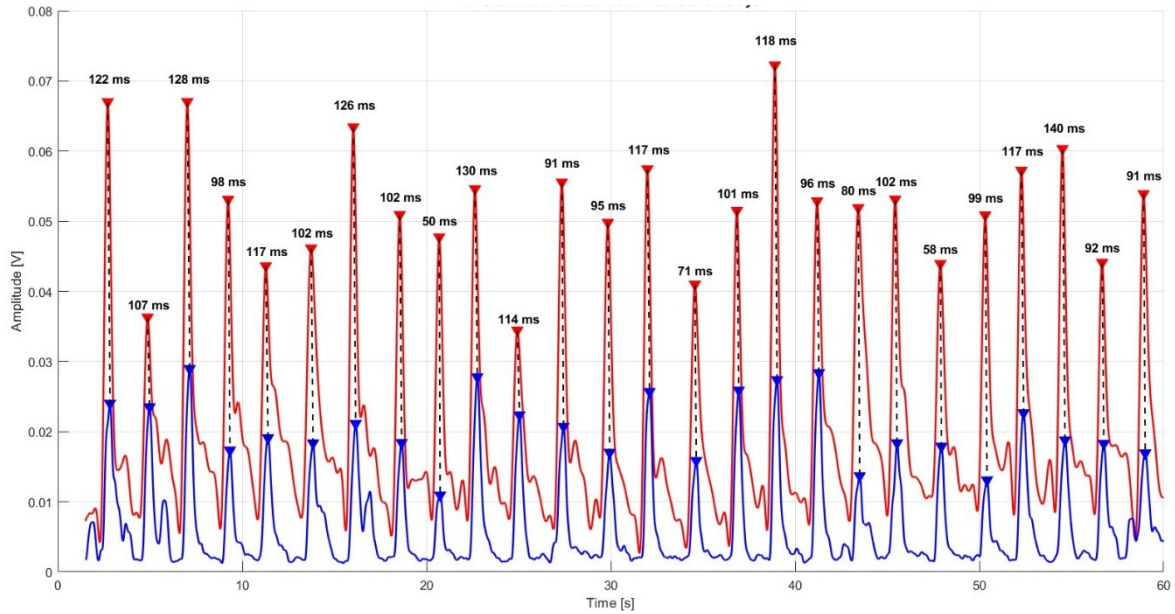


Figure 6.3: EMG and MMG envelopes with peak markers and electromechanical delay intervals.

6.2 DYNAMIC CONDITION RESULTS

6.2.1 Processed EMG and MMG signal profiles

The EMG and MMG processing plots demonstrated the effectiveness of the proposed preprocessing pipeline in isolating physiologically meaningful neuromuscular activity during gait (**Figure 6.4** and **Figure 6.5**).

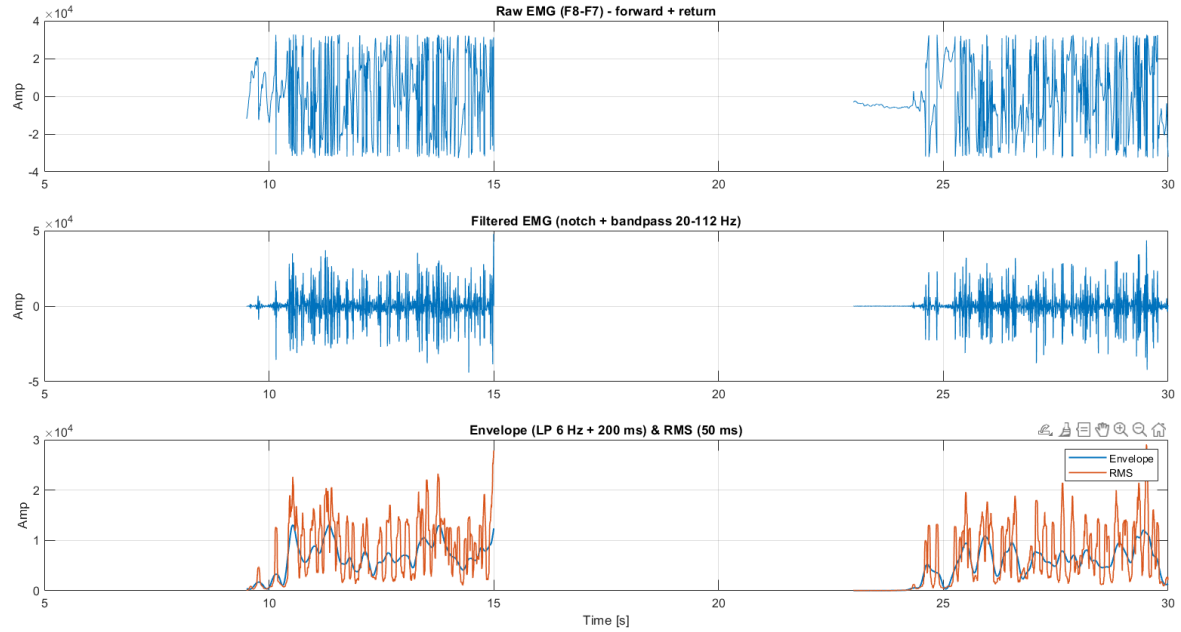


Figure 6.4: EMG signal processing. The three subplots show the raw EMG signal (top), the filtered EMG signal after notch and band-pass filtering (middle), and the extracted EMG envelope together with the RMS profile (bottom).

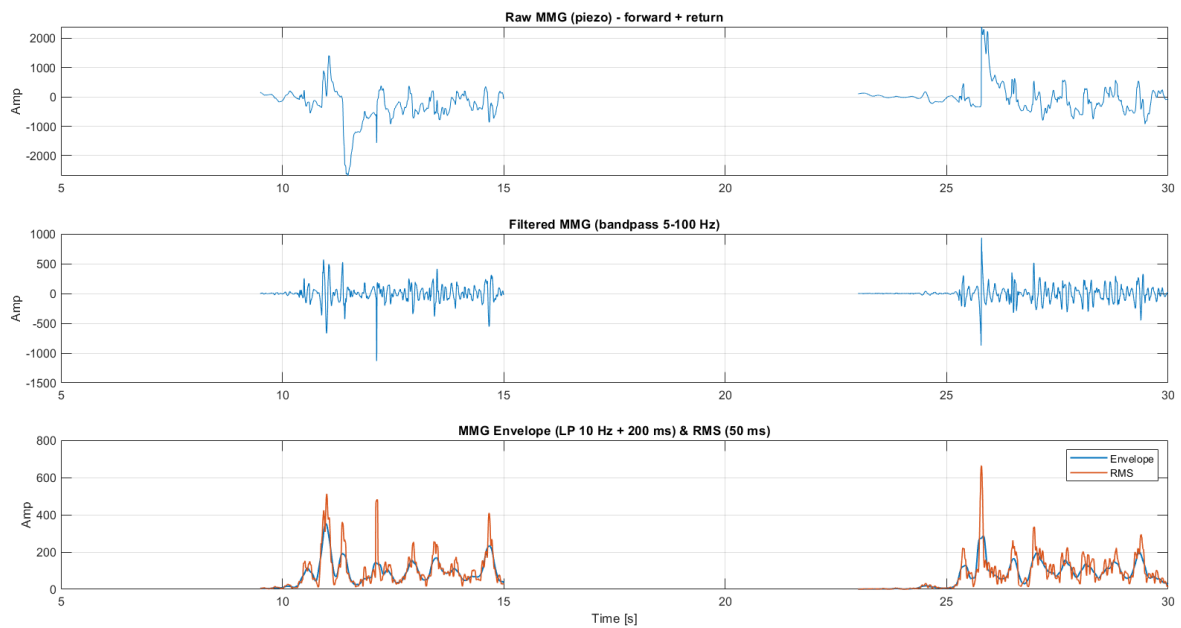


Figure 6.5: MMG signal processing. The three subplots show the raw MMG signal acquired with the piezoelectric sensor (top), the filtered MMG signal after band-pass filtering (middle), and the extracted MMG envelope together with the RMS profile (bottom).

As discussed in the previous chapter, the analysis focuses only on steady-state walking conditions. For this reason, calibration and turnaround stages have been replaced with NaN gaps, as shown in the previous figures. **Figure 6.6** illustrates the original full acquisition session of the EMG signal.

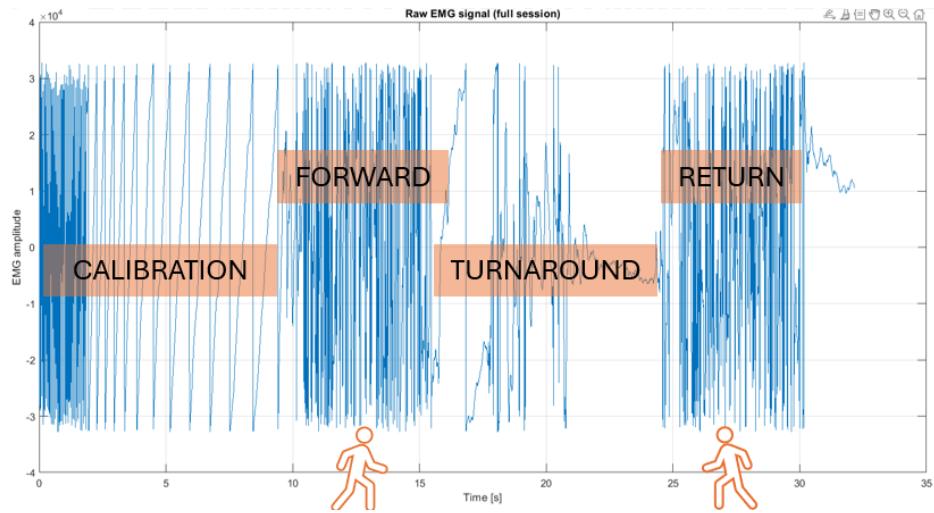


Figure 6.6: Raw EMG signal, full session.

6.2.2 MVC trials ranking results

Five MVC trials were acquired to obtain a reference value for quadriceps EMG normalization. They are presented in **Figure 6.7**, where the characteristic ramp-plateau-release is visible.

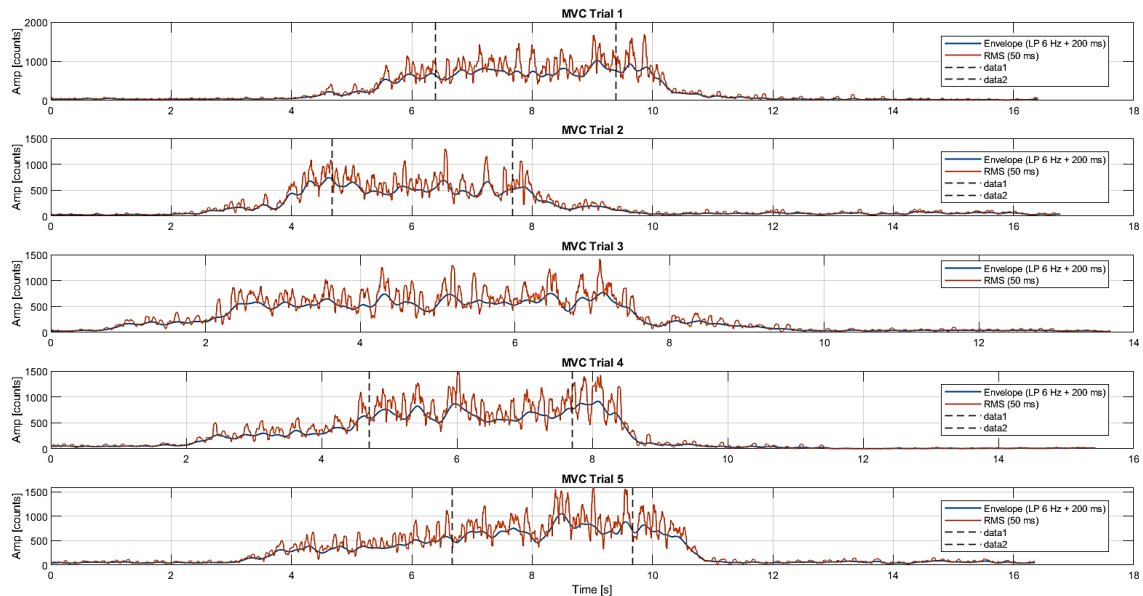


Figure 6.7: MVC trials acquired for the MVC normalization procedure.

Each trial was processed using the same EMG pipeline adopted for walking analysis, and the central plateau region was automatically identified. The trials were ranked according to plateau RMS amplitude, coefficient of variation, baseline RMS activity, and a composite score reflecting both activation intensity and contraction stability, as shown in **Table 6.2**.

Trial	Mean RMS plateau [a.u.]	CV	Baseline RMS [a.u.]	Score	Valid
Trial 1	882.0	0.27	45.07	658.8	Yes
Trial 5	855.1	0.30	62.73	614.2	Yes
Trial 4	797.8	0.27	62.71	582.3	Yes
Trial 2	621.1	0.30	31.25	452.9	Yes
Trial 3	NaN	NaN	NaN	NaN	No

Table 6.2: MVC trial ranking results.

Trial 1 achieved the highest score and was therefore identified as the best MVC trial. It showed the highest plateau RMS amplitude, along with acceptable contraction stability and clear baseline separation. Trials 5 and 4 were also considered reliable, while Trial 2, although technically valid, showed lower plateau activation and higher variability. Trial 3 was excluded because a stable baseline phase could not be clearly identified. The signal showed elevated and irregular activity in the initial portion of the recording, suggesting possible pre-activation or movement-related artifacts. As a result, the ramp-plateau-release structure could not be reliably extracted, and the trial was classified as invalid for MVC reference estimation.

6.2.3 EMG Normalization reference selection

Although Trial 1 provided the highest MVC reference value, equal to:

$$MVC_{ref} = 882 \text{ a.u.}$$

it was not adopted as the final normalization reference for gait EMG. The reason was a mismatch between the MVC and walking sessions, which were conducted on different days. Since surface EMG amplitude is strongly affected by electrode placement, skin-electrode impedance, inter-electrode distance, amplifier gain, cable orientation, and motion artifacts, the MVC reference did not reflect the same acquisition conditions as the walking trial [3]. When the walking EMG was normalized using the MVC reference, preliminary values exceeded 1000% MVC; the occurrence of these values was interpreted as a clear indication of amplitude scaling mismatch, rather than as a physiologically meaningful supra-maximal activation level. For this reason, MVC normalization was considered physiologically unreliable in the present dataset.

A within-session percentile-based normalization was therefore adopted [4, 5]. The 95th percentile of the RMS signal computed across the useful walking segments was used as reference:

$$P95_{RMS} = 17418.49 \text{ a.u.}$$

This normalization expressed EMG activity relative to a high-activation level observed within the same walking session. It preserved internal consistency between forward and return segments and avoided bias from electrode repositioning or gain differences across sessions.

6.2.4 Normalized EMG and MMG signals during gait

After adoption of the %P95 normalization strategy, EMG amplitude was expressed relative to the within-session P95 RMS reference. The normalized EMG results are summarized in **Table 6.3**.

Segment	Mean RMS [%P95]	Peak RMS [%P95]	Mean Envelope [%P95]	Peak Envelope [%P95]
Forward	48.00	160.04	37.63	75.29
Return	35.31	166.95	27.88	69.19

Table 6.3: %P95 normalized EMG results during gait.

It should be emphasized that %P95 normalization does not represent activation as a percentage of maximal voluntary capacity. It is a within-session scaling strategy that allows comparison between forward and return walking segments under the same acquisition conditions. During forward walking, the mean RMS amplitude reached $48.00\%P95$, indicating moderate quadriceps activation relative to the high-activity reference level observed within the same session. The peak RMS reached $160.04\%P95$, as expected, since the 95th percentile is not the absolute maximum of the signal distribution.

During return walking, the mean RMS was lower, equal to $35.31\%P95$, while the peak RMS remained comparable to forward walking, reaching $166.95\%P95$. This suggests that the return segment showed lower average quadriceps activation, yet still contained high-intensity transient bursts. The envelope values were lower than the corresponding RMS values in both walking conditions, as expected due to low-pass filtering and smoothing,

which attenuate short-duration peaks. The results of this normalization procedure on EMG envelope and RMS are shown in **Figure 6.8**.

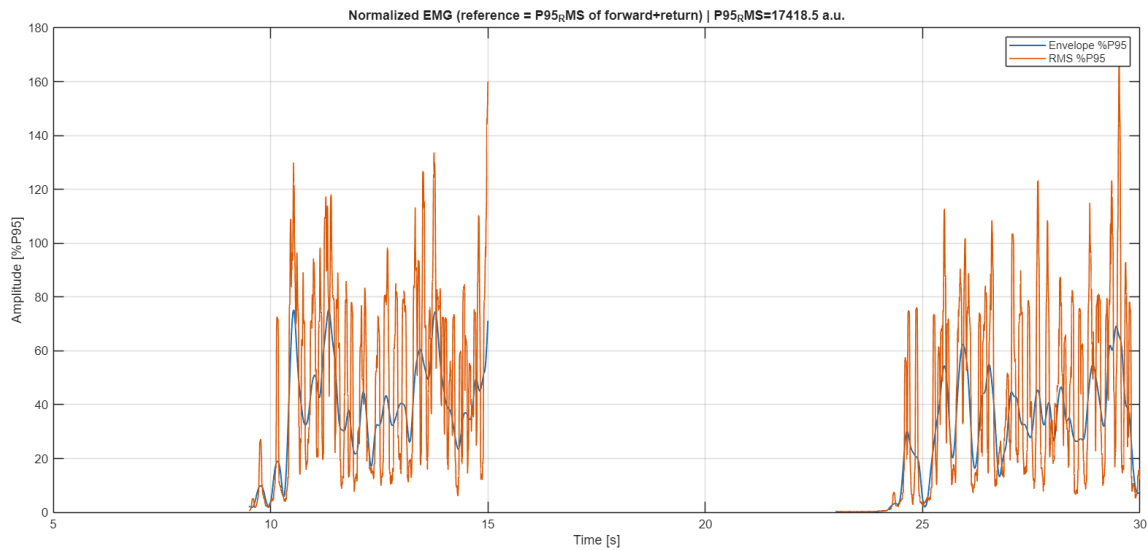


Figure 6.8: %P95 normalized EMG RMS and envelope during forward and return walking.

To obtain a visual comparison of the muscle biosignals under analysis, **Figure 6.9** illustrates how normalized EMG and MMG envelopes are integrated with kinematics information, obtained from IMU data. The processed MMG envelope showed temporally coherent burst patterns during the same walking segments. Although MMG was not normalized to %P95, its envelope and RMS presented periodic modulations aligned with the walking task. The MMG signal, therefore, provided a mechanical counterpart to the EMG activation pattern, supporting the subsequent EMG-MMG comparison.

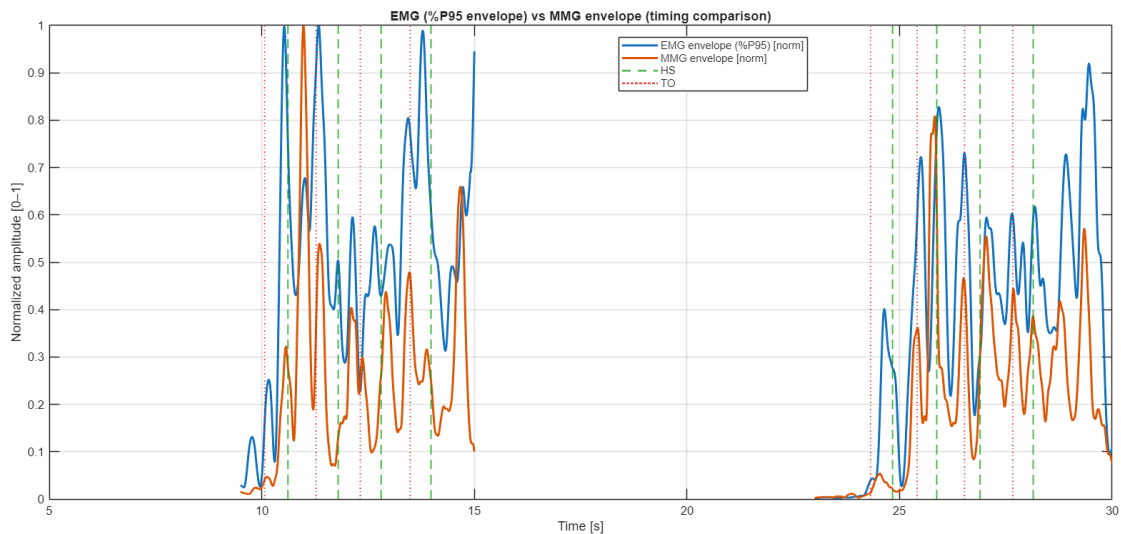


Figure 6.9: EMG and MMG envelopes during forward and return walking.

6.3 IMU SIGNAL PROCESSING RESULTS

6.3.1 IMU sampling frequency and units conversion

The IMU data were acquired using an *LSM6DS3* sensor positioned on the right thigh. After removal of invalid samples, the effective sampling frequency was estimated from the timestamps using the median sampling interval. The resulting sampling frequency was:

$$F_s = 104.00 \text{ Hz}$$

This value is suitable for gait analysis, since the dominant frequency components of normal walking are typically below 6-8 Hz. From the plots in **Figure 6.10**, a preliminary check confirmed the absence of 16-bit saturation in the raw IMU data, indicating that no clipping occurred during acquisition and that amplitude-based event detection could be considered reliable. Raw accelerometer and gyroscope values were converted into physical units using the manufacturer sensitivity factors. For the selected full-scale ranges, the accelerometer was configured at $\pm 4 \text{ g}$, with a sensitivity of 0.122 mg/LSB , while the gyroscope was configured at $\pm 2000 \text{ dps}$, with a sensitivity of 70 mdps/LSB . The converted gyroscope signal showed peak angular velocities of approximately $420^\circ/\text{s}$, which are biomechanically plausible for knee flexion-extension during walking. The dynamic acceleration magnitude ranged from approximately 1.2 to 2.4 g at knee level, consistent with attenuation of impact-related accelerations along the lower limb [6, 7].

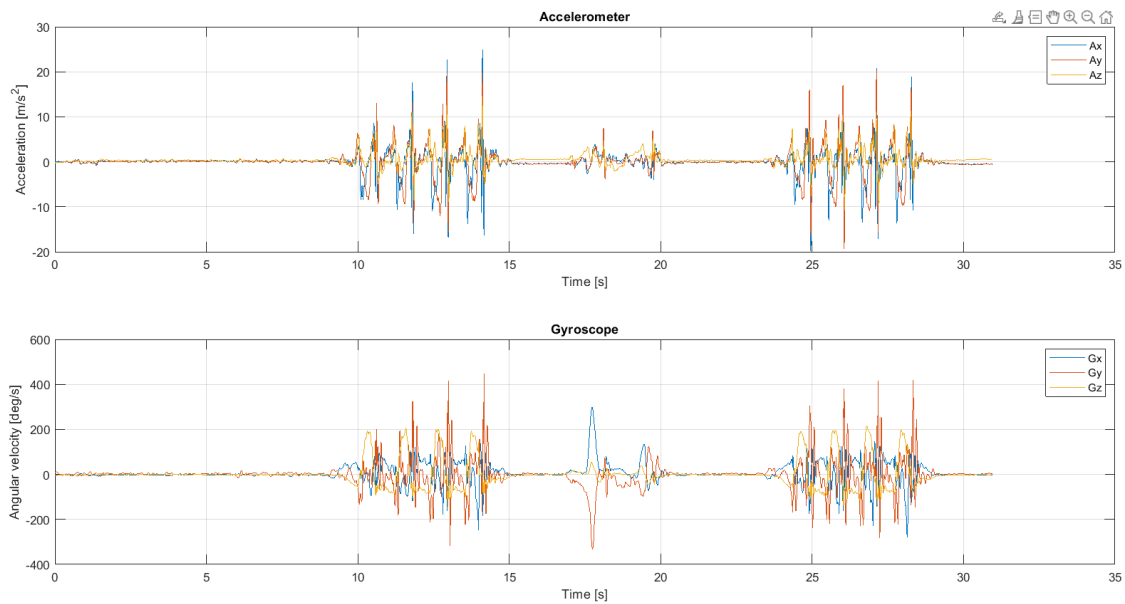


Figure 6.10: Accelerometer and Gyroscope signals with units conversion.

6.3.2 Main gyroscope axis selection

The principal gyroscope axis was selected automatically based on the maximum variance of the low-pass filtered angular velocity signals. The selected axis was G_z . This result indicates that the G_z axis contained the highest dynamic content during the walking task. Since the IMU was positioned on the thigh, this axis was interpreted as the most informative for capturing the dominant flexion-extension component of the lower limb during sagittal-plane walking. The automatic selection of the main gyroscope axis reduced dependence on exact sensor orientation and provided a robust signal for subsequent identification of walking segments and gait events.

6.3.3 Walking segments identification

The gyroscope-energy-based segmentation identified two main walking segments, corresponding to the forward and return phases of the protocol. The first segment extended approximately from 9.56 s to 14.99 s , while the second extended from 23.88 s to 29.03 s . The identification of two distinct walking blocks confirms that the IMU-based segmentation successfully separated the useful steady walking portions from the pause, turnaround, gait initiation, and stopping phases. This result is important because only quasi-stationary walking segments were retained for cycle-level analysis, while transient portions were excluded to avoid introducing non-representative gait cycles.

6.4 IMU-BASED GAIT EVENTS DETECTION RESULTS

6.4.1 Toe Off and Heel Strike detection results

The IMU-based gait event detection algorithm was applied to filtered gyroscope and accelerometer data, and it identified a total of:

- 8 Heel Strike events
- 8 Toe Off events

The events were equally distributed across the two walking segments, with 4 HS and 4 TO events detected in the forward segment and 4 HS and 4 TO events detected in the return segment, as reported in **Table 6.4**.

Segment	HS detected	TO detected
Forward	4	4
Return	4	4
Total	8	8

Table 6.4: IMU-derived gait events accepted by the internal consistency algorithm.

The equal number of HS and TO events in each segment indicates internal consistency of the event detection procedure. Graphical inspection confirmed that TO events occurred before the main swing-related gyroscope peak, whereas HS events corresponded to local maxima of the dynamic acceleration magnitude. The pattern shown in **Figure 6.11** is biomechanically plausible and internally consistent with the expected sequence of TO and HS events, since TO marks the transition from stance to swing and HS corresponds to the impact-related event at foot contact.

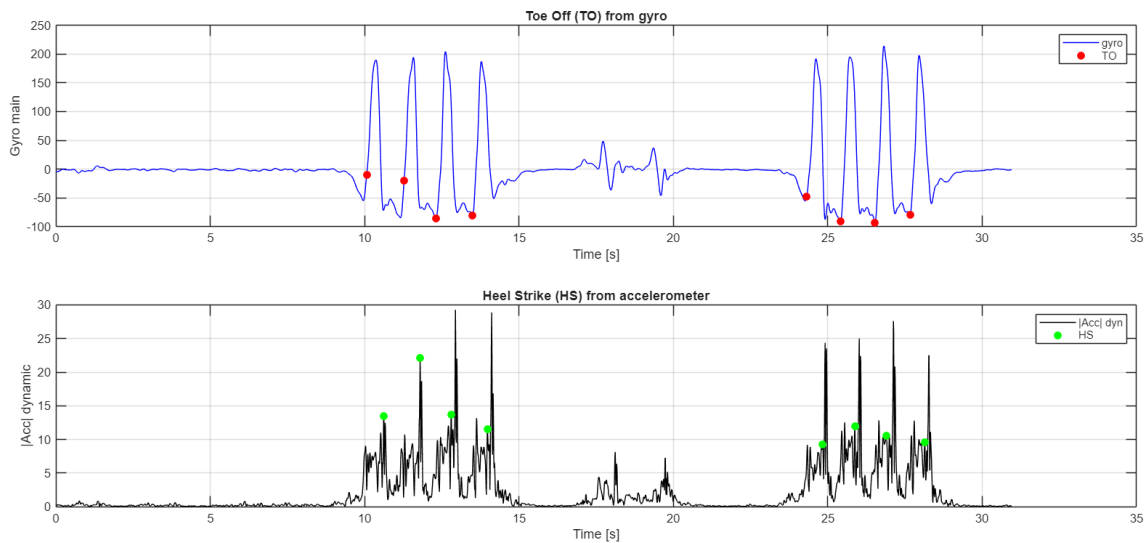


Figure 6.11: TO and HS events detection on the gyroscope and accelerometer filtered signals.

6.4.2 Temporal validation of HS and TO events

Temporal validation was performed separately for forward and return walking in order to avoid distortion caused by the temporal gap between segments [8, 9]. The results are summarized in **Table 6.5**.

Parameter	Forward	Return	Literature Ranges
Segment time [s]	9.56 – 14.99	23.88 – 29.03	
Segment duration [s]	5.43	5.14	
HS count	4	4	
TO count	4	4	
Median step time [s]	1.17	1.04	0.9 – 1.2 [8]
Estimated total cadence [steps/min]	102	116	90 – 120 [8]
Stance time [s]	0.66	0.65	0.5 – 0.8 [9]
Step Variability MAD	0.01	0.03	<0.05 (steady gait) [10]
Stance fraction	0.56	0.63	0.55 – 0.65 [9]

Table 6.5: Temporal validation of HS and TO events.

The forward segment showed a median HS-HS cycle time of 1.17 s , while the return segment showed a shorter median HS-HS cycle time of 1.04 s . Since these values were computed from consecutive HS events of the analyzed limb, the cadence directly obtained from the algorithm represented a single-limb cadence, equal to 51.1 cycles/min for the forward segment and 57.8 cycles/min for the return segment. For comparison with the standard gait literature, where cadence is usually reported as total bilateral cadence, these values were multiplied by 2, yielding estimated total cadences of approximately 102 steps/min for forward walking and 116 steps/min for return walking. Both values fall within the physiological range expected for slow-to-moderate walking, while the HS-HS cycle times are consistent with values typically observed at self-selected walking speed. The stance fractions were 0.56 for forward walking and 0.63 for return walking. These values are consistent with the classical description of normal gait, in which stance occupies approximately 60% of the gait cycle and swing the remaining 40%. The low step-time MAD values indicate temporally stable gait event detection, particularly in the forward segment.

6.4.3 Spatiotemporal parameters and Quality Score

The quality score was used as a compact indicator of the internal consistency and physiological plausibility of the detected gait events. The obtained values were:

- Forward segment: 100/100
- Return segment: 95/100

The score of *100/100* in the forward segment indicates complete agreement between the number of HS and TO events, physiologically plausible step and stance timing, low variability, and coherent event sequencing. The return segment obtained a slightly lower but still high score of *95/100*, mainly due to greater stance-time variability. This does not indicate algorithmic instability but rather reflects moderate temporal variability following the turnaround phase. Overall, the IMU-based gait event detection algorithm showed high internal consistency and biomechanical plausibility across the analyzed walking segments.

6.5 GAIT CYCLE SEGMENTATION AND TIME NORMALIZATION RESULTS

6.5.1 Valid HS-HS cycles

Following the detection of HS and TO events, gait cycles were segmented using consecutive HS events of the same limb. Since each walking segment contained four right-foot HS events, three complete HS–HS intervals could be defined in each condition. This is consistent with the segmentation logic, according to which four consecutive HS events generate three complete gait cycles:

$$4 \text{ HS events} \rightarrow 3 \text{ HS – HS intervals} \rightarrow 3 \text{ complete gait cycles}$$

Therefore, the final dataset included three valid gait cycles in the forward condition ($n = 3$) and three valid gait cycles in the return condition ($n = 3$), as reported in **Table 6.6**.

Segment	HS events	Candidate HS–HS intervals	Valid cycles
Forward	4	3	3
Return	4	3	3

Table 6.6: Valid gait cycles.

This result was consistent with the experimental protocol, which included four right-limb steps per walking segment. Each retained cycle contained one valid TO event and enough EMG-MMG samples for interpolation and temporal normalization.

6.5.2 The TO phase within the normalized gait cycle

After temporal normalization to the 0-100% gait-cycle scale, TO occurred approximately around the expected stance-to-swing transition. In the forward condition, the mean TO phase was approximately 58-60% of the gait cycle, while in the return condition, it occurred around 60%. This result provides important internal validation of the segmentation procedure. In normal walking, TO is expected to occur at approximately 60% of the gait cycle, marking the transition between stance and swing. The agreement between the detected TO phase and the expected physiological timing supports the internal reliability of the IMU-based HS/TO algorithm and confirms that the HS-HS cycle normalization preserved biomechanically meaningful temporal relationships.

6.5.3 Normalized EMG and MMG gait cycle curve

The EMG and MMG envelopes were segmented into valid HS-HS gait cycles and temporally normalized to a 0-100% gait-cycle scale. For each walking condition, the three valid cycles were aligned on the same normalized phase axis, and pointwise mean and standard deviation curves were computed. Therefore, the resulting plots (**Figure 6.12**) represent the average behavior of EMG signals across the gait cycle, while the shaded area indicates ± 1 standard deviation at each normalized phase point.

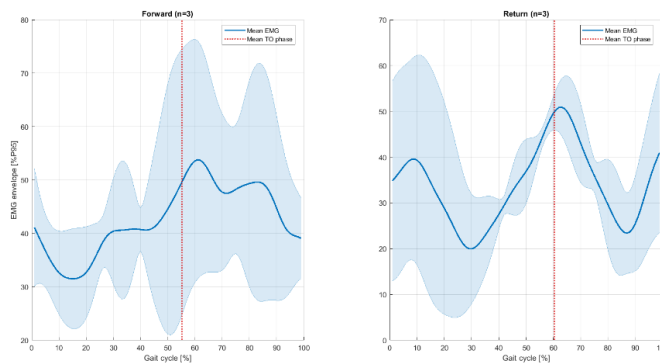


Figure 6.12: Normalized EMG gait-cycle curves during forward and return walking. Mean $\pm$ SD profiles computed across the three valid HS-HS cycles for each walking condition. The normalized phase axis ranges from 0% to 100% of the gait cycle, with 0% corresponding to HS and the TO region occurring around the stance-to-swing transition.

In the EMG signal, the forward walking condition showed a structured quadriceps activation profile across the normalized gait cycle. Moderate activation was observed during the early portion of the cycle, followed by a progressive modulation toward late stance and pre-swing. After the TO region, EMG amplitude decreased in the analyzed cycles, suggesting a reduction of load-bearing demand during the subsequent swing portion of this specific task. The return condition showed a broadly comparable temporal organization, although with lower average amplitude and slightly different variability distribution across the cycle.

The standard deviation band observed in the normalized curves, particularly in the forward condition, should be interpreted within the methodological context of cycle-based normalization and temporal rescaling. Since only three valid cycles were available for each condition ($n = 3$), the standard deviation represents descriptive inter-cycle dispersion rather than population-level variability. With so few cycles, even small differences in burst amplitude, peak timing, or activation shape can broaden the shaded band.

The observed variability was also phase-dependent. A wider standard deviation was mainly visible around late stance and pre-swing, approximately between 45% and 65% of the gait cycle. This region corresponds to the transition toward TO, where quadriceps activation can vary according to unloading strategy, knee stabilization, and preparation for limb advancement. Therefore, the increased dispersion in this region can be interpreted as structured inter-cycle amplitude modulation rather than as random noise.

An additional contribution to the observed dispersion is related to the time-normalization procedure itself. When each gait cycle is rescaled to a common 0-100% phase domain, small absolute differences in the timing of EMG peaks can appear as slight phase shifts after interpolation. During ensemble averaging, these small shifts may smooth the mean waveform and increase the pointwise standard deviation in regions characterized by rapid amplitude changes. This effect is intrinsic to time-normalized gait-cycle analysis and does not necessarily indicate instability of event detection.

Importantly, the temporal validation metrics support the robustness of the segmentation procedure. The low step-time MAD values and the high-quality scores reported for the IMU-based gait event detection indicate that the HS and TO events were temporally consistent

across the analyzed walking segments. Therefore, the variability observed in the normalized EMG curves should be interpreted mainly as amplitude-related inter-cycle modulation under stable timing conditions, rather than because of incorrect HS-TO identification.

In **Figure 6.13**, MMG signal also showed a phase-dependent modulation across the normalized gait cycle, indicating that the mechanical response of the quadriceps could be represented within the same HS-HS framework used for EMG. Compared with EMG, the MMG curve reflects mechanical muscle oscillations rather than electrical motor unit activation. For this reason, differences between EMG and MMG waveform morphology are expected and should be interpreted as complementary information rather than as disagreement between signals.

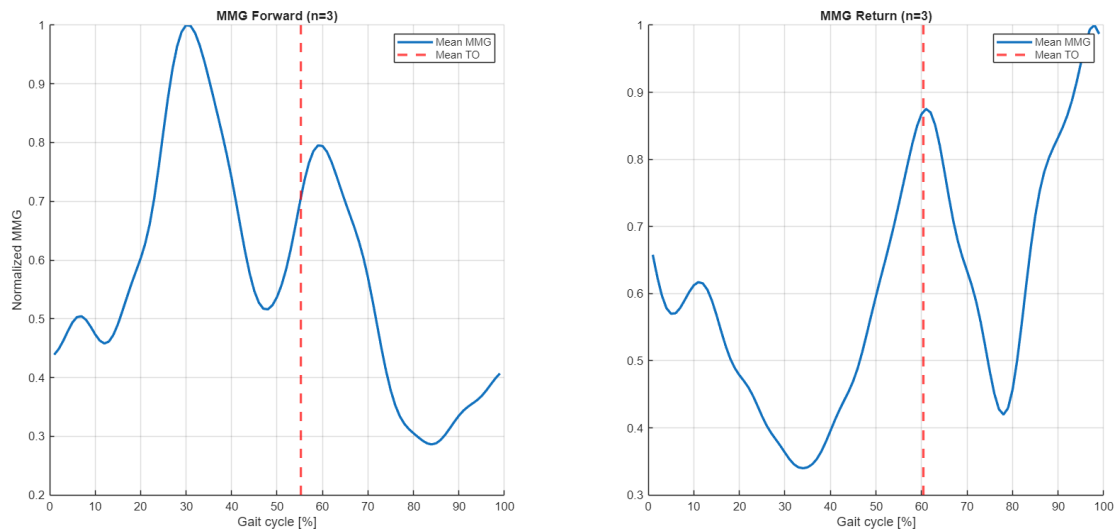


Figure 6.13: Normalized MMG gait-cycle curves during forward and return walking.

Overall, the normalized EMG and MMG curves demonstrate that the adopted segmentation and normalization procedure produced physiologically interpretable ensemble profiles. The EMG curves preserved the expected phase-dependent organization of quadriceps activation, while the MMG curves provided a mechanical representation of muscle behavior within the same gait-cycle structure. These normalized curves constituted the basis for the subsequent EMG–MMG statistical comparison and for the MMG–IMU-based gait-cycle reconstruction.

6.5.4 Biomechanical consistency of the 0-100% normalized gait cycle

The distribution of quadriceps EMG activity across the normalized 0-100% gait cycle showed very good biomechanical consistency with the classical gait phase framework. In

this framework, 0% corresponds to initial contact, marking the beginning of the stance phase. The early portion of the cycle includes loading response and mid stance, during which the quadriceps contribute to knee stabilization, controlled knee flexion, and impact absorption after foot contact. In the present data, moderate EMG activation was observed during the early portion of the normalized cycle, consistent with the stabilizing and shock-absorbing role of the quadriceps during weight acceptance.

Between approximately 30% and 50% of the gait cycle, corresponding to terminal stance, the limb progressively transitions toward unloading. This phase extends toward pre-swing, approximately between 50% and 60% of the cycle, where TO marks the transition from stance to swing. In the experimental data, EMG amplitude increased toward this region and reached a peak close to the detected TO phase. This temporal alignment is biomechanically meaningful because TO normally occurs around 60% of the gait cycle and represents the transition from weight-bearing to limb advancement.

After TO, the gait cycle enters the swing phase, which extends from approximately 60% to 100% of the normalized cycle. During this phase, the limb advances with reduced load-bearing demand, and quadriceps activity is generally lower than during stance. In the present dataset, EMG amplitude decreased after the TO region, consistently with the expected reduction in quadriceps mechanical demand during limb advancement. The detected TO, approximately 58–60% in the forward condition and around 60% in the return condition, closely matched the canonical stance-to-swing transition described in gait analysis literature. This finding supports the internal validity of the IMU-based event detection algorithm and confirms that temporal normalization preserved physiologically meaningful event timing. Furthermore, the preservation of phase-specific activation morphology across both forward and return walking indicates that the fundamental organization of the gait cycle remained intact. Overall, the agreement between the experimentally derived EMG activation profiles and the expected gait phase framework provides evidence of biomechanical plausibility. The 0-100% normalization procedure successfully preserved meaningful temporal relationships between gait events and muscle activation patterns, supporting the robustness of the segmentation algorithm and the interpretability of the ensemble EMG statistics. In **Figure 6.14**, a reference gait cycle model from the literature was overlaid with the experimental results obtained in this study, providing a comprehensive view of the entire gait cycle and enabling a direct comparison between expected physiological patterns and measured data.

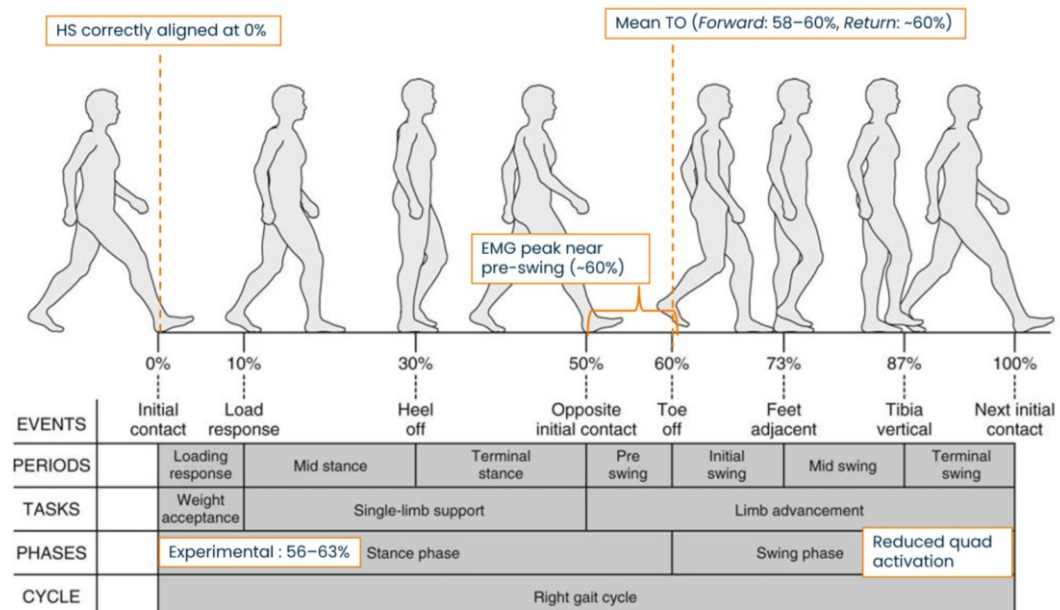


Figure 6.14: Comparison between the reference gait-cycle framework and the experimentally detected HS/TO timing.

Table 6.7 summarizes the correspondence between the expected gait-cycle framework and the experimental activation patterns observed after HS-HS segmentation and temporal normalization. The most relevant element of validation is the clustering of TO around the canonical stance-to-swing transition, which supports both the reliability of the IMU-derived gait events and the physiological interpretability of the normalized EMG profiles.

Gait phase	Literature framework	Experimental finding	Biomechanical interpretation
0% – Initial Contact (HS)	Beginning of the gait cycle and onset of stance	Cycle segmentation was defined from HS to the subsequent ipsilateral HS; 0% was aligned with IMU-derived HS	Correct identification of cycle boundaries and robust temporal anchoring of normalization
~60% – TO	TO typically occurs around 60% of the gait cycle, marking the transition from stance to swing	Mean TO occurred at approximately 58–60% in forward walking and around 60% in return walking	Supports the validity of IMU-based event detection and correct stance–swing partitioning

0–60% (Stance phase)	Stance occupies approximately 60% of the gait cycle	TO was consistently detected near 60% of the normalized cycle	Confirms physiological stance duration and biomechanical coherence of segmentation
0–30% (Early stance)	Loading response and mid stance involve weight acceptance, impact absorption, and knee stabilization	Moderate EMG activation was observed during the early portion of the cycle	Consistent with the quadriceps contribution to shock absorption and knee stabilization
30–50% (Terminal Stance)	Progressive unloading and preparation for limb advancement	EMG amplitude progressively increased toward the late stance region	Reflects modulation of knee control and preparation for the stance-to-swing transition
45–60% (Pre-Swing)	Transition from weight-bearing to Toe-Off; phase characterized by variable muscle modulation	EMG peak occurred near the TO region, with greater SD in this phase	Indicates phase-dependent amplitude modulation and physiologically plausible inter-cycle variability
60–100% (Swing phase)	Swing represents limb advancement with reduced load-bearing demand	EMG amplitude decreased after TO	Coherent with reduced quadriceps demand during limb advancement

Table 6.7: Biomechanical consistency between the normalized gait-cycle framework and experimental EMG findings.

6.6 EMG-MMG STATISTICAL COMPARISON RESULTS

6.6.1 Block-level temporal association

The temporal association between EMG and MMG was first assessed at the block level by comparing the normalized envelopes during forward and return walking. Pearson correlation, Spearman correlation, and RMSE were computed separately for the two walking segments, and their values are shown in **Table 6.8**.

Segment	Pearson r	Spearman ρ	RMSE
Forward	0.54	0.65	0.33
Return	0.74	0.81	0.24

Table 6.8: Block-level EMG–MMG comparison.

The forward segment showed a moderate temporal association between EMG and MMG, with Pearson $r = 0.54$ and Spearman $\rho = 0.65$. This indicates that the two signals followed a similar temporal trend, although their waveforms differed.

The return segment showed a stronger association with Pearson $r = 0.74$ and Spearman $\rho = 0.81$. The RMSE also decreased from 0.33 in forward walking to 0.24 in return walking, indicating a smaller point-by-point difference between normalized EMG and MMG envelopes in the return condition.

6.6.2 Gait-cycle-level similarity

The relationship between EMG and MMG was then assessed within the normalized gait cycle. **Table 6.9** reports two levels of comparison: cycle-by-cycle correlation and mean waveform comparison.

Segment	Cycle correlation	Mean waveform correlation	RMSE	Cycles
Forward	0.24 ± 0.16	-0.05	0.42	3
Return	0.64 ± 0.13	0.57	0.26	3

Table 6.9: Gait-cycle-level EMG–MMG comparison.

The discrepancy between block-level and cycle-level results indicates that EMG–MMG association depends on the temporal scale of analysis. While block-level envelopes showed moderate-to-strong co-modulation, cycle-normalized profiles, especially during forward walking, revealed lower waveform similarity, probably due to phase shifts, a limited number of cycles, and the different physiological origins of the two signals.

In the forward condition, the cycle-by-cycle correlation was relatively low at 0.24 ± 0.16 , and the mean waveform correlation was close to zero. This indicates weak similarity between individual EMG and MMG normalized cycles, possibly due to inter-cycle variability and the limited number of valid cycles included in the analysis.

In contrast, the return condition showed higher cycle-level similarity, with a cycle correlation of 0.64 ± 0.13 and a mean waveform correlation of 0.57 . The RMSE was also lower in the return condition, indicating closer waveform similarity between EMG and MMG within the normalized gait-cycle representation.

6.6.3 Interpretation of EMG-MMG relationship

The statistical comparison indicated a temporal association between EMG and MMG signals during walking, although their waveform shapes were not identical, as shown in **Figure 6.15**.

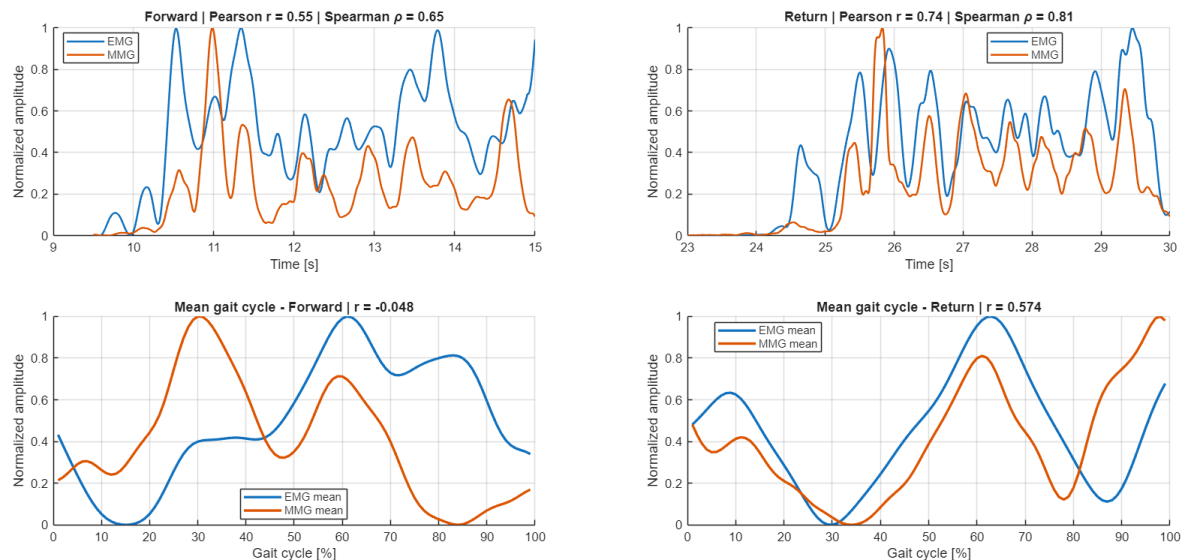


Figure 6.15: Visual representation of EMG and MMG temporal comparison.

This is physiologically expected because EMG and MMG originate from different mechanisms: electrical activation of motor units and the mechanical oscillations associated

with muscle fiber contraction and tissue vibration. The block-level analysis showed moderate-to-strong correlations, with values ranging from *0.54 to 0.74* for Pearson correlation [11, 12] and from *0.65 to 0.81* for Spearman correlation. These values are compatible with the general interpretation of MMG as a mechanical signal related to muscle activation during dynamic contractions, although the limited number of cycles and the absence of lag-compensated analysis prevent stronger conclusions. The stronger association observed in the return segment suggests that, in this condition, the mechanical response measured by MMG more closely followed the electrical activation pattern. However, the differences between EMG and MMG should not be interpreted as inconsistencies. Rather, they reflect the complementary nature of the two modalities: EMG provides information on neural activation, while MMG provides information on the mechanical response of muscle tissue.

6.7 MMG-IMU-BASED GAIT CYCLE RECONSTRUCTION RESULTS

The final stage of the analysis focused on reconstructing the gait cycle from MMG signals acquired by the piezoelectric sensor and segmented using IMU-derived gait events. This section represents one of the central outcomes of the thesis, because it evaluates whether the mechanical muscle response captured by MMG can be organized within a biomechanically meaningful gait-cycle framework without using EMG for the segmentation step. The novelty of this analysis lies in the fact that the gait-cycle structure was obtained from IMU data, while the muscle-related information was provided by a mechanical piezoelectric MMG signal rather than by EMG. In this analysis, EMG was considered as the conventional reference for neuromuscular activation, while MMG was investigated as a wearable mechanical alternative capable of describing phase-dependent muscle behavior. The IMU provided the temporal structure of the gait cycle through the automatic detection of Heel Strike and Toe-Off events, whereas the MMG envelope represented the mechanical response of the quadriceps muscle across the normalized gait cycle. This MMG-IMU integration was therefore used to assess whether a piezoelectric MMG sensor could support gait-cycle reconstruction in a compact multimodal wearable framework.

6.7.1 MMG-only gait cycle reconstruction

Building on the previous EMG-MMG comparison, the analysis was extended to evaluate whether the MMG signal acquired from the piezoelectric sensor could be used to reconstruct the gait cycle when combined with IMU-derived gait events. The MMG-IMU reconstruction yielded three valid normalized MMG cycles for each walking condition, consistent with the HS-HS segmentation previously obtained for the EMG-based gait-cycle analysis. The TO phase was located close to the expected stance-to-swing transition, occurring around 55-60% of the normalized gait cycle. This temporal alignment supports the coherence between the IMU-derived gait events and the MMG mechanical signal and confirms that the reconstructed MMG profiles preserved the fundamental timing structure of gait. The most important MMG-IMU gait-cycle reconstruction results are presented in the **Table 6.10**.

Parameter	Forward	Return	Interpretation
Valid MMG cycles	3	3	Same number of valid HS–HS cycles for both conditions
Cycle definition	HS–HS	HS–HS	Consecutive IMU-derived HS events used as boundaries
Internal gait marker	TO	TO	IMU-derived TO used as stance–swing transition marker
Normalized gait-cycle scale	0–100%	0–100%	Allows phase-based comparison between cycles
Mean TO phase	≈55–60%	≈60%	Consistent with physiological stance–swing transition
Dominant MMG activation phase	Terminal stance	Terminal swing	Indicates condition-dependent mechanical behavior
Signal used for reconstruction	MMG envelope	MMG envelope	Mechanical muscle response acquired from piezoelectric sensor

Table 6.10: Summary of MMG-IMU gait-cycle reconstruction results.

The fact that TO occurred near the canonical stance-to-swing transition in both conditions provides an important validation of the reconstruction procedure. It indicates that the MMG envelope, when segmented using IMU-derived events, can be represented within a

physiologically plausible gait-cycle structure. This result supports the feasibility of using a piezoelectric MMG sensor as a mechanically based signal for gait-cycle reconstruction.

6.7.2 Phase-based MMG modulation

After gait-cycle reconstruction, the normalized MMG profiles were analyzed according to standard gait phases. The objective was to determine how the mechanical response of the quadriceps was distributed across the gait cycle and whether this distribution changed between forward and return walking. The phase-based descriptors extracted from the normalized MMG envelope included the mean MMG amplitude, standard deviation, and peak value within each gait phase. Since the MMG signal was normalized, these values should be interpreted as relative descriptors of mechanical muscle response rather than absolute amplitudes. The complete phase-based values are reported in **Table 6.11**.

Gait phase	Forward Mean ± SD	Forward Peak	Return Mean ± SD	Return Peak
Loading response	0.48 ± 0.02	0.50	0.60 ± 0.03	0.66
Mid stance	0.65 ± 0.18	0.98	0.50 ± 0.08	0.62
Terminal stance	0.75 ± 0.18	1.00	0.41 ± 0.07	0.57
Pre-swing	0.67 ± 0.10	0.80	0.72 ± 0.09	0.85
Initial swing	0.67 ± 0.10	0.80	0.74 ± 0.10	0.87
Mid swing	0.33 ± 0.05	0.45	0.54 ± 0.11	0.75
Terminal swing	0.35 ± 0.03	0.41	0.90 ± 0.08	1.00

Table 6.11: Phase-based values from MMG profile.

In the forward condition, the highest mean MMG amplitude was observed during terminal stance (0.75 ± 0.18), with a normalized peak value of 1.00. High values were also present during pre-swing (0.67 ± 0.10), initial swing (0.67 ± 0.10), and mid-stance (0.65 ± 0.18). In contrast, mid swing and terminal swing showed markedly lower MMG amplitudes, with mean values of 0.33 and 0.35, respectively.

This pattern indicates that, during forward walking, the quadriceps mechanical response was predominantly concentrated during the stance and stance-to-swing transition. The high MMG activity in terminal stance is consistent with the role of the quadriceps in knee

stabilization, control of limb unloading, and mechanical preparation for the transition toward swing. The subsequent reduction during mid and terminal swing reflects the lower mechanical involvement of the quadriceps when the limb is unloaded.

In the return condition, the dominant MMG activation shifted toward terminal swing. The highest mean MMG amplitude was observed in terminal swing (0.90 ± 0.08), with a normalized peak value of 1.00. High values were also observed during the initial swing (0.74 ± 0.10) and pre-swing (0.72 ± 0.09). Conversely, the terminal stance showed a lower mean MMG amplitude (0.41 ± 0.07) compared with the forward condition.

This redistribution of MMG activity suggests that, during return walking, the mechanical response of the quadriceps was more pronounced during limb advancement and preparation for the following heel strike. The increase in terminal swing may be compatible with post-turn stabilization, anticipatory muscle stiffening, or impact-preparatory mechanical adjustments, although these interpretations require confirmation with additional subjects and external biomechanical references. Since MMG reflects mechanical oscillations and tissue-level responses rather than direct neural excitation, this phase-specific modulation may include components related to muscle stiffness, soft-tissue vibration, and impact transmission. Overall, the phase-based MMG descriptors confirmed that the piezoelectric MMG signal was not randomly distributed across the gait cycle but exhibited structured, condition-dependent modulation. This supports the use of MMG as a mechanical descriptor of muscle behavior within an IMU-defined gait-cycle framework.

6.7.3 Forward and Return walking comparison

The comparison between forward and return walking revealed a clear shift in the distribution of MMG activity across gait phases. **Figure 6.16** and **Figure 6.17** are helpful to understand these condition-dependent behaviors. In the forward condition, the dominant MMG activation phase was terminal stance, whereas in the return condition, the dominant phase shifted to terminal swing. Within the present proof-of-concept dataset, this difference represents one of the most relevant findings of the MMG-IMU reconstruction analysis, because it shows that MMG was sensitive not only to the general structure of the gait cycle, but also to condition-dependent changes in mechanical muscle behavior. During forward walking, MMG activity was mainly *stance-dominant*. The largest mean amplitude occurred during terminal stance, and high values were also observed during mid stance and pre-swing.

This distribution is consistent with a more canonical steady-walking pattern, in which the quadriceps contribute to supporting the body, stabilizing the knee, and controlling the transition from stance to swing. During return walking, the MMG profile showed a different mechanical organization.

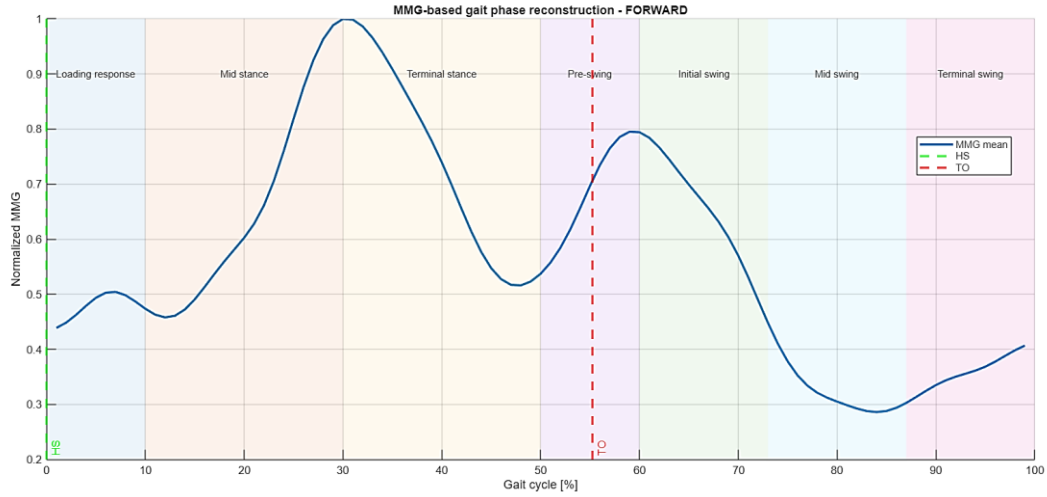


Figure 6.16: MMG-based gait reconstruction for the forward walking segment.

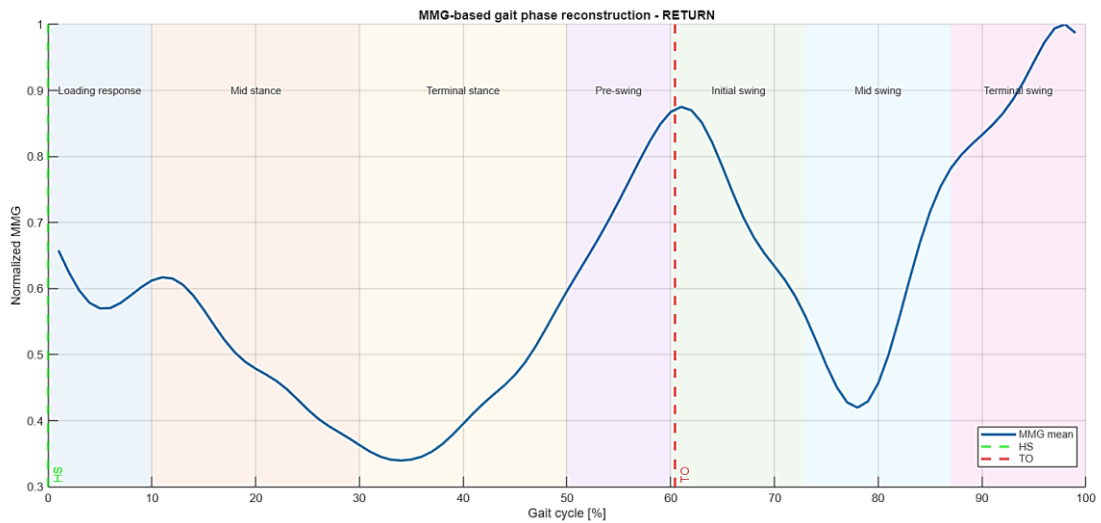


Figure 6.17: MMG-based gait reconstruction for the return walking segment.

The highest mean and peak MMG values occurred during *terminal swing*, while pre-swing and initial swing also showed elevated amplitudes. This suggests that the return segment involved greater mechanical activity during limb transition and preparation for the next foot contact. The shift toward terminal swing may be related to the preceding turnaround phase, which requires additional postural adjustments and anticipatory control before resuming steady walking. **Table 6.12** provides a detailed insight into MMG behavior.

Aspect	Forward walking	Return walking	Interpretation
Dominant activation phase	Terminal stance	Terminal swing	Different phase distribution of mechanical muscle response
Highest mean MMG	0.75	0.90	Greater relative mechanical response in return terminal swing
Highest peak MMG	1.00	1.00	Peak normalized activity reached in different phases
Stance-related activity	Higher in mid and terminal stance	Lower in terminal stance	Forward shows more stance-dominant mechanical behavior
Swing-related activity	Lower during mid and terminal swing	Higher during initial and terminal swing	Return shows greater mechanical involvement during limb advancement
Functional interpretation	Weight support, knee stabilization, controlled unloading	Limb transition, post-turn stabilization, preparation for HS	MMG captures condition-dependent motor strategy

Table 6.12: Functional interpretation of MMG responses in bidirectional walking.

These differences should not be interpreted as inconsistencies or artifacts. Rather, they highlight MMG's sensitivity to changes in motor strategy and mechanical loading. Unlike EMG, which primarily reflects neural activation, MMG captures the mechanical manifestation of muscle behavior, including oscillations, stiffness-related responses, and impact-related dynamics. The observed forward-return difference therefore supports the hypothesis that piezoelectric MMG, when combined with IMU-based gait segmentation, can provide complementary information about the mechanical organization of gait.

Overall, the forward condition confirmed a biomechanically coherent stance-dominant MMG pattern, whereas the return condition revealed a shift toward swing-related mechanical activity. This condition-dependent behavior strengthens the main outcome of the thesis: the proposed MMG–IMU framework can reconstruct the gait cycle and detect subtle variations in muscle mechanical response using a compact piezoelectric sensing approach.

6.8 GENERAL DISCUSSION

This section provides an integrated discussion of the main findings obtained from the multimodal EMG-MMG-IMU analysis. The aim is to interpret the results not as isolated outcomes, but as evidence supporting the reliability, physiological plausibility, and scientific relevance of the proposed processing framework. Attention is given to the pipeline's ability to progress from controlled static validation to dynamic gait analysis, and finally to the reconstruction of the gait cycle using piezoelectric MMG signals combined with IMU-derived gait events.

6.8.1 Methodological reliability of the pipeline

The results obtained in this thesis support the preliminary methodological reliability and internal consistency of the proposed multimodal pipeline. The processing framework was first evaluated under a controlled static condition on the brachioradialis muscle and was then extended to dynamic gait trials involving the quadriceps muscle. This progression from static to dynamic analysis allowed the robustness of the signal treatment strategy to be assessed under increasingly complex experimental conditions.

In the static condition, the pipeline successfully identified repeated voluntary activations in both EMG and MMG signals. The extraction of activation windows, peak events, amplitude-related features, and electromechanical delay provided initial validation of the system's ability to detect both the electrical and mechanical components of muscle activity. The presence of a consistent positive EMG–MMG peak-to-peak delay supported the expected temporal sequence between neural activation and mechanical muscle response.

Under dynamic conditions, the pipeline's reliability was supported by the successful integration of EMG, MMG, and IMU data. The IMU signal allowed the automatic identification of forward and return walking segments, while the HS-TO detection algorithm provided a temporal reference for gait-cycle segmentation. The detection of an equal number of HS and TO events in the two walking segments, together with physiologically plausible step timing, stance fraction, and high-quality scores, indicates that the IMU-based event detection was temporally consistent and biomechanically coherent.

The subsequent HS-HS segmentation generated valid gait cycles for both forward and return walking. The occurrence of TO close to the expected stance-to-swing transition further confirmed the internal validity of the normalization procedure. This is particularly important because all subsequent analyses, including EMG-MMG comparison and MMG-IMU gait reconstruction, depended on the accuracy of the temporal segmentation.

To sum up, the results indicate that the pipeline preserved meaningful physiological and biomechanical information across the different processing stages. The combination of robust preprocessing, adaptive normalization, IMU-based gait event detection, and phase-based analysis provided a coherent methodological framework for investigating both electrical and mechanical muscle activity during walking.

6.8.2 Physiological and biomechanical interpretation

The results obtained from EMG, MMG, and IMU signals are physiologically consistent with the complementary nature of the three modalities. EMG provided information on neuromuscular electrical activation, MMG described the mechanical response of muscle tissue, and IMU data supplied the kinematic reference required to organize the signals within the gait cycle.

The static analysis confirmed that MMG activity followed EMG activation with a measurable electromechanical delay. This temporal relationship reflects the physiological sequence in which motor unit depolarization precedes force generation, muscle fiber displacement, and tissue vibration. Therefore, the MMG signal can be interpreted as the mechanical manifestation of muscle activation rather than as a direct substitute for EMG.

During gait, the normalized EMG profiles showed phase-dependent quadriceps activation patterns that were coherent with the expected biomechanical role of the muscle. In early stance, quadriceps activity contributes to knee stabilization and impact absorption after HS. Toward late stance and pre-swing, modulation of the activation profile reflects preparation for unloading and transition toward swing. The reduction of EMG amplitude after TO is consistent with the decreased load-bearing demand during limb advancement.

The IMU-based gait events also showed strong biomechanical plausibility. The detected TO phase occurred close to the canonical stance-to-swing transition, approximately around 60% of the normalized gait cycle. This agreement supports the validity of the HS-HS segmentation and confirms that the 0-100% normalization preserved physiologically meaningful timing relationships.

The MMG results added a mechanical layer to this interpretation. In the forward walking condition, the MMG profile was mainly stance-dominant, with stronger activity during phases associated with stabilization, weight support, and limb unloading. In the return condition, the dominant MMG activity shifted toward pre-swing and terminal swing, suggesting increased mechanical involvement during limb transition and preparation for the following Heel Strike. This difference can be interpreted as an adaptive response to the non-steady nature of the return segment, likely influenced by the preceding turnaround and associated postural adjustments.

Importantly, differences between EMG and MMG waveform morphology should not be interpreted as inconsistencies. EMG and MMG originate from different physiological mechanisms. EMG reflects neural excitation, whereas MMG captures mechanical oscillations, tissue displacement, stiffness-related responses, and impact-related dynamics. Therefore, the two signals are expected to be temporally related but not identical. This supports the interpretation of MMG as a complementary modality that enriches the analysis of muscle function during gait.

6.8.3 Significance of the piezoelectric MMG-IMU approach

The results demonstrate that MMG signals acquired from an AlN-based piezoelectric sensor can be segmented using IMU-derived gait events and organized into a normalized 0-100% gait-cycle representation. This provides a mechanically based description of quadriceps

activity during walking, without relying on EMG for segmentation. This result is particularly relevant because conventional wearable gait-analysis approaches often rely on EMG–IMU integration, in which EMG is used to assess neuromuscular activation and IMU data provide kinematic timing. In contrast, the proposed framework investigates a less-explored approach based on piezoelectric MMG-IMU integration, in which the muscle-related signal is mechanical rather than electrical. In this configuration, the IMU defines the gait-cycle structure through HS and TO events, while MMG describes the phase-dependent mechanical response of the muscle.

The reconstructed MMG profiles showed that the mechanical signal was not randomly distributed across the gait cycle but followed a phase-dependent organization. In the forward condition, MMG activity was mainly concentrated during stance-related phases, especially terminal stance, consistently with knee stabilization, weight support, and controlled limb unloading. In the return condition, the dominant MMG activity shifted toward terminal swing, suggesting increased mechanical involvement during limb advancement, post-turn stabilization, and preparation for the subsequent heel strike. These differences confirm that MMG is sensitive not only to the canonical structure of gait, but also to condition-dependent variations in motor strategy and mechanical loading. The significance of this approach is summarized in **Table 6.13**.

Feature	Conventional EMG–IMU approach	Proposed piezoelectric MMG–IMU approach	Relevance
Muscle-related signal	Electrical activation of motor units	Mechanical muscle response acquired by a piezoelectric sensor	Provides complementary information on muscle function
Main physiological domain	Neural activation	Mechanical output of contraction	Captures oscillations, stiffness-related responses, and impact-related dynamics
Gait-cycle segmentation	IMU-derived HS/TO events, often interpreted with EMG activation	IMU-derived HS/TO events used to organize MMG activity	Enables mechanical reconstruction of the gait cycle
Sensor interface	Surface electrodes	Piezoelectric mechanical sensor	Potentially suitable for compact wearable integration

Main limitations	Electrode placement, skin impedance, electrical noise, cable motion	Mechanical coupling, tissue vibration, sensor pressure, impact transmission	Different limitations but also different information content
Main output	Neuromuscular activation timing across gait phases	Mechanical muscle response across gait phases	Adds a mechanical layer to gait interpretation
Scientific contribution	Established multimodal framework	Less explored MMG–IMU framework	Supports the novelty of the thesis

Table 6.13: Relevance of the piezoelectric MMG–IMU framework.

From a physiological perspective, the proposed approach should not be interpreted as a replacement for EMG. EMG remains the reference technique for directly assessing neural activation of muscle fibers. However, the present results show that MMG can provide complementary information by capturing the mechanical manifestation of muscle activity. This is particularly important for dynamic tasks such as walking, where tissue oscillations, muscle stiffness, and impact-related vibrations may contain biomechanical information not directly represented in the EMG signal.

From a technological perspective, a piezoelectric MMG sensor may offer advantages for wearable applications. Compared with surface EMG electrodes, piezoelectric MMG sensing is not directly affected by skin-electrode impedance or electrical interference. However, this advantage is offset by MMG's greater sensitivity to mechanical coupling, contact pressure, soft-tissue motion, and impact transmission. Moreover, the possibility of integrating piezoelectric sensors into compact wearable platforms makes this approach potentially attractive for simplified gait-monitoring systems. At the same time, MMG requires careful control of mechanical coupling and sensor placement, because the signal is sensitive to tissue motion, contact pressure, and transmitted vibrations.

Overall, the results support the feasibility of using MMG, combined with IMU-derived gait events, to reconstruct the gait cycle and characterize muscle mechanical activity across gait phases. The forward condition confirmed a biomechanically coherent stance-dominant MMG pattern, whereas the return condition revealed adaptive mechanical dynamics associated with non-steady-state gait. Therefore, the proposed piezoelectric MMG–IMU framework represents a promising and relatively underexplored approach for wearable gait

analysis, capable of complementing conventional EMG–IMU pipelines with information on the mechanical dimension of muscle function.

6.8.4 Limitations

Although the results are encouraging, several limitations should be considered when interpreting this thesis's findings.

First, the dynamic gait analysis was based on a limited number of valid gait cycles. Only three valid HS–HS cycles were available for each walking condition. This small sample size limits the statistical robustness of mean and standard deviation estimates, making the results more sensitive to individual cycle variability. Therefore, the normalized curves and phase-based descriptors should be interpreted as preliminary evidence of feasibility rather than as population-level conclusions.

Second, the analysis was performed on a limited experimental dataset. The results demonstrate the internal consistency of the proposed pipeline, but they cannot yet establish inter-subject generalizability. A larger cohort would be required to evaluate variability across participants, walking speeds, sensor placements, and motor strategies.

Third, the IMU-based gait event detection was internally validated using temporal plausibility, event consistency, stance fraction, step-time variability, and a quality score. However, no external gold standard, such as force plates, pressure insoles, or optical motion capture, was available. Consequently, the results support the internal validity of the HS/TO detection algorithm, but they do not provide an absolute estimate of event detection error.

Fourth, the IMU was positioned at the knee or thigh level rather than at the foot. This placement is advantageous for integration with the muscle sensors, but it may attenuate impact-related accelerations compared with foot-mounted IMUs. As a result, Heel Strike signatures may be less sharp than those obtained from distal sensor locations. Nevertheless, the detected events remained temporally plausible and consistent with the expected gait-cycle structure.

A further limitation concerns the novelty of applying piezoelectric sensing to dynamic gait measurements. AlN piezoelectric sensors are commonly used in contexts such as pulse wave velocity assessment, heart sound monitoring, and cardiorespiratory measurements, where

the subject is typically in a stationary or quasi-stationary condition. Walking, however, introduces a substantially more complex mechanical environment, characterized by repetitive impacts, segment accelerations, soft-tissue oscillations, and changes in sensor-skin coupling. Consequently, the MMG signal acquired during gait may contain both contraction-related mechanical components and movement-related vibrations. This makes signal interpretation more challenging and requires careful validation. This aspect also limited the possibility of estimating electromechanical delay during gait, as in the static brachioradialis recordings. In the static condition, voluntary contractions were clearly separated in time, allowing the identification of activation windows and the comparison between EMG and MMG peak timing. In contrast, during walking, muscle activity is cyclic, phase-dependent, and partially overlapped with movement-related mechanical oscillations. For this reason, it was not possible to apply the same activation-region detection algorithm used in the static analysis to define isolated EMG and MMG activation intervals and compute a reliable peak-to-peak delay. The dynamic condition, therefore, required a different analytical approach, based on gait-cycle segmentation, temporal normalization, and phase-based comparison rather than direct EMD estimation. In this perspective, the present study should be considered an exploratory application of piezoelectric MMG sensing in a dynamic locomotor task. The results support the feasibility of the approach, but further validation is needed to distinguish muscle-specific mechanical activity from global movement artifacts and to confirm the robustness of the piezoelectric MMG–IMU framework under broader experimental conditions. Future studies should also investigate whether electromechanical delay can be estimated during gait using more advanced approaches, such as cycle-based cross-correlation, onset detection within specific gait phases, or comparison with external biomechanical reference systems.

Fifth, MVC and walking trials were acquired in separate sessions. This prevented the use of MVC normalization as the final reference for dynamic EMG analysis, because differences in electrode placement, skin impedance, and acquisition conditions produced an unreliable %MVC scaling. The adoption of within-session P95 normalization was therefore appropriate for preserving internal consistency, but it limits the interpretation of EMG amplitude as a percentage of maximal voluntary activation.

Finally, MMG itself is sensitive to mechanical factors, including sensor pressure, tissue motion, soft-tissue vibration, mechanical coupling, and impact transmission. These factors

are not only potential sources of variability but also part of the physiological information captured by MMG. For this reason, MMG interpretation requires caution, especially when comparing it directly with EMG. Future validation should therefore include controlled assessment of sensor placement, attachment pressure, and repeatability across sessions.

Taken together, these limitations do not invalidate the proposed approach, but they define the boundaries within which the present results should be interpreted. The study provides a methodological proof of concept for piezoelectric MMG–IMU gait-cycle reconstruction, which requires further validation on larger datasets and with external reference systems.

6.8.5 Future developments

Future developments of this work should primarily focus on extending the proposed multimodal framework to a larger, more comprehensive sensor configuration. In the present thesis, the analysis was mainly based on one EMG channel, one AlN piezoelectric sensor for MMG, and one IMU reference. However, the electronic PCB has already been designed to support an expanded acquisition setup, including an additional bipolar EMG channel and two further MMG sensors. This would allow the simultaneous monitoring of multiple muscles and would make it possible to investigate the mechanical and electrical behavior of agonist and antagonist muscle groups during gait.

A first relevant extension would therefore be the acquisition of MMG signals from different muscles involved in locomotion, such as quadriceps, hamstrings, gastrocnemius, and tibialis anterior. This would allow the evaluation of inter-muscular coordination, co-contraction patterns, and phase-dependent activation strategies. In particular, the simultaneous analysis of agonist and antagonist muscles could provide important information on joint stabilization, compensatory strategies, and neuromechanical control during walking.

A second future direction concerns the further validation of the mechanical signal acquired by the piezoelectric MMG sensors. In the present study, EMG was used as a reference signal to assess whether MMG preserved a meaningful temporal relationship with neuromuscular activation. Future studies should aim to determine whether MMG can be used as a complementary signal to EMG or, in specific applications, as a simplified alternative. If the mechanical signal can be validated with sufficient reliability, the dependence on EMG could be reduced, leading to a less complex acquisition system. This would be particularly

advantageous because EMG requires careful electrode placement, skin preparation, stable skin–electrode impedance, and management of cables and electrical noise. In contrast, a validated MMG-based system could offer a more compact and potentially more robust solution for wearable gait monitoring.

Another important future development concerns applying the proposed approach in clinical and rehabilitative contexts. Piezoelectric MMG–IMU sensing could be investigated for monitoring compensatory gait strategies in subjects with lower-limb prostheses or in patients who have undergone hip arthroplasty. In these populations, altered muscle recruitment, asymmetrical loading, and compensatory movement patterns may occur during walking. A wearable system capable of capturing mechanical muscle responses and gait-phase information could provide useful indicators of motor adaptation, rehabilitation progress, and functional recovery.

In this perspective, two possible technological strategies could be explored. The first consists of maintaining an external wearable system, such as the one proposed in this thesis, in which piezoelectric MMG sensors and IMUs are placed on the skin or integrated into wearable supports. This approach would be non-invasive, easily adaptable, and suitable for repeated measurements during rehabilitation. The second possibility consists of sensorizing the prosthetic or implant-related structure itself by integrating piezoelectric elements directly into the device to measure mechanical responses, loading patterns, or vibration transmission. Comparing these two strategies would help determine whether it is more effective to monitor muscle-related mechanical activity externally or to acquire mechanical information directly from the prosthetic system.

Future work should also include validation against external reference systems, such as force plates, pressure insoles, motion capture, or clinical gait analysis platforms. These tools would allow a more accurate evaluation of the IMU-based HS/TO detection algorithm and would help distinguish muscle-specific MMG components from global movement artifacts. Moreover, larger datasets including multiple subjects, different walking speeds, repeated sessions, and pathological gait conditions would be required to assess repeatability, inter-subject variability, and robustness of the proposed framework.

Finally, the long-term objective of this research direction is to clarify the relationship between EMG and MMG in dynamic movement conditions. Rather than if one signal can

directly replace the other, future studies should determine under which conditions the two modalities provide complementary information and under which conditions MMG alone may be sufficient for specific monitoring tasks. This distinction is essential for optimizing the complexity, cost, and usability of future wearable systems. If validated across broader experimental conditions, the piezoelectric MMG–IMU approach could serve as a simplified, scalable platform for gait analysis, rehabilitation monitoring, and the assessment of compensatory movement strategies in clinical populations.

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CONCLUSION

This thesis investigated the feasibility of a wearable multimodal sensing framework integrating surface electromyography (sEMG), inertial measurement units (IMUs), and an aluminum nitride (AlN)-based piezoelectric mechanomyography (MMG) sensor for the assessment of muscle activity during human gait. The proposed approach aimed to evaluate whether the developed MMG sensor could provide physiologically meaningful information on muscle mechanical behavior and complement conventional electrophysiological measurements.

The experimental results demonstrated that the implemented acquisition and processing pipeline was capable of reliably extracting synchronized EMG, MMG, and IMU information under both static and dynamic conditions. The IMU-based algorithms successfully identified gait events and enabled accurate gait-cycle segmentation and normalization, providing a robust temporal framework for multimodal signal analysis. Furthermore, the comparison between EMG and MMG confirmed that the two modalities exhibit consistent temporal relationships while describing different physiological aspects of muscle function. Rather than reproducing electrical activation, the MMG signal captured the mechanical response of the muscle, highlighting complementary characteristics related to muscle oscillations, loading conditions, and contraction dynamics.

An additional contribution of this work is the preliminary investigation of an EMG-free framework based exclusively on MMG and IMU signals. Although still exploratory, the obtained results suggest that the combination of these two sensing modalities may provide sufficient information to reconstruct phase-dependent muscle behavior throughout the gait cycle, opening new perspectives for simplified wearable monitoring systems that reduce reliance on surface electromyography.

From a technological perspective, the study demonstrates the successful integration of a miniaturized AlN-based piezoelectric MMG sensor into a multimodal wearable platform, confirming its capability to acquire stable mechanical muscle signals during

walking. This represents an important proof of concept toward the development of compact, low-power, and non-invasive sensing solutions suitable for continuous gait monitoring outside laboratory environments.

The main limitation of the present work is that the experimental validation was performed on a single healthy participant. Consequently, the results should be interpreted as a proof of feasibility rather than a comprehensive clinical validation. Future investigations should therefore include larger cohorts, multiple muscles, different locomotor tasks, and pathological populations to evaluate the repeatability, robustness, and clinical significance of the proposed methodology.

In particular, the multimodal framework developed in this thesis could be extended to patients undergoing Total Hip Arthroplasty (THA), where the simultaneous assessment of muscle electrical activation, mechanical response, and gait kinematics could provide valuable insights into compensatory strategies, functional recovery, and rehabilitation progress. In this context, the proposed piezoelectric MMG sensor has the potential to become a valuable complementary component of wearable systems designed for long-term and ecologically valid monitoring of gait.

Overall, this work provides further evidence that piezoelectric MMG represents a promising complementary sensing modality for wearable neuromuscular assessment. Beyond validating the proposed acquisition and processing framework, the study contributes to the growing interest in multimodal biomechanical monitoring by demonstrating the potential of combining MMG, EMG, and IMU measurements to obtain a more comprehensive characterization of human movement. These findings establish a solid foundation for future developments toward clinically applicable wearable systems capable of supporting objective gait assessment and personalized rehabilitation.