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EMG-Driven control in a Human Lower Prosthesis

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a mio fratello, il GGG
a mio zio, perché " lo zio c'é "
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Only two things are infinite,
the universe and human
stupidity, and I'm not sure
about the former.

(Albert Einstein)

EMG-Driven control in a Human Lower Prosthesis

Abstract

Recent technological improvements in the field of neurorobotics have led to developments of numerous wearable robotic assistive devices in the field of rehabilitation. Such new prosthetic and orthotic devices should ideally recognize a users intention to act and aid with different environmental interactions. While the mechanical design of such devices remains a demanding challenge, it is equally important to address and investigate novel control strategies that allow the control of these devices in an intuitive and seamless way. In fact, the objective of novel control paradigms in prostheses and orthoses is to recognize effectively the user intention through bio-signals those generate spontaneously during movement, like electromyography. Even though myoelectric prostheses are nowadays a common reality for upper limb amputees, none of the available lower limb prosthesis on the market provide EMG-driven control. The aim of this work is therefore the definition of a novel approach for myoelectric control in lower limb prosthesis capable of overcome state-of-the-art controller limitation. In fact, since modern lower limb prostheses can generate net positive mechanical work, they also have the capability to restore natural gait in amputees. Configuration of these devices imposes a new control layout with respect to conventional prostheses. The new control layout driven from user intention to move should consider peculiar differences between rhythmic and the voluntary movements, in order to combine and optimize the control strategy. To successfully accomplish this task, a novel machine learning based approach for gait-cycle classification and impedance law controller is derived. The first layer of the proposed control framework is implemented with supervised machine learning classifiers for optimal walking phase identification. For each identified phase impedance control law parameters are subsequently tuned automatically through gaussian regression and applied to the knee and ankle joints of the prostheses. Both classification and regression machine learning models are investigated through input signals and parameters combination. Performance of the controller is evaluated through online simulations of the controller: minimization of the error between the predicted control output and the measured physiological joint torque is used to assess the different proposed approaches. The results show that inclusion of EMG-signals in the control framework do increase slightly the gait-cycle classification accuracy

with respect to traditional sensors. What is shown, is that the inclusion of a machine learning algorithm avoids the need of other sensorial information needed, such as the Ground Reaction Force.
For now, the inclusion of EMG signals do not seem to favor the performance of the gait cycle, but prior analysis indicate that it may well be used in motor task transitions, such as start walking or standing up. In fact, the extension of the classifier with an additional layer which includes the EMG signals to distinguish between standing or walking condition may increase the performance and aid the wearer to a more consistent and voluntary control.

Indice

Capitolo 1

Background and Motivation

1.1 Human locomotor system

Locomotion is the ability to move and is one of the most important characteristics of living organisms. Locomotion and movements in vertebrates, including man, are brought about by skeleton, joint and muscles. The human walking process is defined as a bipedal, two-phased forward propulsive locomotion leading to a translation in space of the centre of gravity of the body [1] [2] . By alternating coordinated movements of different segments of the body using the least amount of energy as possible, it involves the synergical cooperation among its components.

The human locomotive apparatus, as all the vertebrates, is composed by three main agents: the muscular system, the skeletal system (forming together the muscoskeletal system) and the nervous system. All three together form an organ system that gives humans the ability to move. While the muscoskeletal provides form, support, stability and movement of the body, the nervous system is responsible for the control and the correct execution of each part involved. The legs are the two lower limbs of the human body. They provide support of weight, adaption to gravity and a range of movements, enabling the body to freely move around and shift its centre of gravity. The lower limbs consist of three segments each - the thigh, the tibia and the foot - and three joints - the hip, the knee and the ankle - containing altogether 30 bones and 54 muscles. In the next subsections each segment and joint will be explained individually. In the following chapters all three of the agents will be discussed, related in particular to the lower limbs.

1.1.1 Lower limb muscoskeletal system

Skeletal system

The human skeleton is the internal framework of the body, composed of 206 bones, cartilages, ligaments and other tissues [3] . Bone tissue is a hard,

Figura 1.1: Muscoskeletal system of the human body

dense connective tissue that forms most of the adult skeleton. In the areas of the skeleton where whole bones move against each other, cartilage, a semi-rigid form of connective tissue, provides flexibility and smooth surfaces for movement. Additionally, ligaments composed of dense connective tissue surround these joints, connecting the bones to the adjacent ones. Together they protect the internal organs, store and release fat and minerals, produce blood cells, facilitate movement and support the body. The skeletal system also provides attachment points for muscles to allow movements at the joints.

The human lower limbs are connected to the upper axial skeleton part through the left and right hip bones: the pelvic girdle. The femur is the largest bone in the body and the only bone of the thigh region. The femur forms the ball and socket hip joint with the hip bone and forms the knee joint with the tibia and patella (also known as kneecap). The tibia and fibula are the bones of the tibia region. The tibia bone is much larger then the fibula and bears almost all of the body's weight. The fibula is mainly a muscle attachment point and is used to help maintain balance. The tibia and fibula form the ankle joint with the talus, one of the seven tarsal bones in the foot. The tarsals are a group of seven small bones that form the posterior end of the foot and heel. The tarsals form joints with the five long metatarsals of the foot. Then each of the metatarsals forms a joint with one of the set of phalanges in the toes. Each toe has three phalanges, except for the big toe, which only has two phalanges.

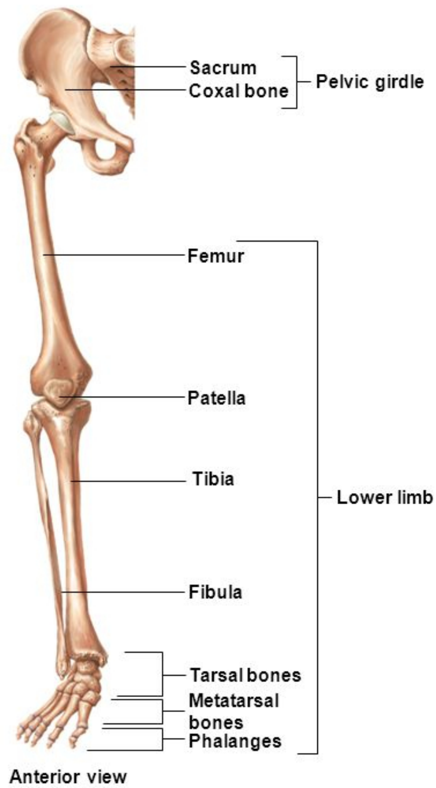


Figura 1.2: Lower limb skeletal system [38]

Joint structure and lower limb ranges of motion When muscles contract they produce a motion of the joint to which they are related to. In the lower limb the joints are the hip, knee and ankle joint. All of them are synovial joints. Synovial joints are the most common type of joint in the body. A key structural characteristic is the presence of a joint cavity. This fluid-filled space is the site at which the articulating surfaces of the bones have contact with each other. The articulating bone surfaces at a synovial joint are not directly connected to each other with fibrous connective tissue or cartilage. This gives the bones the ability to move smoothly against each other, allowing for increased joint mobility.

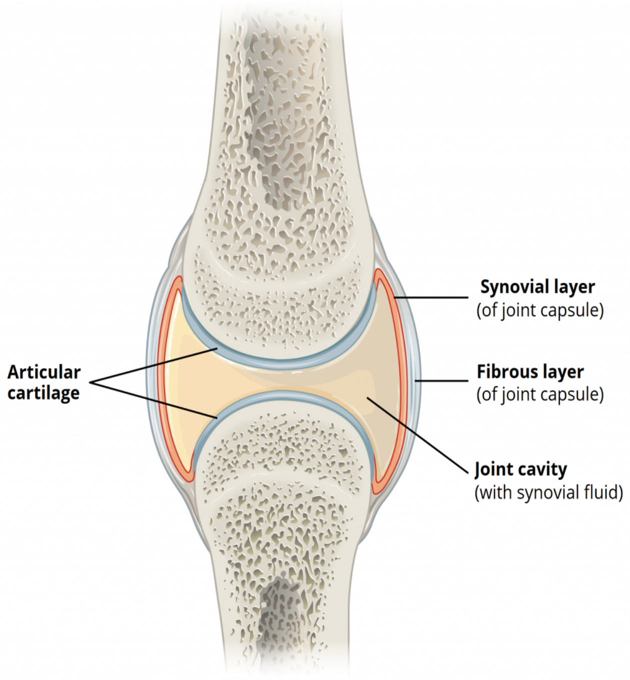


Figura 1.3: Synovial joint [39]

Each joint has its one range of possible movements [4], as listed in table 1.1.

Muscular system

The muscular system, attached to the bones of the skeletal system, is responsible for the movement of the human body. There are approximately 700 known and named muscles and each one of them is a discrete organ constructed of soft contractile tissue, blood vessels, tendons and nerves. There are three types of muscle tissue: visceral, cardiac and skeletal.

Visceral and cardiac muscles are found in the inner part of the body. The former is found inside organs like the stomach, intestines and blood vessels and makes them contract to move substances through them. The second type is only found in the heart and its contraction in a rhythmic pattern pumps blood throughout the body. They are both controlled by the autonomic nervous system and they are known as involuntary muscles. While cardiac muscle appear striped under the microscope, visceral muscle lack that characteristic and are therefore also called smooth muscle.

Joint	Motion	Range	Mean
Hip	Extension	0 to 35°	9.5°
	Flexion	90 to 150°	120°
	Abduction	15 to 55°	38.5°
	Adduction	15 to 45°	30.5°
	Internal rotation	20 to 50°	32.5°
	External rotation	10 to 55°	33.6°
Knee	Extension	0 to -10°	-1.6°
	Flexion	115 to 160°	143.7°
Ankle	Dorsiflexion	5 to 40°	15.3°
	Plantarflexion	10 to 55°	39.6°
	Eversion	15 to 50°	27.7°
	Inversion	15 to 50°	27.7°

Tabella 1.1: Human lower limb joint ranges and movements

Skeletal muscles on the other hand are the only voluntary muscle, controlled from the somatic nervous system and they concern with movement, posture and balance of the human body. Skeletal muscles are attached to the skeleton by tough connective tissues called tendons. The muscles span over the joints and connect the bones. When the muscles contract, they pull on the bones, causing them to move. As cardiac muscle they have a striped appearance and longer muscle fibres. They contract due to stimuli sent by the nervous system's motor neurons. Skeletal muscles rarely work solely to movement generation, instead they usually work in groups to produce precise movements. The muscle that produces any particular movement of the body is known as an agonist or prime mover. The agonist always pairs with an antagonist muscle that produces the opposite effect on the same bone [5].

In addition other muscles, called synergists, work to support the movements of the agonist. Synergists are muscles that help stabilize a movement and reduce extraneous movements [6]. They are usually found in regions near the agonist and often connect to the same bones. Because skeletal muscles move the bones they are attached together, fixator muscles assist the movement by stabilizing the origin of the agonist and the joint that the origin spans. The majority of fixator muscles are found working around the hip and shoulder joints.

Lower limb muscular system The thigh is the segment located between the hip and the knee and contains some of the largest muscle masses. The thigh muscles are divided in three main categories: hamstrings, quadriceps and adductors:

- The hamstrings are the three big muscles located at the back of the

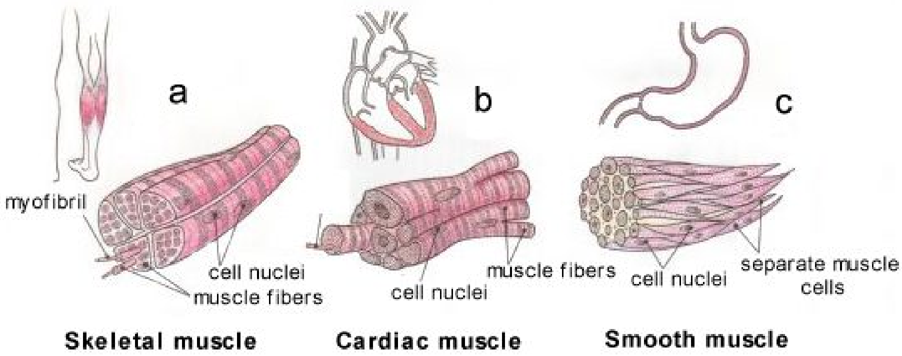


Figura 1.4: Different muscles types [40]

thigh. They include the biceps femoris, semitendinosus and the semimembranosus. Each hamstring crosses two joints: the hip and the knee. By contracting they flex the knee joint, adduct the leg and extend the thigh to the backside of the body.

- The quadriceps are the four muscles located on the front of the thigh, consisting of the vastus intermedius, vastus medialis, vastus lateralis and rectus femoris. When the quadriceps contract, they straighten the leg at the knee joint. Since they extend over the kneecap, they also help to keep the kneecap in its proper position in a groove at the end of the thigh bone. The rectus femoris also crosses the hip joint and can assist in hip flexion and hip extension.

- The adductors are the muscles located on the inside of the thigh. There are five muscles in this group: gracilis, obturator externus, adductor brevis, adductor longus and adductor magnus. By contracting they pull the legs together and help stabilize the hip joint. Although all of these muscles adduct the hip, the adductor magnus is also responsible for stabilizing the knee when the hamstrings are engaged but to weak or restrained to sustain the actions of the knee.

The tibia is the part of the leg located between the knee and the ankle joints. The muscles located on the tibia are divided in two compartments: anterior and back muscles.

- There are four muscles in the anterior compartment of the leg: tibalis anterior, extensor digitorum longus, extensor hallucis longus and fibularis tertius. Collectively they act to pull the toes and feet upward and invert the foot at the ankle joint. The extensor digitorum longus and extensor hallucis longus also extend the toes.

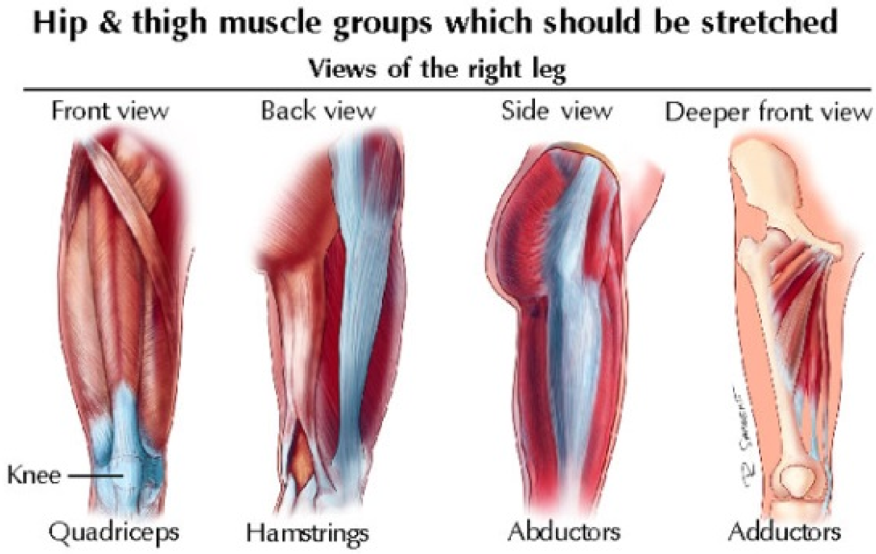


Figura 1.5: Hip and thigh muscle groups [41]

- The backside compartment instead hosts the calf muscle, which is actually made up of two muscles: the bigger gastrocnemius and the smaller soleus. The gastrocnemius doesn't actually attach to the bones of the shin, skipping them to connect to the femur bone and the heel. The gastrocnemius crosses paths with the hamstrings as it attaches on either side of the femur. The calf muscles through their interaction with the foot and the leg lift the heel of the ground and facilitate all bipedal locomotions.

The foot is the part of the leg located distally with respect to the ankle joint. The muscles acting on the foot can be divided into two distinct groups: extrinsic and intrinsic muscles.

- Extrinsic muscles originate from the lower leg, their long tendons cross the ankle joint and insert onto one of the bones of the foot. They are mainly responsible for actions such as eversion, inversion, plantarflexion and dorsiflexion of the foot.

- The intrinsic muscles are located within the foot and are responsible for the fine motor actions of the foot. There are 10 intrinsic muscles located in the sole of the foot. They act collectively to stabilize the arches of the foot, and individually to control movement of the toes.

Skeletal muscle structure and movement generation Each skeletal muscle is an organ that consists of various integrated tissues. These tissues include the skeletal muscle fibres, blood vessels, nerve fibres and connective

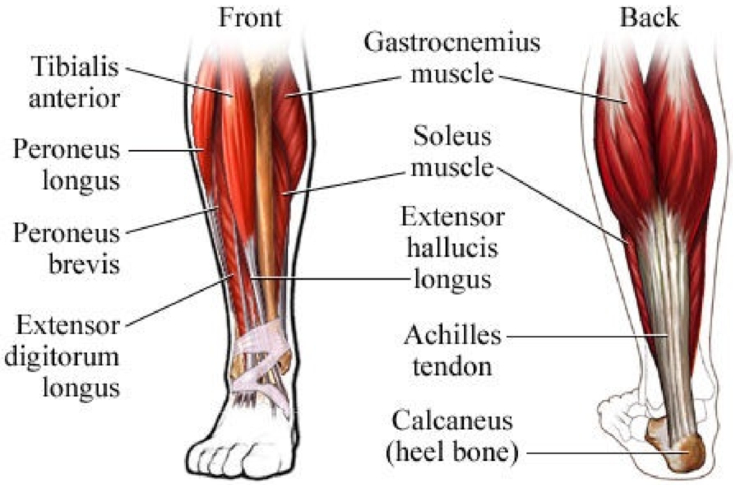


Figura 1.6: Tibia muscles, front and back view [42]

tissue. Each skeletal muscle has three layers of connective tissue - called mysia - that enclose it and provide structure to the muscle as a whole, and also compartmentalize the muscle fibres within the muscle. Each muscle is wrapped in a sheet of dense, irregular connective tissue called the epimysium, which allows a muscle to contract and move powerfully while maintaining its structural integrity. The epimysium also separates muscle from other tissues and organs in the area, allowing the muscle to move independently. Inside each skeletal muscle, muscle fibres are organized into individual bundles, each called a fascicle, by a middle layer of connective tissue called the perimysium. This fascicular organization is common in muscles of the limbs; it allows the nervous system to trigger a specific movement of a muscle by activating a subset of muscle fibres within a bundle, or fascicle of the muscle. Inside each fascicle, each muscle fibre is encased in a thin connective tissue layer of collagen and reticular fibres called the endomysium. The endomysium contains the extracellular fluid and nutrients to support the muscle giber. These nutrients are supplied via blood to the muscle tissue. Every skeletal muscle is also richly supplied by blood vessels for nourishment, oxygen delivery, and waste removal. In addition, every muscle fibre in a skeletal muscle is supplied by the axon branch of a somatic motor neuron, which signals the fibre to contract.

Skeletal muscle fibres have a long cylindrical shape. They can be quite large call for human cells, with diameters up to 100 Î¼m and lengths up to 30 cm. Within each muscle fibre are myofibrils, long cylindrical structures that lie parallel to the muscle fibre. They attach to the plasma membrane, called sarcolemma, at their ends, so that as myofibrils shorten, the entire muscle cell contracts. The striated appearance of skeletal muscle tissue is a result of repeating bands of the proteins actin and myosin that occur along the length of myofibrils. Myofibrils are composed of smaller structures called myofilaments. There are two main types of myofilaments: thick filaments and thin filaments. Thick filaments are composed of the protein myosin, while the primary component of thin filaments is the protein actin.

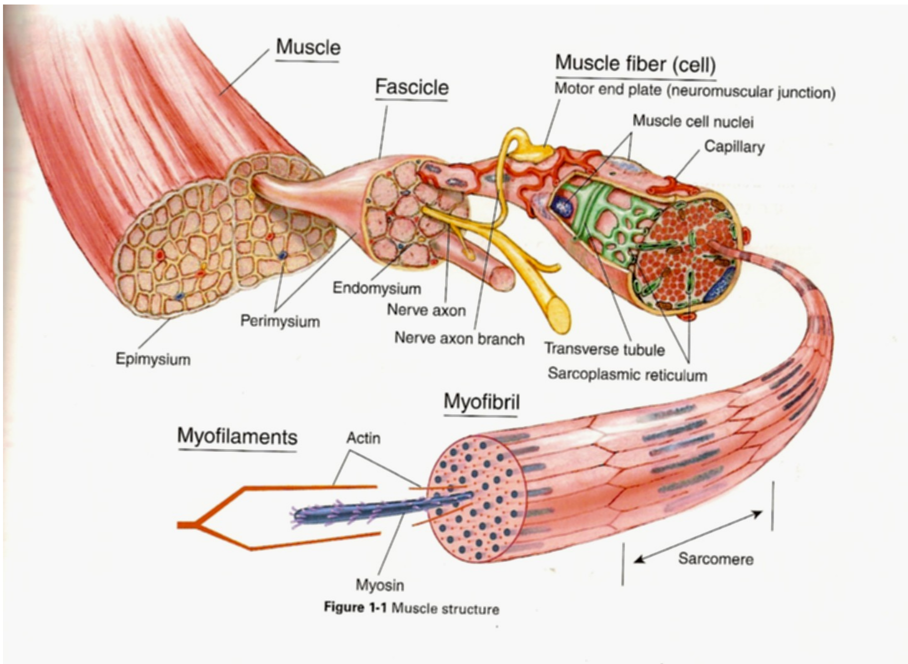


Figura 1.7: Skeletal muscle structures [43]

The thick and thin filaments alternate with each other in a structure called a sarcomere. The sarcomere is the unit of contraction in a muscle cell. Contraction is stimulated by an electrochemical signal from a nerve cell associated with the muscle fibre. For a muscle cell to contract, the sarcomere must shorten. However, thick and thin filaments do not shorten. Instead, they slide by one another, causing the sarcomere to shorten while the filaments remain the same length. The sliding is accomplished when a molecular extension of myosin, called the myosin head, temporarily binds to an actin filament next to it and through a change in conformation bends, dragging the two filaments in opposite directions. The myosin head then releases its actin filament, relaxes, and then repeats the process, dragging the two filaments further along each other. The combined activity of many binding sites and repeated movements within the sarcomere causes it to contract. The coordinated contractions of many sarcomeres in a myofibril leads to contraction of the entire muscle cell and ultimately the muscle itself. The movement of the myosin head requires ATP (adenosine triphosphate), which provides the energy for the contraction.

Each skeletal muscle fibre is stimulated to contract by chemicals released

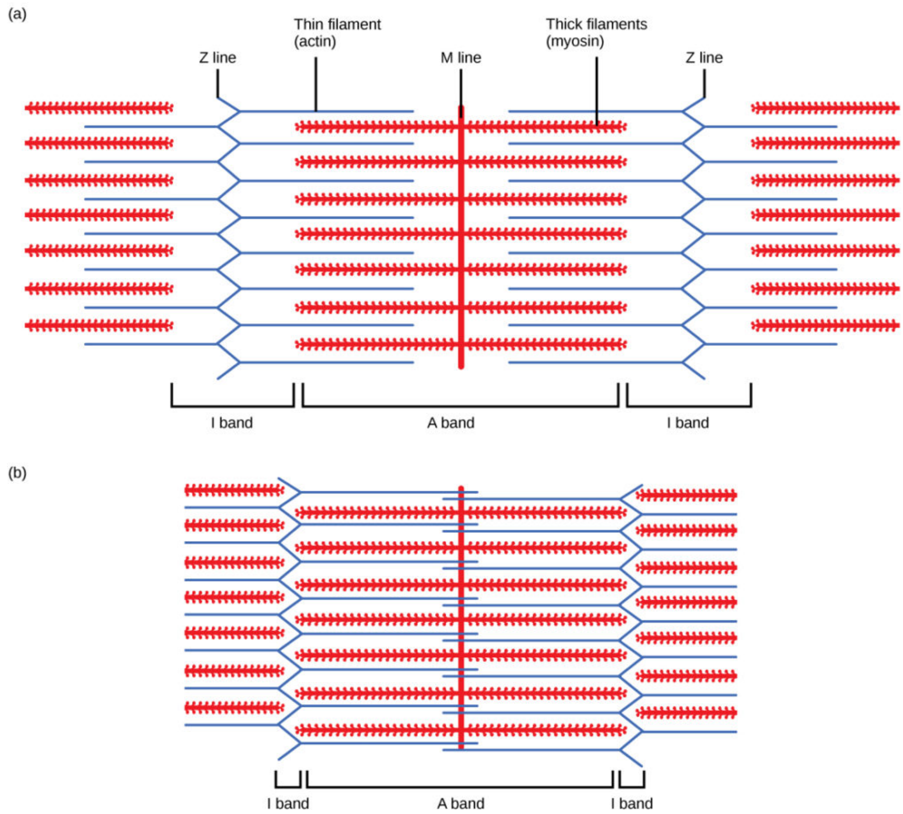


Figura 1.8: Sarcomere filaments a) and contraction b) [44]

from a somatic motor neuron (also known as the alpha motor neuron). Most of these elongated nerve cells originate in the gray matter of the spinal cord, their thread-like axon processes run inside nerves and carry electrochemical impulses to target muscles. After entering a target muscle a motor neuron axon branches many times making its way to different muscle fibres. As it approaches the midpoint of one muscle fibre, the axon splits again, forming a small cluster of terminal branches. The tips of the terminal branches expand into small synaptic bulbs, which fit into grooves along the surface of the muscle fibre. Together, the expanded axon tips and the nearby muscle fibre membrane make up a neuromuscular junction.

The motor unit A motor unit is the term applied to a single motor neuron and all of the muscle fibres that it innervates. When a motor neuron fires, all the muscles fibres in the motor unit contract at once. The size of the motor unit correlates with the function of the muscle. In muscles, involved with fine coordinated control, the motor units are very small with three to five muscle fibres per motor neuron. Muscles instead that are involved with more powerful but less coordinated actions have thousands of muscle fibres per motor neuron. When an action potential travels down the motor neuron, it will result in a contraction of all of the muscle fibres associated with that motor neuron. The contraction generated by a single action potential is a called a muscle twitch. A single muscle twitch has three components: the latent period, the contraction phase and the relaxation phase. The latent period is a short delay - one to two milliseconds (ms)- from the time when the action potential reaches the muscle until tension can be observed in the muscle. The contraction phase takes place when the muscle is generating tension and the relaxation phase spans the time for the muscle to return to its normal length. The length of the twitch varies between different muscle types and could be as short as ten ms or long as hundred ms.

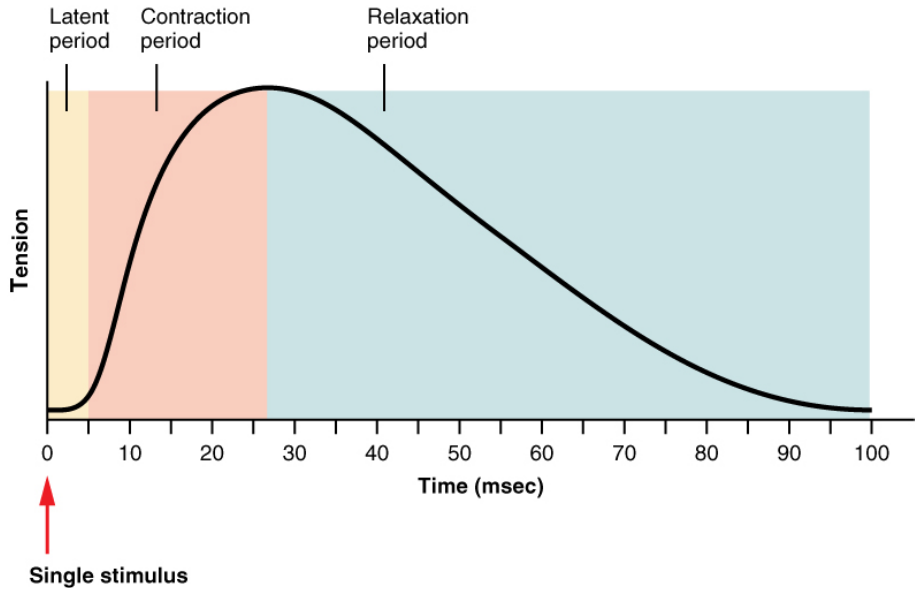


Figura 1.9: Single muscle stimulus [45]

To avoid explosive and sudden movements, motor units fire asynchronously. As one motor unit contracts, before it has the chance to relax another motor unit fires, leading to a smooth and controlled muscle contraction. Even when a muscle is at rest, there is random firing of motor units. This random firing is responsible for what is known as muscle tone.

Skeletal muscle are capable of generating different levels of force during whole muscle contractions. To differ the amount of generated force means to differ the number of firing motor units at a given time. This phenomena is called multiple-motor unit recruitment, which consists in recruiting more motor units to generate more force. Normally only a 1/3 of the total motor units are fired at one time. As fibres begin to fatigue they are being replaced by others in order to maintain the force. Motor unit recruitment can occur in two possible ways. One is the wave summation, which means stimulating the same single motor unit with progressively higher frequencies of action potential generating a gradual increase in the generated force. For the second, eventually the frequency of action potentials would be so high that there would be no time for the muscle to relax between successive stimuli and it would remain totally contracted.. This condition is called tetanus.

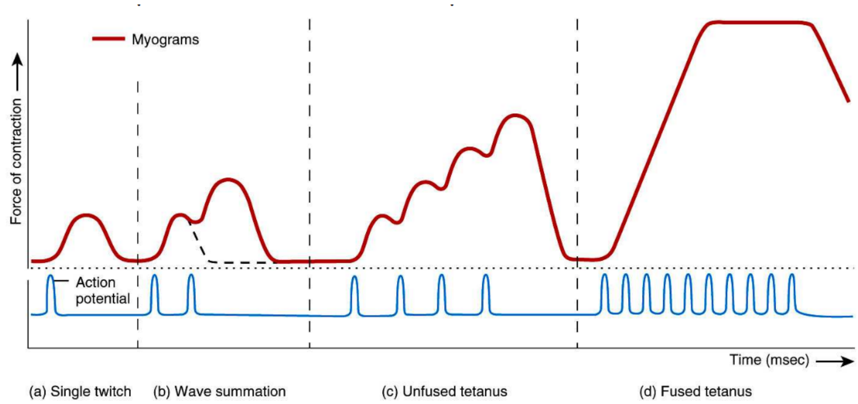


Figura 1.10: Types of skeletal muscle contraction [46]

Nervous system

The nervous system has two main parts: the central nervous system (CNS) - brain and spinal cord - and the peripheral nervous system (PNS) - nerves that carry impulses to and from the CNS. Efferent nerves are motor neurons that carry neural impulses away from the CNS and towards muscles to cause movement, while afferent nerves carry impulses from sensory stimuli towards the CNS.

The CNS controls most functions of the body and mind. It is referred as *central* as it collects information from the entire body and coordinates activities across the whole organism. A small structure, the cerebellum, is located at the back of the brain and processes incoming information from outside the body, thanks to sensory nerves of sight, touch, smell, sound and taste, and within some organs, such as the stomach. Although the cerebellum accounts for approximately 10% of the brain's volume, it contains over 50% of the total number of neurons in the brain. Motor commands are not initiated in the cerebellum, but rather modified as they descend along the spinal cord to make movements more adaptive and accurate, The cerebellum is responsible for maintaining posture and balance, coordinating voluntary movements, increase accuracy in movements by trial and error and cognitive functions, such as language[62]. The spinal cord can be seen as the main stream path for communication between the body and the brain. It extends from the brain down the bony spinal column, which serves as its protection.

The spinal cord is a tube made up of nerve fibres. Electrical impulses travel through the nerves and allow the brain to communicate with the rest of the body. The CNS differs from other systems of the body as it does many jobs at the same time. It controls all voluntary movement, such as speech and walking, and involuntary movements, such as blinking and breathing. It is also the core of our thoughts, perceptions, and emotions.

The PNS instead is the division of the nervous system containing all the nerves that lie outside of the CNS. The primary role of the PNS is to connect the CNS to the organs peripheral and apparatus. These nerves extend from the CNS to the outermost areas of the body. The PNS allows the brain and spinal cord to receive and send information to other areas of the body, which allows it to react to stimuli from the environment. The PNS itself is divided into two parts: the somatic nervous system, responsible for carrying sensory and motor information to and from the central nervous system, and the autonomic nervous system, which controls aspects of the body that are usually not under voluntary control - the internal organs.

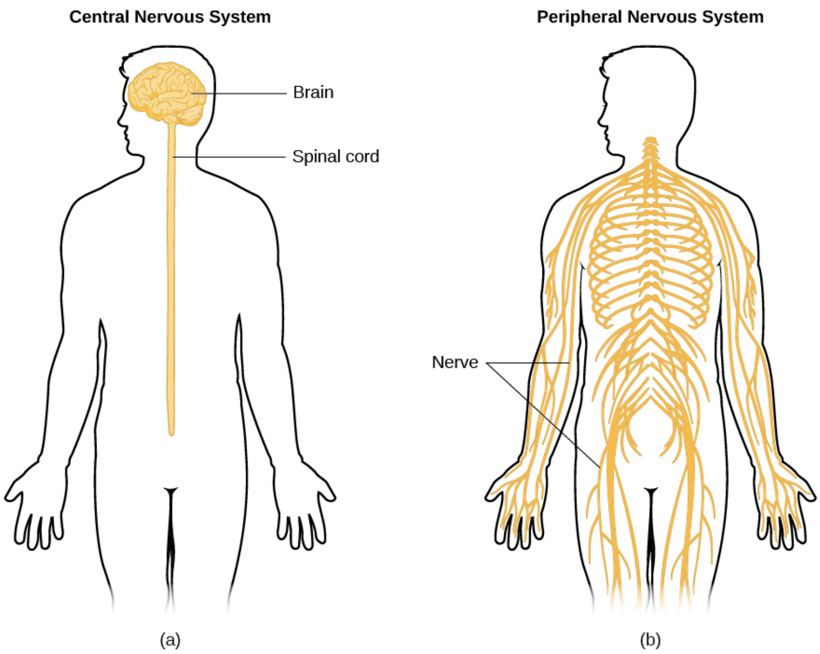


Figura 1.11: Central Nervous System and Peripheral Nervous System [47]

1.1.2 Locomotion control - rhythmic and volitional

Human locomotion depends on a strong collaboration between volitional motion pattern generation and reflex-dependent fine control of these patterns at different levels. Basic motor patterns are thought to be generated by a multi-layered organization of the spinal neural work, often referred to as the central pattern generator (CPG) [7]. Efferent stimulation is transmitted through motor neurons to individual muscle groups, which are recruited to effect the movement. Afferent feedback, including information from the muscles, joints and sensors, is used to directly modulate motor commands and thus contributing to efficiently perform gait, aid with stability and balance if needed, and control of precise movements.

Rhythmic locomotion

Rhythmic locomotion consists of a cycle of patterned and rhythmic activity of different muscle groups, working coherently together to produce a cyclical output. The rhythmic activity is generated by the CPG inside the spinal cord. There are three major features that represent a rhythmic locomotion: its rhythmic and cyclical occurrence, the coordinated alternation between flexor and extensor activity within the same limb and the alternation between opposite limbs. The CPG is thought to consist of networks of neurons that are synaptically or electrically connected, with cellular properties that generate rhythmic firing. Possible examples could be walking or running.

Gait analysis

Bipedal walking is an important characteristic of humans. It provides both support and propulsion, in a rhythmic alternated motion, where at least one foot always touches the ground. While the terms gait and walking are often used interchangeable, gait is just an attribute of the walking locomotion.

The gait cycle is a repetitive pattern involving steps and strides. A single gait cycle is also known as a stride. The step time is the time between heel strike of one leg and heel strike of the contra-lateral leg. Step width may be described as the mediolateral space between the two feet.

The generation of movement during walking involve the following steps:

- registration and activation of the gait command within the CNS
- transmission of the gait cycle to the PNS
- contraction of the muscles
- generation of several forces
- regulation of joint forces and moments across synovial joints and skeletal segments
- generation of the ground reaction forces

The gait biomechanics during ground-level walking can be classified into two main phases [9]: the stance phase and the swing phase. The stance phase occupies 60% of the gait cycle while the swing phase only 40%. Gait involves a combination of open- and close-chain activities.

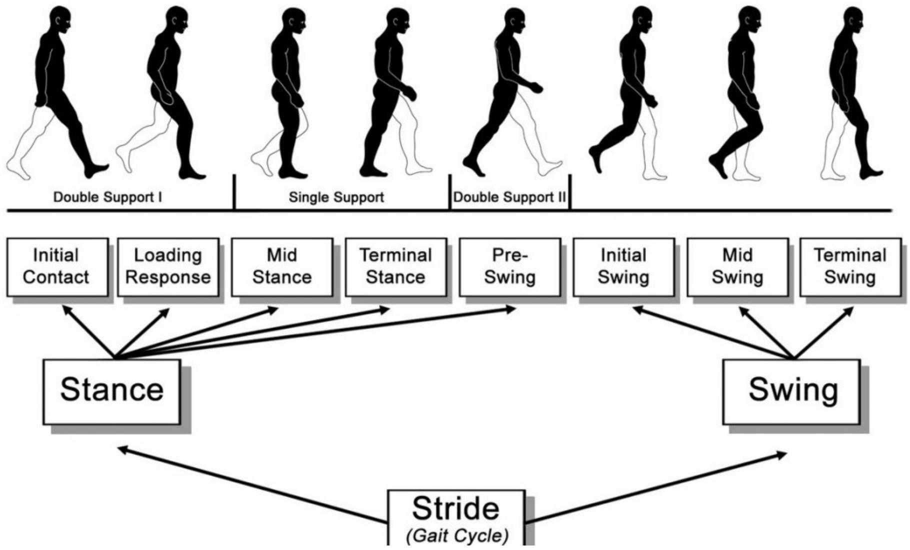


Figura 1.12: Phases of the Gait Cycle [48]

The stance phase is the part of the gait cycle where the foot is in contact with the ground, absorbing the shock and propelling the body forward. Within the cycle particular biomechanics sub-phases may be identified:

- heel strike: the heel strike happens in the moment when the heel comes in contact with the ground; the ankle is in a neutral position, the knee is slightly flexed to lessen the shock and the hip is approximately in 30 degrees of flexion; with the heel strike the body weight begins to shift onto the stance limb.

- foot flat: continuing the walking motion, the entire foot comes in contact with the ground; the ankle moves into approximately 5-10 degrees of plantar flexion and the knee moves into 15 degrees of flexion; the hip moves into extension allowing the trunk and body to catch up to the limb; the weight of the body continues to shift on the stance limb.

- mid-stance: during mid-stance the body passes over the stance limb and where the leg is approaching the vertical position offering single-limb support with the other limb freely swinging forward; the ankle moves into slight dorsiflexion, the knee extends and the hip continues to extend; the trunk is in neutral position of rotation and arms are parallel to the body.

- heel off: hell off occurs when the heel just begins to lift off the floor; the ankle is in dorsiflexion initially and the foot in plantar flexion; the knee is extended and prepares to flex; the hip is in hyperextension and the trunk rotates to the same side.

- toe off: simultaneously, when the toes leave the ground, the opposite foot is in foot flat phase; it is the end of the stance phase and the beginning of the swing phase; the toes go into hyperextension and the ankle rotates towards plantar flexion; the knee keeps moving to flexion; by end of this phase the hip starts flexing.

The swing phase of the gait cycle occurs when the foot is not in contact with the ground. It begins when the foots leaves the floor and ends with the heel strike. It is the nonweight bearing phase of the gait cycle and consists of the following sub-phases:

- acceleration: in the acceleration phase, the limb is behind the body and moving to catch up as the ankle moves into dorsiflexion; both knees and hip continue to flex.

- mid-swing: the mid-swing involves the shortening of the limb to clear ground; the ankle is in a neutral position and the knee is in maximum flexion; the hip continues to flex.

- deceleration: during deceleration the limb shortens to clear ground; the ankle is in a neutral position and the knee is in maximum flexion; the hip continues to flex.

Double support is the period in the gait cycle when both feet are in contact with the ground. It occurs when one limb is ending the stance phase and the opposite limb begins stance phase. About 10% of the gait cycle is spent in double support and it changes with speed: faster gait leads to less double support time and slower gait leads to more time in double support.

Single support is the period when only one foot is in contact with the ground. There are two periods of single support, right stance and left stance.

Stride length is the distance travelled in one stride i.e. between two consecutive heel strike of the same foot.

The step is the period covered between the heel strike of one foot to the heel strike of the opposite foot.

Step length is the distance covered between heel strike of one limb and heel strike of the other limb.

Step width is the distance by which feet are apart during walking. For measurement purpose, the distance between the heel centres of two consecutive foot contacts is taken as step width, around 5 to 10 centimetres.

Cadence is the number of steps taken per minute and varies with walking speed.

In running there is a period when none of the foot is on the ground. It is called non-support and this differentiates running from walking as non-support does not occur in walking.

Volitional control

Voluntary movements differ from reflexes and basic locomotive rhythms as the brain sends stimuli with a precise scope to the target muscle [10]. Voluntary movements improve with practice as one learns to anticipate and correct for environmental obstacles that perturb the body. According to [11] ideas for movement are translated into specific motor commands in some areas of the cerebral cortex, the basal ganglia (group of nuclei located under the cerebral cortex) and the cerebellum. This coded information is then usually recalled from the motor cortex, which acts on brain-stem neurons and spinal motoneurons to achieve the intended voluntary motion. Although a voluntary movement is initiated for a certain goal, it can be influenced by sensory feedback, such as external perturbations or muscle fatigue, and be adjusted [9].

1.2 Limb amputations

Amputation is described as the separation of a bone in healthy tissue or the removal of a limb at a joint (ex-articulation). Amputation surgery may be necessary if an injured or diseases limb is not expected to heal and if the patient's life is endangered as a result. Possible causes include circulation issues, infections, accidents, cancer or a congenital malformation of the limb. In these cases it is usually known well in advance that an amputation will become necessary. In contrast, sometimes it is necessary to amputate unexpectedly, for example due to a severe injury after an accident.

Amputation procedures vary, depending on the limb or extremity being amputated and the patient's general health. When performing an amputation, the surgeon removes all damaged tissue while leaving as much healthy tissue as possible, smooth uneven areas of the bone, seal off blood vessels and nerves and cut and shape muscles to facilitate the attachment of an artificial limb. Recovery from amputation depends on the type of procedure and anaesthesia used. The immediate goals after the surgery are threefold: little to no pain, the residual limb should be able to bear weight and move optimally in all directions. To accelerate recovery and be able to wear a prostheses, the patient is encouraged to load the stump as soon as possible, to accommodate the transition to the prostheses.

Levels of lower limb amputations include:

- foot amputation - toes, partial foot or ankle
- transtibial amputation - below the knee
- knee disarticulation - at the knee
- transfemoral amputation - above the knee

- hip disarticulation - at the hip
- hemipelvectomy - removal of the entire leg and part of the pelvis

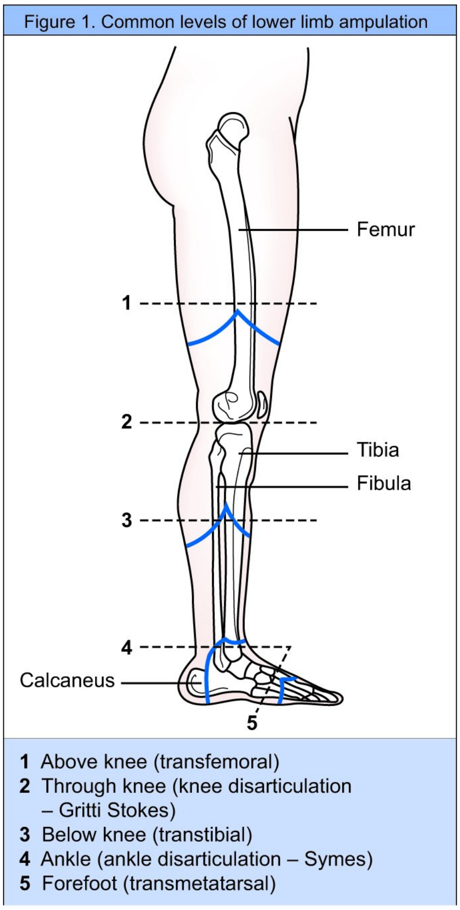


Figura 1.13: Common levels of lower limb amputation [49]

A partial foot amputation is one where the toes and part of the long bones of the foot are amputated. This is also known as a trans-metatarsal amputation. This amputation allows to still maintain a high level of functional mobility because many major muscle attachments are preserved during the surgery. Also, foot balance and shape are maintained in this type of amputation, which can help with keeping a proper gait.

A transtibial amputation, is an amputation through the shin bone, sparing the knee-joint. This amputation is the most common type of amputation performed, and the risk of serious post-operative-complications is far less than in a transfemoral amputation. Walking with a prosthesis is typically more successful. The transtibial prosthesis consists of a socket, which contains the residual limb, a prosthetic foot, as well as adapters and connecting elements.

Disarticulation refers to an amputation through a joint. It can make walking easier, since the bone of the residual limb is left intact. There is a decreased chance of bone infection from the amputation surgery. In knee disarticulation surgery the knee joint is separated and the lower leg is removed. The entire thigh is retained in the process. The prosthesis consists of a socket, which contains the residual limb, a prosthetic knee joint and foot, as well as adapters and connecting elements.

In a transfemoral amputation, the amputation occurs through the femur, or thigh bone, of the upper leg, so that the knee is no longer present. The prosthesis consists of a socket, which contains the residual limb, a prosthetic knee joint and foot, as well as adapters and connecting elements.

A hemipelvic amputation is one where the hip-joint and part of the pelvis is amputated. This type of amputation is also known as a transpelvic amputation. It is most often performed because of a malignant tumour or as the result of trauma. Walking after a hemipelvic amputation is difficult since there is no residual limb on which a prosthesis can be fitted.

1.3 Lower limb prosthetic devices

A prosthesis is a crucial technical substitute that should restore biomechanical function and body integrity for people with lower limb loss or congenital limb absence [11]. Different types of prosthetic limbs are designed with different goals in mind. Often these goals depend on the site of the amputation and the needs of the patient. For example, a cosmetic prosthetic limb is designed with appearance in mind rather than controllability. Other prosthetic limbs are designed with usability and function as a central purpose, which can be controlled in a variety of ways. Prosthesis have usually three components: the prosthetic device, the interface and the controller, which need to work coherently together to guarantee a correct and smooth functioning.

Functional prosthetics can be broadly categorized into two groups: body-powered and externally-powered prosthetics. Body-powered prosthetics use cables and harnesses strapped to the individual to mechanically manoeuvrer the artificial limb through muscle, joint and residual limb motion. While they are highly durable, they often sacrifice a natural appearance for moderate functionality. As well, though the user experiences direct control and feedback through its mechanical operation, the process can be fatiguing. Externally-powered artificial limbs are an attempt to solve this physical exertion through using a battery and an electronic system to control movement. At the forefront of this technology is the myoelectric prosthetic.

The components of a prosthetic device include terminal mechanisms (artificial fingers, hands, feet and toes) and joints (wrists, elbows, hips, and knees). Metal shafts and customized fiber structures, which function as bones, are used when extra strength, flexibility and energy return are needed. For more advanced prostheses, there are control elements available that allow the user to move the prosthesis mechanically or electrically.

Problems that may rise from a lower-limb prosthesis are miscellaneous but all connected to the impossibility or difficulty of executing basic symmetric movements related to the missing limb. For example walking down a ramp without control of the knee joint will cause it to bend and flex on its own. This may cause a forward falling sensation and the amputee instinctively compensates for that. Equally if the joints offer more resistance, it can make walking in the other direction, up a hill or a flight of stairs a painful struggle. Without enough movement in the ankle a prosthetic leg wearer has to pivot around their prosthetic leg with their healthy leg to advance. Transfemoral and transtibial amputees expend respectively 60% to 15% more energy [13] during walking then non amputees. A prosthesis that only supports but does not aid the wearer during the actual gait leads to an over-compensative motion in the hip which results in severe back pain caused by the unnatural gait and stances they have to adopt. Another result of these asymmetric motion is osteoarthritis in knee of the sound leg [14]. It occurs when the protective cartilage on the ends of the bones wears down over time affecting the joint.

1.3.1 Type of prosthetic devices

Prosthesis can be organized in three groups: passive, semi-active and active devices. They differ in dynamics-kinetics related properties and their ability to provide active power to the user.

Passive devices

Passive prosthesis do not have power supply, therefore they can not produce net power and do not have electronics circuits on board. They provide basic functional capabilities such as pushing, pulling, stabilizing, and supporting. The passive prosthesis is certainly the simplest but certainly also the most unstable and unsafe solution among passive leg prosthesis. Not being able to change the impedance property of the joint may be the cause of high risk stumbling and falling. In some particular designs, as for example ESAR (Energy Store And Return) feet, the prosthesis is able to provide energy absorption, storage and some return [15]. However, they are not able to provide the net positive work normally needed during the stance phase of gait. This loss of net power generation at the lower limb impairs the ability of the prosthesis to restore biomechanically normal locomotive function during many locomotive activities, as for example an above-knee amputee, a fixed passive leg prosthesis allows walking in a rather artificial way [16]. In the absence of net power generation at the knee and ankle, transfemoral amputees with passive prostheses have been shown to expend up to 60% more metabolic energy and exert three times the affected-side hip power and torque when compared to healthy subjects during level walking [17]. Currently the vast majority of lower-limb prostheses are passive devices [17].

a) Sach feet b) Echelon VT c) 3R60 EBS
(https://www.spsco.com/by-product-type/prosthetics/prosthetic-feet/k1-feet-k2-feet-1/sach-foot-with-titanium-pyramid.html)
(https://www.indiamart.com/proddetail/echelon-vt-prosthetic-foot-14160438562.html)
(http://www.resolutdesign.com/portfolio-items/3r60-ebs-and-3r60-ebs-pro/)

Figura 1.14: Three examples of lower limb passive prosthetic devices

Figure 2.25 shows two examples of passive ankle prostheses and one of a passive knee prostheses. The Solid Ankle, Cushioned Heel (SACH) feet (2.25 a) [50] are prosthetic feet at their most basic, inexpensive and ideally suited for low activity and lighter weight users. SACH feet have no moving parts and an internal keel. In passive SACH feet the keel will not flex within the foot. To perform the necessary foot function(s), rubber regions provide areas which will bend, flex or deform under load, but provide only minimal shock absorption. A heel wedge compresses at heel strike. This lowers the forefoot to the ground as weight is transferred onto the foot. As the user rolls over the toe the toe break flexes to smooth the transition. On the other hand the EchevlonVT (2.25 b) [51] provides the active user with terrain conformance, rotation and shock absorption. It is ideal for robust, moderate impact activities like hiking that require a multi - axial, biomimetic function with a high level of energy return. The combination of hydraulic ankle and titanium spring means that the foot adapts fluidly to promote good posture and excellent traction even on rough ground and ramps. During swing phase the toe dorsiflexes to enhance ground clearance. The integral shock absorber ensures minimal shear force between socket and skin for a comfortable ride throughout the twists and turns of the day. The third shown example is the 3R60 EBS (Ergonomically Balanced Stride) knee joint (2.25 c) [52] whose functionality lies in its adapting capability to the weight and activity of the user, ensuring comfortable walking with a high level of safety - including on uneven terrain or inclines. It features a high flexion angle and a virtually natural gait pattern. During heel strike, the knee can be flexed at an angle up to 15°in a controlled and stabilising manner, similar to the natural version, improving knee safety. High-performance swing phase hydraulics that are straightforward to adjust enable easy initiation of the swing phase, optimum progressive damping for natural movement patterns and comfortable end position damping for a wide range of walking speeds.

Semi-active devices

Advancements in mechatronic designs gave rise to the semi-active prostheses. They include a microprocessor-controlled system which regulates the opening and closure of hydraulic or magneto-rheological valves. Furthermore they integrate sensory information to gather kinematic, inertial and dynamic data elaborated in real time to identify the stride phase and, with help of the controller, switch the locomotion modality [19]. Controllers elaborate the sensors'informations in order to change the stiffness and damping coefficients of the joints according to the external environment and device status. This control strategies permit to minimize energy expenditure of the wearer even in challenging and energy consuming gait situations. Although semi-active systems are a big step forward, similar to the passive prostheses, they are not able to produce positive net power during the gait, but are limited to generate only modulated resisting forces.

Below (figure 2.26) three examples of semi-active devices are shown. The Raize Ankle/Foot System (2.26 a) [53] is a microprocessor ankle/foot system in a low profile, lightweight design. Its plantar/dorsiflexion range reduces damaging forces on the residual limb and greatly enhances stability on slopes and slippery surfaces. By simply pressing a button the wearer can control roll-over resistance, lock or unlock the ankle, and adjust the heel height as needed. Figure 2.26 b) and 2.26 c) show microprocessor controlled knee-joints imitating the natural walk. The C-Leg 4 prosthetic knee (2.26 b) [53] system receives sensor inputs from the knee angle sensor to determine sagittal knee position and from the ankle moment sensor to determine sagittal moments about the ankle. Beyond these two sensors, the Genium system (2.26 c) [53] includes four additional sensors including an accelerometer and a gyroscope, allowing the device to measure its exact position and orientation at all times. This enables the user to walk backwards, step over obstacles, take small- or large steps, and even descend stairs without fear of the knee buckling.

a) Raize Ankle/Foot system b) C-Leg 4 c) Genium
(https://www.spsco.com/raize-ankle-foot-system.html)
(https://www.ottobock.it/protesizzazioni/prodotti-dalla-a-alla-z/nuovo-ginocchio-elettronico-c-leg-4/)
(https://www.ottobockus.com/prosthetics/lower-limb-prosthetics/solution-overview/genium-above-knee-system/)

Figura 1.15: Three examples of lower limb semi-active prosthetic devices

Active devices

Active or powered prostheses provide external power through motors and consequently they have the ability restore almost totally main locomotive actions like walking, running, stairs and slope ascending, sitting down and standing up [18] [19]. While they offer greater performance and greater functionality, they represent the system with the highest complexity. Unfortunately they do not provide greater functionalities without incoming sensory informations from the nervous system. Over the last years various active ankle joints, knee joints and systems combining ankle and knee dynamics were developed.(M. Windrich et al., "Active lower limb prosthetics: a systematic review of design issues and solutions", Robotics: Science and Systems 2013 Berlin, Germany. 28-Jun-16) The important difference between semi-active and active prostheses is the capability of the latter ones to generate net positive forces and torques. Therefore a control scheme that ensures a reliable amputee/device interaction, while taking fully advantage of this capability, is needed. The controller, by sampling sensory information coming from the interface, the prosthetic device and the user itself, identifies and categorizes user intended motions. Successfully it sends the necessary driving commands to the actuators. Moreover inclusion of different locomotions modes in the controller require complex control algorithms and sensory data elaboration [17] demonstrated that although subjects with amputation that may initially have poor volitional control of their residual lower-limb muscles, through training with an active device which includes sensory information coming from the nervous system, substantially improved their volitional control.

Below are shown two examples for active devices. The BIOM Ankle System (figure 2.27 a) [56] aids the wearer across all level-ground walking speeds. It provides natural bionic propulsion, emulating muscle function about the healthy human ankle during the load-bearing stance phase of walking, decreasing the impact force and knee moment on the unaffected leg during level-ground walking near the preferred gait speed relative to passive prostheses. The Power Knee from Össur (figure 2.27 b) [57] is a motor powered knee joint. It provides active motion and superior powered stance stability to replace lost muscle function, aiding the wearer during the stand-up motion and add a controlled resistance when descending. By active flexion and extension during walking it allows the wearer to reach even further walking distances.

a) BIOM Ankle System b) Power Knee Össur
(https://www.infinitetech.org/biom-ankle-foot)
(https://www.ossur.com/prosthetic-solutions/products/dynamic-solutions/power-knee)

Figura 1.16: Two examples of lower limb active prosthetic devices

1.3.2 Interfaces

The prosthesis attaches to the body at the interface, which consists of a socket and a rigid frame. The socket is the part directly in contact with the amputee, it is usually made of plastic or laminated material. The frame, which is made of graphite or similar materials, provides structural support for the socket. A liner is worn between the residual limb and the socket to provide cushioning and to make the fit tight. The liner is made of soft polyurethane or silicone, which clings to the skin without causing friction. Instead of a liner also a prosthetic sock may be worn. Socks are made of wool, nylon or synthetic fabrics. Socks are available in different thicknesses. By changing the number of sock-layers users can increase comfortability during the day, as the stump varies in size throughout the day when activities, weather and other factors change. The interface may include a suspension system, which helps hold the prosthesis on securely. The following suspension systems are commonly used:

- Suction valve: When the residual limb is put in the socket, air is forced out through an opening at the bottom of the socket. A one-way suction valve on the socket closes the opening and forms a seal that holds the prosthesis in place.
- Liners with a locking pin: Most liners are locked into the bottom of the socket by a notched pin. Because the pin is pressed tightly against the residual limb, the parts of the limb near it can become irritated and inflamed, fluid may accumulate, and sores may develop.
- Belts and harnesses: Sometimes the prosthesis is attached by a belt or harness. These devices may be used if keeping the prosthesis on with a suction valve or locking pin is difficult or the pin cannot be tolerated. However, the harness is relatively rigid and thus can be uncomfortable and cumbersome. It may also restrict movement.

Novel smart prostheses prototypes include a controller on board, which needs to ensure a reliable interaction between the prosthetic device and the amputee. This is guaranteed by its ability to read and contextualize incoming information from the socket and prostheses sensors and, by feeding them into a predefined control state, change the prostheses actuation. The architecture of the controller is influenced by the type of used interface and the design and purpose of the device.

Volitional control is designed to guarantee direct communication between the user and the device so as to directly modulate the prosthesis state. For that scope an additional level of sensors have to be added, able to record information from the peripheral nerves in an amputees residual limb and forward them to the micro-controller circuitry. This will allow the prosthesis user's brain and nerves to effortlessly coordinate the movements of the prosthesis knee and ankle joints simultaneously so that limb motions are smooth and natural. Some applications include brain computer interfaces, intra-neural signals and myoelectric interfaces.

Myoelectric interfaces

Myoelectric control is an advanced technique concerned with the detection, processing, classification, and application of myoelectric signals to control human-assisting robots, rehabilitation devices and modern day prosthetics. Nowadays it is the most used approach for electrically-powered upper limb prostheses [21]. A myoelectric signal, also called a motor action potential (see paragraph "The motor unit"), is an electrical impulse that produces contraction of muscle fibres in the body and is used to provide feed-forward volitional control to the prosthetic device. The main obstacle in this approach lies in the difficulty of recording reliable signals from the residual limb within the socket.

The electrical recording of the muscle contractions is called Electromyogram (EMG) [22]. EMG can be recorded using different types of electrodes, the two most common being fine wire and surface electrodes. Although fine-wire electromyography (fEMG) provides a better quality and muscle-specific signals (especially for deep muscles) it remains an invasive technique creating discomfort for the subject. Surface electromyography (sEMG) instead is simple, totally ergonomic and provides, although muscle-specific signals are excluded, satisfying acquisitions [22] [23] [5]. The EMG signal is a complicated signal, which is controlled by the nervous system and is dependent on the anatomical and physiological properties of muscles. EMG signal acquires noise while travelling through different tissues. Moreover, the EMG detector, particularly if it is at the surface of the skin, collects signals from different motor units at a time which may generate interaction of different signals. Standard signal processing procedure therefore involve amplification, filtering, rectifying to avoid a zero average, due to the raw EMG signals having positive and negative components [24].

Some innovative surgical procedures, such as target muscle reinnervation (TMR) [25] can improve the control of the limb prostheses. TMR transfers residual nerves from the amputated limb to reinnervate new muscle targets that have otherwise lost their function [26]. These reinnervated muscles then serve as biological amplifiers of the amputated nerve motor signals, allowing for more intuitive control of advanced prosthetic arms.

1.3.3 Control strategies

Hierarchical controller

Tucker et al. [27] proposes a generalized framework based on Varol et al. [28] and then extended to accommodate the needs of various control approaches for active lower limb prostheses or orthotics (P/O).

The diagram (figure 1.17) reflects the physical interaction and signal-level feedback loops underlying powered assistive devices during practical use. The framework consists of a hierarchical controller, the user of the P/O device, the environment with which he interacts and the device itself. The schematic representation intends to display how the building blocks interact with each other and the information they exchange.

The hierarchical controller has three levels.

At the high level, the controller must understand the user's locomotive intent. Activity mode recognition identifies the current locomotive task (for example level walking or stair descension). Direct volitional control allows the user to voluntarily manipulate the device's state (joint positions, velocities and torques). Combining the two it is possible to change the device's behaviour within a particular activity, which is also the aim of this thesis.

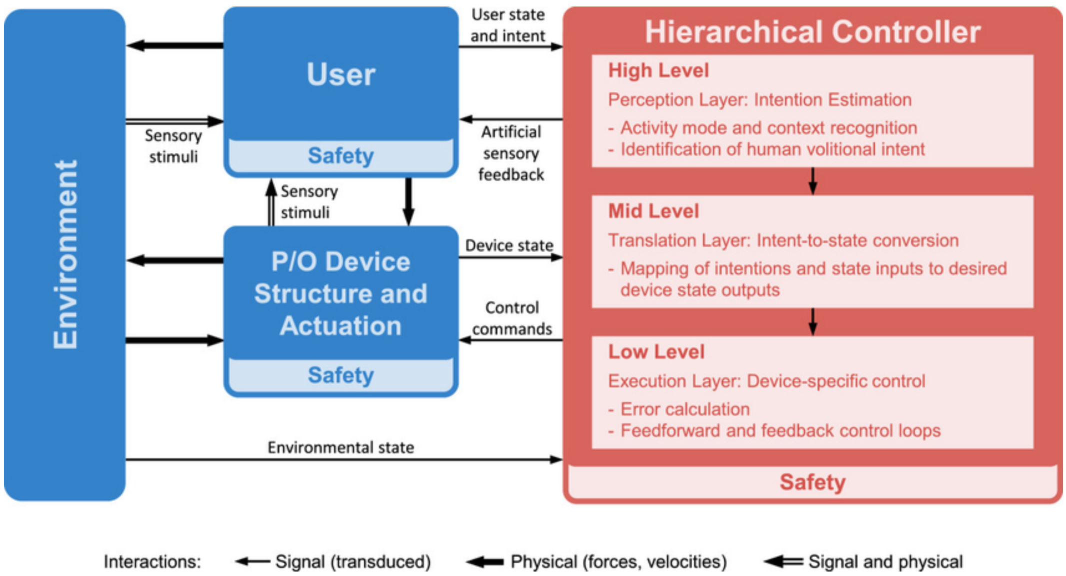


Figura 1.17: Hierarchical controller layout [59]

The mid level controller is responsible for translating the user's motion intentions from the high level to the low level controller. It usually defines a particular control law, for example based on impedance or position, which parameters vary based on the high level output.

The desired device state is passed to the low-level controller, which computes the error with respect to the current state and then sends commands to the actuators, trying to minimize the error. Finally, the P/O device is actuated to execute these commands and the control loop is closed. Additionally an artificial sensory feedback may be implemented to further increase the dialogue accuracy between the user-environment-device throuple.

Considering the substantial output forces a robotic P/O device can generate and the close physical contact with the user, safety layers which limit excessively and therefore dangerous outputs must be included in all subsystems, despite the lack of explicit connections.

Each subsystem within a generalized control architecture can be defined by a set of physical and signal-level inputs, by a set of processes that operate on those inputs to control the power exchange though the sub system and by a set of outputs that transmit power and signals to connected subsystems.

Interactive extrinsic and computational intrinsic controller

Control of active prosthetic devices can be classified by the source of input data. There are two possible types of controller: computational intrinsic controllers (CIC) and interactive extrinsic controllers (IEC).

CICs have no direct input to the nervous system and therefore do not permit volitional control of the prosthesis. They effectively coordinate movement of a prosthetic device through its own internal feedback loop [29] where for example a classification algorithm detects the intention of the user. This kind of control can be found even in vertebrate locomotion control, where the CNS acts as the CIC. In [30] it was shown that in decerebrated cats and decapitated dogs, after stimulating an area of the midbrain (mesencephalic locomotor region) electrically, the spinal cord still was able to produce reflex stepping, This demonstrates that reflex like mechanisms can create basic motion patterns without brain interaction.

ICEs instead allow a communication between brain and device, occurring for efferent commands but also on the afferent feedback sites. This capability is necessary in case of non-cyclic locomotion or irregular limb movement. A commonly used signal in commercial prostheses is electromyography but also other signals can be implemented such as cortical, or peripheral nerve sensors. A main benefit of IEC is that it can provide intent control signals already before the movement occurs.

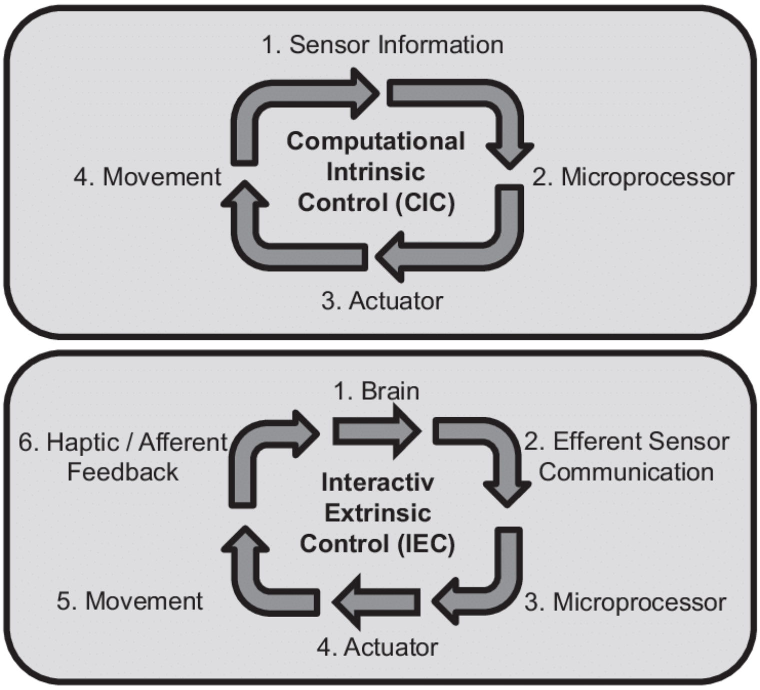


Figura 1.18: Computational Intrinsic Control and Interactive Extrinsic Control layout [60]

Taking into account the characteristics of both controllers it seems useful to have both approaches, CIC and IEC, combined in prosthetic control to get advantages of decentralized primary locomotion functions and in addition intended based control. Therefore it is possible to reduce the mental effort required from the user during cyclic motions, like it is implemented in modern prosthesis. At the same time, instead, introducing EMG signals will permit to drive the prosthetic device voluntarily in a different configuration if needed.

Myoelectric control

Beside the standard application of EMG signals to analyse disabilities or to track progress in rehabilitation, more focus has been put on controlling robot arms, exoskeletons [31] and modern day prosthetics with EMG signal in recent years. The major challenges to overcome, in the control of human actuated devices, are the acquisition of the user's intention through biological signals and correlate and contextualize them in an appropriate control framework. The advantage of EMG signals is that they create spontaneously during movement and therefore they form an intuitive interface for the user.

The main approach in myoelectric control is to extract significative features from the acquired signals and use them to define and understand the intention of the user. The problem with classification in EMG-driven control is that it inherently leads to a control scheme that is substantially different from the natural control. Natural movements are continuous and require the coordination of multiple physiological degrees of freedom (DOF) across several joints. The parameter space that describes natural movements (EMG, kinematics and kinetics) is therefore continuous. On the other hand, the number of patterns in a pattern classification-based controller is limited. This leads to a crude discrete approximation of the continuous parameter space obtained by classification [23]. One common strategy used to overcome this issue is typically to increase the number of observed states in the gait-cycle minimizing this approximation.

Finite state machine and heuristic rule based approach A Finite state machine is a model of computation based on a hypothetical machine made of one or more states. Only one single state of this machine can be active at the same time. Every state has a set of transitions and every transition is associated with an input and pointing to a state. The state will change based on inputs, providing the resulting output for the implemented changes. Once a state is reached the rules identified by the state will be applied to the system until a transition forces the state to change [32].

The most frequent approach for finite state machine is the heuristic rule based classifier. Heuristic rule-based classifiers are a very simplistic, but fairly effective method for identifying mode transitions patter recognition and are therefore quite valuable in activity mode recognition. Examples include finite state machine and decision trees. They all operate under the same principle: given the set of all states the designer identifies a fixed set of rules

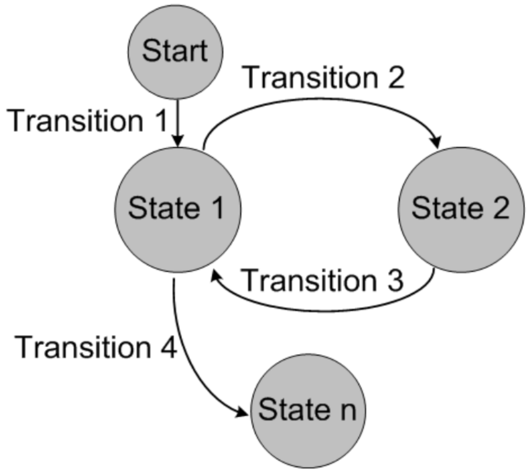


Figura 1.19: Finite state machine cycle example

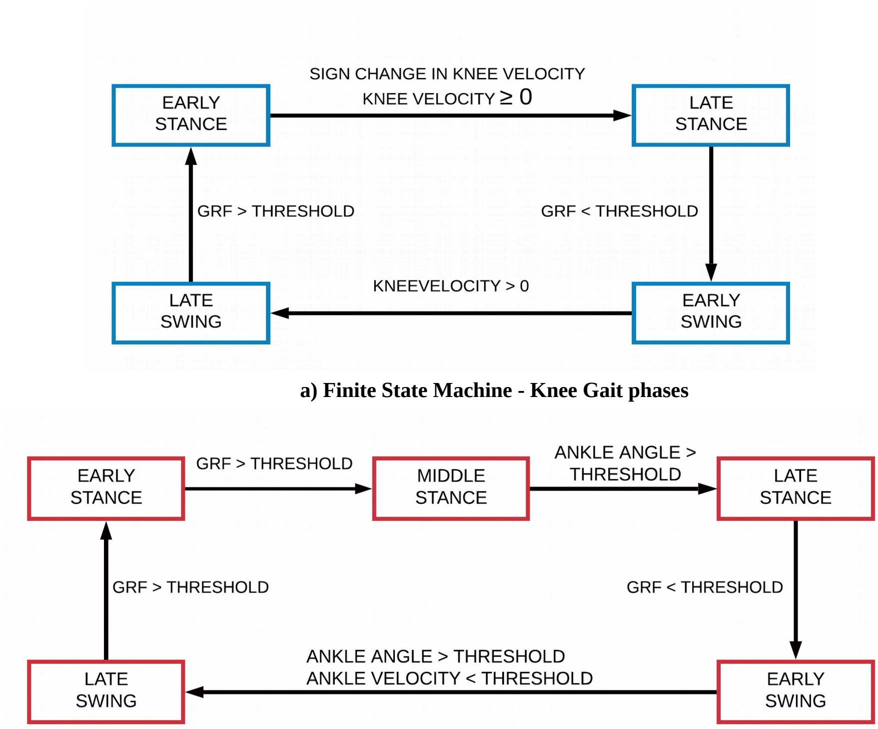
that indicate the transition from one state to the other. The rules, selected heuristically, may be chosen manually or determined through analytical means. The number of rules and thresholds that must be established increases nearly combinatorially with the number of states. Being the gait cycle a personal characteristic, it is likely necessary to manually tune the parameters that allow the transition from on state to the other. Two examples, dividing the gait cycle respectively into four or five states, as shown in Figure ... take into separate account the knee and ankle joint.

1.3.4 Volitional Impedance controller

In [33] Hoover and Fite formulate a simple model of the dominant mechanical properties of individual muscles for the torque curve generation at the knee joint. Specifically, variations in muscle force with length, rate of change of length, and alpha motoneuron activity during slow, large amplitude movements are included. The relationships between these variables are assumed bilinear, that is, the slopes of the force-length and force-contraction rate curves are assumed to be linear. Based on these characteristics, the muscles are modelled as a parallel spring-damper.

Figure 1.21 depicts the simplified neuromuscular knee joint model with a single pair of agonist-antagonist variable impedance muscles. The lower leg is modelled as an inertia I subject to environmental loads τ_{env} and driven by the moments of antagonist muscles.

Net muscle forces F_f and F_e, multiplied by the moment arm r, yields the net torque of each muscle. Accounting for first order force/length stiffness and force/contraction rate damping characteristics, the flexive torque τ_f and extensive torque τ_e of the muscles are:



a) Finite State Machine - Knee Gait phases

b) Finite State Machine – Ankle Gait phases

Figura 1.20: Diagrams of Finite State Machine for level ground walking

$$\tau_f = rF_f = K_f(\Theta_{max} - \Theta) - B_f\dot{\Theta}$$
$$\tau_e = rF_e = K_e(\Theta_{min} - \Theta) - B_e\dot{\Theta}$$

where Θ is knee joint angle, Θ_{max} is the flex rest angle, Θ_{min} is the extensor rest ankle, K_f is the flexor stiffness, K_e is the extensor stiffness, B_f is flexor damping and B_e is extensor damping.

1.3.5 Machine learning approach

Artificial intelligence (AI) is the theory and development of computer systems able to perform tasks normally requiring human intelligence, such as visual perception, speech recognition, decision-making, and translation between languages. These processes include learning, reasoning and self correction. Machine learning (ML) is a core application of AI based around the idea that the machines having access to data and rules applied to the learning process, may learn for themselves. One sub-field of ML is automated pattern recognition. The main goal is to classify input data into objects or

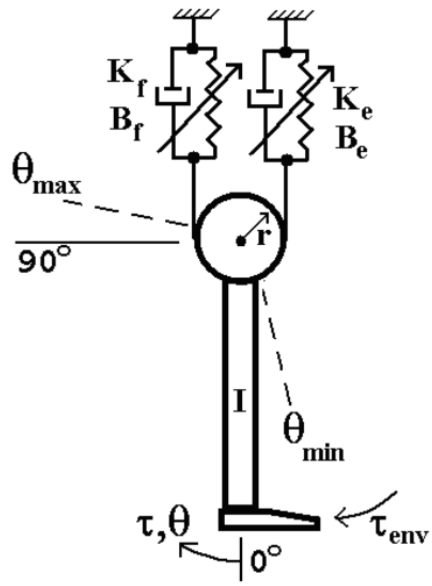


Figura 1.21: Simplified knee joint model with variable impedance antagonist muscles

classes based on certain features. Pattern recognition can be either "supervised", where previously known patterns can be found in a given data, or "unsupervised", where entirely new patterns are discovered.

Unsupervised Learning finds patterns based only on input data and is therefore used when further insight of the input data is needed (exploratory analysis of raw data). In unsupervised learning there is no correct answer and no teacher. Algorithms are left to their own devises to discover and present the interesting structure in the data. It can further grouped into clustering and association problems:

- Clustering groups data items that have some measure of similarity based on characteristic values
- Association discovers rules that describe large portion of data, such as that people that buy X also buy Y.

Supervised Learning instead finds patterns (and develops hence predictive models) using both input and output data. The goal is to approximate the mapping function so well that when new input is submitted, the algorithm can predict the output variables for the data. It is called Supervised Learning because of the process of an algorithm learning from the training data-set can be thought of as teacher supervising the learning process. Knowing the correct answer, the algorithm iteratively makes predictions on the training data and minimizes the error. Learning stops when the algorithm achieves an acceptable level of performance. Supervised learning problems can be further grouped into regression and classification problems. The main difference between a classification and a regression problem lies in the fact, that in the first the output variable takes class labels, while in the second the output variable takes continuous values.

Some popular examples of supervised machine learning algorithms are listed in table 1.2:

Classification	**Regression**
Support vector machines for classification problems Random forest classification problems	Linear regression for regression problems Random forest regression problems

Tabella 1.2: Examples of supervised machine learning algorithms

Classification and Pattern recognition

Pattern recognition is the automated recognition of recurrent regularities in the data, by using machine learning approaches. The main idea is to endow the control system with the ability to learn from the experience generated by the interaction with the environment [34] and offers the ability to control multiple movements in a seamless manner [35]. Pattern recognition can be either "supervised," where the controller classifies data based on prior knowledge gained, or "unsupervised," where entirely new patterns are discovered. One of the important aspects of pattern recognition is its speed and accuracy in recognizing and classifying familiar and unfamiliar patterns. The entire data set is divided into two categories, one which is used in training the model - Training set - and the other that is used in testing the model after training - Testing set.

Support Vector Machine

Support Vector Machines (SVM) are based on the concept of decision planes that define decision boundaries. A decision plane separates a set of objects having different class memberships.

The above (Figure 1.22) is a classic example of a linear classifier. Most classification tasks, however, are not that simple and often more complex structures are needed in order to make an optimal and correct separation. Classification tasks based on drawing separating lines to distinguish between objects of different class memberships are known as hyperplane classifiers. SVM are particularly suited to handle such tasks. By using mathematical

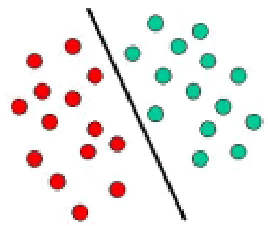


Figura 1.22: Linear classifier

functions, known as kernels, objects can be rearranged, simplifying the latter membership classification and avoiding the construction of a complex separating curve.

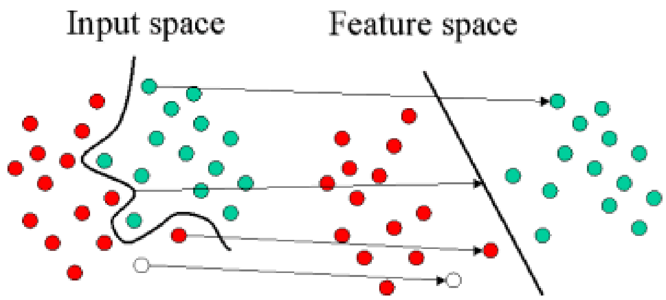


Figura 1.23: Hyperplane classifier

To construct an optimal hyperplane, SVM employs an iterative training algorithm, which is used to minimize an error function. According to the form of the error function, SVM models can be classified into four distinct groups:

- Classification SVM Type 1 (C-SVM classification)
- Classification SVM Type 2 (nu-SVM classification)
- Regression SVM Type 1 (epsilon-SVM regression)
- Regression SVM Type 2 (nu-SVM regression)

Regression

The problem of learning continuous input-output models starting from the observed empirical data, known as regression has been widely studied. There are two classic approaches: the first is to restrict the class of soughed functions, for example taking into account only linear functions of the inputs; the second is to set a probability a priori to each possible function by assigning the greatest probabilities to functions considered most likely. The first approach suffers from a poor predictive ability if the objective function cannot be modelled well enough by the fixed class, while the second presents the problem that the set of possible functions is infinite and not countable. This last difficulty, however, can be overcome in the context of Gaussian processes, which provides a sophisticated approach allowing easy computational tractability.

In the following two sections both approaches are briefly discussed [37].

Linear regression model A couple formed by the input vector x (of dimension D) and the corresponding output vector y is defined as an observation [37]. The set of n observations forms together the training set $D = \{\ (x_i, y_i) \mid i = 1..n\ \}$. The set of n x-vectors forms the matrix X of dimensions $D \times n$, while the vector y collects all the outputs. The set of all observations can be rewritten as $D = (X, y)$. Introducing a noise ε, the equation can be written as:

$$y = f(x) + \varepsilon \qquad f(x) = x^T w$$

where x is the input vector, w is the vector of weight parameters of the linear model, f is the value of the functions, while y is the observed value. y differs from $f(x)$ because of the added noise ε, which is notoriously present in every empiric observation.

The best way to estimate the weight parameters, is to take the mean of parameters w that minimize the residual sum of squares (RSS). RSS is the total of the squared differences between the known values f(x) and the mean of the predicted model outputs $\widehat{y}$. RSS is a function of the model parameters:

$$RSS(w) = \sum_{i=1}^{n}(f_{(i)} - \widehat{y}) = \sum_{i=1}^{n}(f_{(i)} - w^T x_i) \quad [61]$$

The above equation has a closed form solution for the model parameters w, that minimize the error. This is known as the maximum likelihood estimate of w because it is the value that is the most probable given the inputs X and outputs y. The closed form solution expressed in matrix form is:

$$\widehat{w} = (X^T X)^{-1} X^T y \quad \text{leading to} \quad \widehat{y} = \widehat{w^T} X \quad .$$

To verify that the vector contains the right parameters, the predicted output may be compared to the expected ones through the Root Mean Square Error (RMSE) analysis. Both outputs are squared to avoid the cancellation of similar but opposite results, subtracted from each other and divided by the number of samples. The result is then square rooted.

$$RMSE = \sqrt{\frac{f_{(x)}^2 - y^2}{n}}$$

The closer the RMSE value is to zero, the closer the approximation is to the real output.

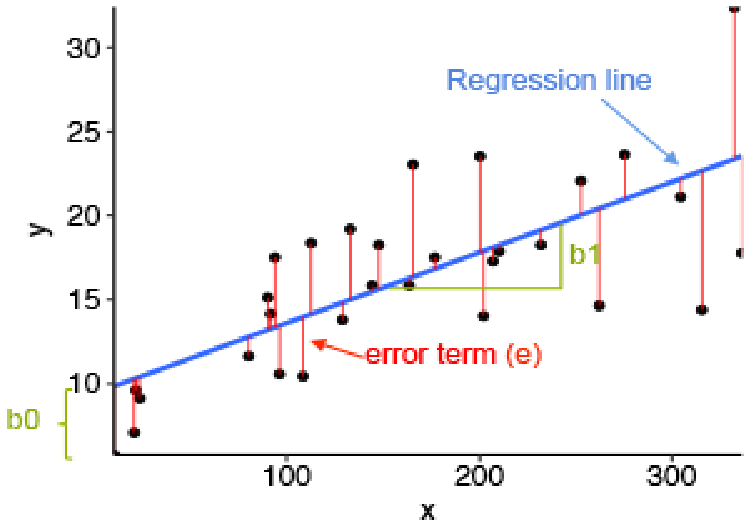


Figura 1.24: Example of linear regression model estimation

Although Bayesian linear regression is a straight forward method for estimating the best parameters fitting a linear function, this is also its limitation. In a continuous non-linear function space the error between the expected and estimated output can mostly never be optimally minimized.

Gaussian Process The GP [36] approach, in contrast, is a non-parametric approach, as it produces a distribution of all possible functions given the training points, getting rid of the limitation of linear regressive solutions. The probability of all possible output functions

$$p(f(x_1),...,f(x_N))$$

is set jointly Gaussian, with some mean $\mu(x)$. By specifying a covariance matrix

$$\sum = k(x_i, x_j) \quad .$$

where k is a positive definite kernel function, the covariance matrix allows the GP to set values that are close together in input space will produce output values that also are close together.

Setting the joint probability of two variables x_1 and x_2 as

$$\begin{pmatrix} x_1 \\ x_2 \end{pmatrix} \sim N\left(\begin{pmatrix} \mu_1 \\ \mu_2 \end{pmatrix} , \begin{pmatrix} \sigma_{11}\sigma_{12} \\ \sigma_{21}\sigma_{22} \end{pmatrix} \right) .$$

it is possible to get the conditional probability of one of the variables given the other. Extending this definition to the values of $f(x)$ for all the possible x values, the joint probability can be redefined as

$$\begin{pmatrix} f \\ f_* \end{pmatrix} \sim N\left(\begin{pmatrix} \mu \\ \mu_* \end{pmatrix} , \begin{pmatrix} K\mathrm{K}_* \\ K_*^T K_{**} \end{pmatrix} \right) .$$

Here, K is the matrix gotten by applying the kernel function to the observed values x, i.e. the similarity of each observed x to each other observed x. K_* finds the similarity of the training values to the test values whose output values the GP is trying to estimate. K_{**} gives the similarity of the test values to each other. Following this thread the probability distribution $p(f_*|x_*, x, f)$ can be found, assuming that f and f_* together are jointly Gaussian as defined above. At the end the GP defines the mean μ_* and covariance matrix $\sum$ that point out the distribution $f_* \sim N(\mu_*, \sum)$.

Once the GP is trained, it can be applied to a new input vector x, estimating the most probable output value f.

1.4 Thesis overview and objectives

The following chapter provides an overview of the database that was used for the generation of the classification algorithm and the regression protocol. It briefly outlines its characteristics to better understand the starting point and then interpret the conclusions of this study.

The objectives of this study are threefold:

1. find a suitable control algorithm that provides a better performance then the FSM for the gait analysis at the knee and ankle joint;
2. cross-check various input data configurations and verify which proves to have a more accurate torque curve generation by minimizing torque error;
3. find a suitable generalized control approach appliable to multiple subjects.

Chapter 3 presents the classification analysis. This part wants to show how a novel machine learning approach may increases the accuracy of the gait state control algorithm with respect to a FSM heuristic rule based controller. By integrating different combinations of the kinematic informations with EMG signals and Ground Reaction Force (GRF), it is verified which combination provides the most stable and accurate controller. Methods are presented and preliminary results discussed.

In Chapter 4, the second part of the research is described. Mainly, find through the gaussian process a suitable parameter combination which estimates the best torque curves applied to the knee and ankle joint, minimizing the root mean square error between the generated and real torque curve. At the end, again, preliminary results are discussed and differences to the linear regressor technique are underlined.

In Chapter 5, finally, main conclusions about all the experience and results are drawn. Limitations of this study and possible future work are finally discussed.

All algorithms and testing were realized on the 2018b student version of MATLAB.

At the end of this thesis the bibliography and an appendix about part of the codes and formulas used for the classification and regression algorithms have place.

Capitolo 2

A novel approach

2.1 Methodology

2.1.1 Data acquisition

This chapter presents a brief introduction of the database made available online by the team working on the "Journal of Biomechanics" and made available for download on the www.simtk.org website. It includes informations about the leg kinematics, EMG signals of the rectus femoris, medial and lateral hamstring muscle and the GRF.

The experiment involved eight children walking at four different walking speeds. The walking speeds were categorized post-hoc as very slow, slow, free and fast according to the following scheme:

$$\begin{array}{llcccl}
\text{very slow} & 0 & < & v^* & \leq & \bar{v}^*_{free} - 3\sigma^*_{free} \\
\text{slow} & \bar{v}^*_{free} - 3\sigma^*_{free} & < & v^* & \leq & \bar{v}^*_{free} - \sigma^*_{free} \\
\text{free} & \bar{v}^*_{free} - \sigma^*_{free} & < & v^* & \leq & \bar{v}^*_{free} + \sigma^*_{free} \\
\text{fast} & \bar{v}^*_{free} + \sigma^*_{free} & < & v^* & &
\end{array}$$

where non-dimensional walking velocity $v^* = \frac{v}{g*L_{leg}}$ (v is absolute walking velocity, L_{leg} is leg length and g is gravitational acceleration; Hof 1996), and v^*_{free} and σ^*_{free} are the mean and standard deviation, respectively, of the non-dimensional free walking speed of the subject cohort reported by Schwartz et al. (2008). The eight subjects from this cohort achieved at least one double-stance phase on the force plates at each walking speed, which provided the bilateral GRF data. The obtained data base was used to generate subject-specific simulations at each walking speed. The original data set contains informations about the mechanisms that modulate vertical supportive and fore-aft progressive accelerations of the body mass centre at different overground walking speeds. The GRF was sampled at 1080Hz and lowpass filtered at 20Hz. The EMG data was sampled at 1080Hz, bandpass filtered between 20 and 400Hz, rectified and then lowpass filtered at 10Hz. To estimate the angular joint velocity, the time rate of change of its angular position was evaluated.

$$\omega = \frac{\Theta_{(t_k)} - \Theta_{(t_{k-1})}}{t_k - t_{k-1}}$$

As the database included only informations about one step length and as walking is a repetitive side-switching motion, to replicate a whole stride length, the data flow was repeated and lowpass filtered. To simulate the data acquisition of a real-time controller the signal was buffered acquiring 32 sample frames and shifting by eight. Each time the mean value of the buffer was taken and applied to the calculations.

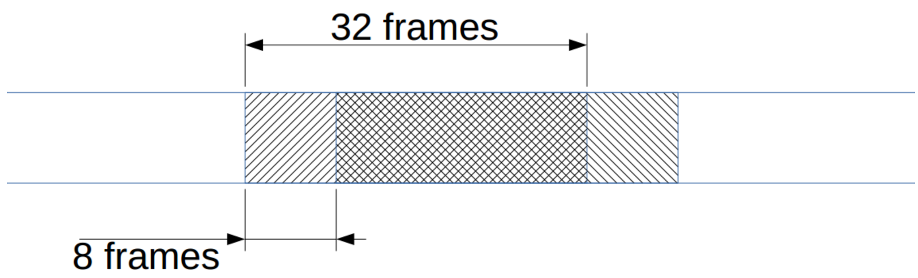


Figura 2.1: The sampling frames scheme

Walking phase identification

As explained in chapter ... the state of the art lower limb smart prostheses uses an onboard FSM controller to identify the gait state. In order to confront future results, it was necessary to develop a FSM, as based in literature, for the knee and ankle joint. Further, to find a classifier that takes into account EMG signals and is able to guarantee an automated not heuristic rule based state transition, it was thought to apply a machine learning approach, more precisely the Support Vector Machine (SVM).

To verify the accuracy of the classifiers, the obtained results were compared frame by frame with the actual gait states. If they matched, the accuracy for this frame was set to a 100%, while if the did not the accuracy was set to 0%. At the end of the whole gait cycle analysis the mean value of the overall accuracy was taken.

FSM The FSM knee controller is composed by four states: early and late stance, and early and late swing. During the ground level walking process, once overcoming the GRF threshold, the early stance state is initialised. Continuing the walking process, there will be a change of sign of the knee joint velocity and once the velocity is increasing the late stance phase is reached. Leaving the ground the GRF acting on the foot is zero, leading the controller to the swing phase. Once the knee velocity increases the late swing phase is initialised and the cycle begins from the beginning.

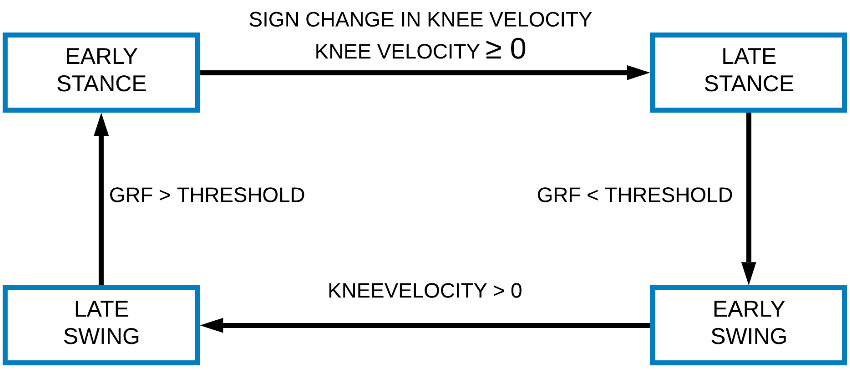


Figura 2.2: Knee controller FSM

The ankle controller has five states, as the ankle with respect to the knee joint needs a preciser gait analysis and phase separation. Therefore an additional state between the early and late stance, called middle stance, was introduced. Once overcoming two GRF thresholds, one being slightly higher then the other, first the early and then the middle stance is initialised. As the shin continues is forward motion the ankle angle increases, introducing the controller to the late stance. As the foot leaves the ground the early swing phase is initialised and when both, the ankle velocity and angle are respectively lower and higher then the imposed threshold, the controller reaches the late swing.

SVM - from heuristic rule based classification to machine learning based classification The SVM is a supervised machine learning method. To be able to apply it, it needs to be trained. To accomplish this task the "leave-one-out" approach was adopted: to test if the SVM works properly and accurately it was first trained an all trials, except the one being analysed.

The database includes overall 32 ground level walking trials, divided into four walking speeds. The classifier is trained in two approaches. The first approach is to train the classifier on each subject (single subject wise - SS), taking account only of three ground level walking trials and testing it one the remaining one. This approach was adopted for all subjects and for all trials in a cyclical matter, to enforce the highest amount of results. In a second approach the classifier was trained on seven subjects and tested on

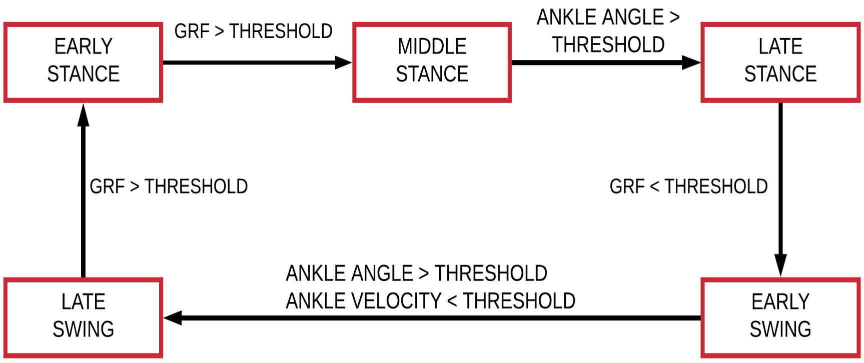


Figura 2.3: Ankle controller FSM

the remaining one (multi subject wise - MS). Again a cyclical pattern was applied. The table in figure 2.4 is a graphical representation of the two approaches:

	Very slow walking	Slow walking	Natural walking	Fast walking
Subject 1	Training data for	Trial to be tested	the classifier for a single subject	
Subject 2	Training data for the classifier for multiple subject			
Subject 3				
Subject 4				
Subject 5				
Subject 6				
Subject 7				
Subject 8				

Figura 2.4: graphical representation of the two used approaches

A SVM classifies between two possible classes. As mentioned before the knee junction has four gait state classifications and the ankle junction has five of them. Therefore for both, a cascade classification approach was needed.

To classify the different gait states for the knee joint the following scheme, shown below, was developed. The first level splits the gait between main stance or main swing phase. In a second level a further division was introduced, for both the swing and stance phase, separating respectively early and late swing, and early and late stance phase (figure 2.5).

For the ankle junction an analogue approach was applied, but as the stance phase has three sub states, being early, middle and late stance, an additional level was introduced. The added level separated the early stance from the other two stance phases. The logical procedure is shown in figure

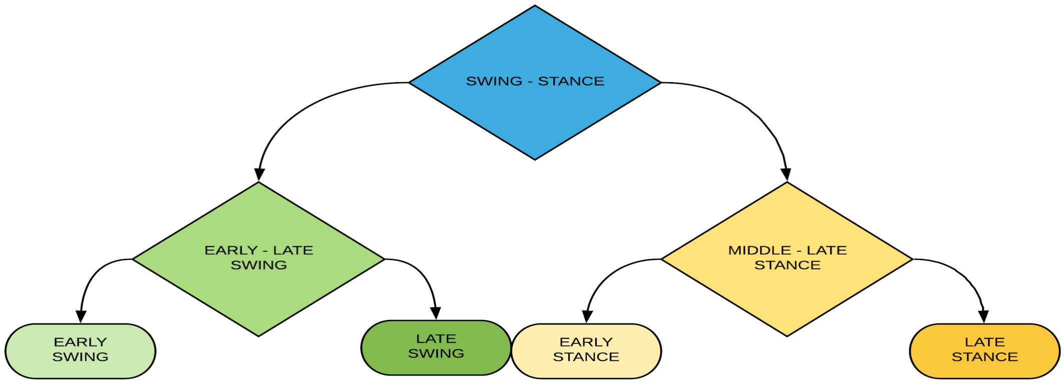


Figura 2.5: Knee SVM classifier

2.6.

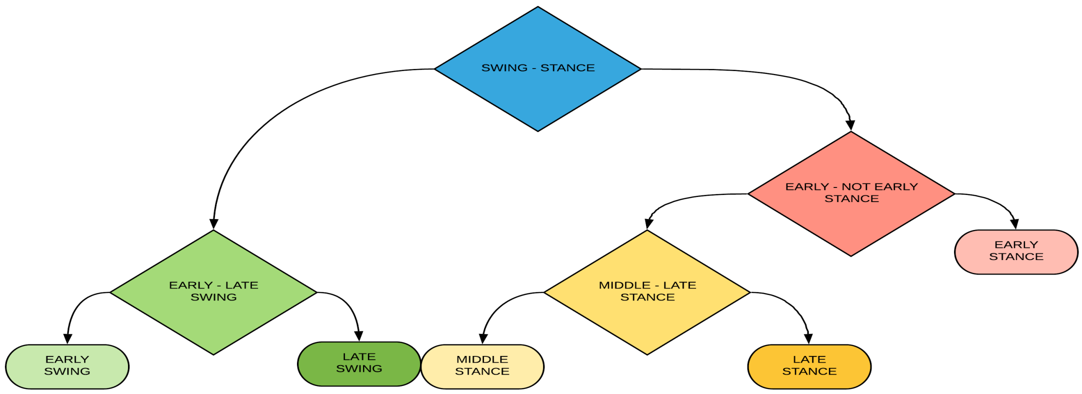


Figura 2.6: Ankle SVM classifier

State related impedance control

As mentioned in Chapter 1.3.4 the torque curve of the joint can be represented by the following equation:

$$\tau = K(\theta - \theta_K) - \beta\omega$$

where K is the joint stiffness, β is the joint damping factor, θ is the joint angle, θ_K is the joint rest angle and ω is the joint angular velocity.

The same formula can be rewritten as:

$$\tau = -K\theta_K + K\theta - \beta\omega$$

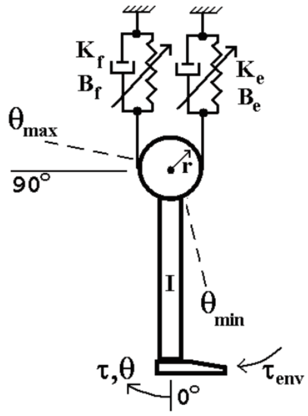


Figura 2.7: Mechanical scheme of the knee joint

where $-K\theta_K$, K and β can be seen as variables to be estimated by the regressor, instead of heuristic chosen parameters.

The equation can then be rewritten in matrix form:

$$\tau = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} \begin{bmatrix} 1 \\ \theta \\ \omega \end{bmatrix}^T$$

where the x-vector contains the parameters to be evaluated.

Stiffness and damping can be assumed to have a linear relationship expressed by epsilon having a range from 0.01 to 0.05.

$$\tau = \beta K$$

The torque equation can therefore be rewritten as:

$$\tau = -K\theta_K + K(\theta + \epsilon\omega)$$

expressed in matrix form:

$$\tau = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \begin{bmatrix} 1 \\ \theta + \epsilon\omega \end{bmatrix}^T$$

The same structure will be used in the whole work, to divide the parameters that work on the stiffness with respect to the ones working on the damping effect of the joint.

To integrate the EMG signals coming from the rectus femoris and the medial and lateral hamstring muscles, it is possible to make the following mathematical assumptions. Taking the minimum value between the EMG signals from the two opposite muscles - rectus femoris and hamstrings - it is possible to define an EMG dependent stiffness. Different cases were taken into account: if none of the muscles contract the stiffness is low, ff both muscles contract the stiffness is high and if just one muscle contracts but the other not, the stiffness remains low.

$$K_{EMG} = min\left(EMG_{rf}, \frac{EMG_{mh} + EMG_{lh}}{2}\right)$$

K_{EMG} is the EMG dependent stiffness, while the subscripts indicate respectively the rectus femoris, the medial and lateral hamstring muscles.
Analogically an "EMG-angle" can be defined as the difference between the two muscles. If both or none muscles contract the angle is null, if just one of the muscles contract the angle has a high.

$$\theta_{EMG} = EMG_{rf} - \frac{EMG_{mh} + EMG_{lh}}{2}$$

In the second database the last analysed control algorithm includes a combination of all available kinematic informations (joint angle, joint angular velocity and shank acceleration) and EMG signals, where each singular nervous muscle information is fed to the training algorithm. All five applied torque curve equations are presented in the appendix.

Linear To have a comparison between the linear and gaussian regressor the first needs to be applied to find the parameters of the torque curve equation. As the gait is divided in various states, depending on the joint, the regressor needs to find for each state the according parameters for the torque curve generation. As the database includes different informations about the joint kinematics, the GRF and the EMG signals, multiple combinations were developed and compared. Once the parameters were found, they were tested and the resulting torque curve was compared to the actual one through the Root Mean Square Error (RMSE) approach.

Gaussian The Gaussian Process (GP), wrt to the linear regressor, as explained in chapter ... does not estimate a single parameter vector for each state, but defines a parameter distribution over the function. This permits a better approximation of the estimated torque to the actual torque.

Before being usable, similarly to the SVM, the GP needs to be trained. To do so the expected torque output and input combinations defined in the equation are fed to the GP. The GP is then tested for each trial frame by frame. First the SVM classifies the gait state, then the GP applies the correct control law for the torque curve generation. Again, to estimate the discrepancy between the estimated and real torque, the RMSE approach is applied.

2.2 Results

2.2.1 Classification

SVM The tables below represent the combinations for which the SVM reached the highest accuracy. First are shown the combinations (in red) for which the knee junction, single subject wise and multi subject wise, has reached the highest accuracy. Secondly the ankle junction (in blue). In order to have an immediate result of the combinations that worked the best, the next explained logical thread was followed:

1. test best working SVM including the GRF
2. test best working SVM excluding the GRF
3. test best working SVM including GRF and EMG signals
4. test best working SVM including EMG and excluding GRF

	KNEE							
	SVM combination for SS				SVM combination for MS			
	1	2	3	4	1	2	3	4
Joint angle		X	X	X		X		X
Joint angular Velocity	X	X	X	X	X	X	X	X
GRF	X		X		X		X	X
Shank Acc	X	X	X	X	X	X	X	
EMG			X	X			X	X

Tabella 2.1: Knee SVM input combinations for SS and MS; X denotes the inclusion of the parameters

	ANKLE							
	SVM combination for SS				SVM combination for MS			
	1	2	3	4	1	2	3	4
Joint angle	X	X	X	X	X	X	X	X
Joint angular Velocity	X	X	X	X	X	X	X	X
GRF	X		X		X		X	
Shank Acc	X	X	X	X				
EMG			X	X			X	

Tabella 2.2: Ankle SVM input combinations for SS and MS; X denotes the inclusion of the parameters

SS wise the classifier performed better with the knee junction then the ankle junction. In the two bar graphs below are represented the classifier accuracies for the different combinations of the SVM. In red is shown the accuracy level of the FSM classifier, while in blue are shown the accuracy levels of the different SVM combinations. Overall the knee SVM performed better then the ankle SVM. The FSM for the knee junction reached an accuracy level of 89.7% with a standard deviation of 3.5. The SVM combination including all kinematic parameters and the GRF performed at an accuracy of 93.2%, while the combination including all parameters reached an accuracy of 89.3%. The FSM for the ankle junction instead, reached an overall accuracy of 93.7%, while the best performances were reached by the combinations of all kinematic parameters with the GRF and the combination of all parameters. The SVM including all kinematic parameters and the GRF reached an accuracy of 90.9% with a standard deviation of 5.5, while the combination of all parameters reached an overall accuracy of 85.3% with a standard deviation of 9.3.

MS wise again the classifier performed better with the knee junction then the ankle junction, but this time for a much higher margin. In the two bar graphs below are represented the classifier accuracies for the different combinations of the SVM. The accuracy levels for the knee and ankle junction are the same as for the SS. Overall the knee SVM performed better then the ankle SVM. The SVM combination including all kinematic parameters and the GRF performed at an accuracy of 93.8%, while the combination including all parameters reached an accuracy of 93.6%. The SVM for the ankle joint including all kinematic parameters and the GRF reached an accuracy of 92.6%, while the combination of all parameters reached an overall accuracy of 91.9%. The two graphs below represent the accuracy levels reached by the different SVM combinations.

Before applying the GP to the SVM to evaluate the joint torque curve, it was necessary to confront the FSM and SVM with the true effective labels of the gait cycle. The table below is a summary of all SVM considering the best accuracy levels for the different combinations, including also the standard deviations. The column to the left determines the SVM combination. In blue are shown the results for the knee joint and in red the results for the ankle joint. Overall the SVM performed better MS wise then SS wise, increasing the accuracy level for both, the knee and ankle junction.

2.3 gaussian regressor

The first analysis confronted the linear regressor with the GP based on the effective gait cycle states. Overall the GP performed better then the linear regressor, more for the knee joint then the ankle joint. The table below represents a summary the RMSE of all possible torque curve combinations. The column to the left indicates the combination of parameters used: (more accurate explanations are presented in the appendix):

In most test trials the GP regressor performed quiet well, except in some. In those it seems the GP was not able to estimate the correct torque output, but overreached. Below are represented three examples of a torque curve generation at the knee junction. The first shows the torque curve of a SS test. The second and third show a MS torque curve, one where the GP estimated correctly the torque and one where it did not.

Regarding the knee joint, the results show, that although in some cases the GP performs quiet poorly, the RMSE is actually slightly lower in all parameter combinations. For the ankle joint the opposite is the case. The table below depicts the summary of the RMSE for the knee and ankle junction, single subject and multi subject wise, confronting case by case the linear regressor with the GP. Single subject wise there are five different torque equations including all possible combinations between kinematic, nervous system and GRF sensory informations, whereas multi subject wise there are just three. This choice had two reasons: first, mainly because the students pc did not have the memory to elaborate the amount of data, secondly the aim of this research is to verify which informative combination beside the kinematic one, can be used to optimize the classifier, appliable to multiple subjects.

In the appendix are present the bar graphs showing graphically the achieved results for each SVM combination applied to each torque curve equation.

2.4 Discussion

2.4.1 Classification

Overall the SVM performed better then the FSM, mostly working with the same parameters, means kinematic and GRF. Noteworthy although is, that in the MS analysis the accuracy level only dropped by a slight percentage for the knee junction in the case of the kinematic combination, excluding the GRF. This results may mean that future modern prostheses may could avoid the integration of a GRF sensor, which would mean less costs for the development and the manufacture. EMG sensory wise the SVM did not perform too poorly. The overall mean accuracy for the knee joint lies slightly below the FSM laid margin, while for the ankle junction the EMG signals certainly should not be taken into account.

2.4.2 Regression

Regarding the torque curve evaluation the novel approach did achieve some good results in the SS analysis and some lesser results in the MS analysis, meaning estimating an overall RMSE slightly higher for the GP then for the linear regressor.

This final results, although not confirming that the adaption of the SVM classification and the GP regression elaboration, may increase the joint torque performance for the knee and ankle joint.

2.4.3 Future steps

Future steps in the direction laid by this research in the ground level walking gait analysis could be the following:

- as the ankle SVM did not quite perform as well as the knee SVM it may be advisable to integrate the second in the first. Leading in an upper level the knee classifier could send informations to the ankle SVM, conditioning the gait state classification and increasing the performance
- apply the same type of analysis to a different set of input informations, which may not only include joint angle and velocity but also informations about segments (thigh, tibia and foot) orientation, linear and angular acceleration along all three axis
- extend the data acquisition to a various set of subjects including male and female of various ages

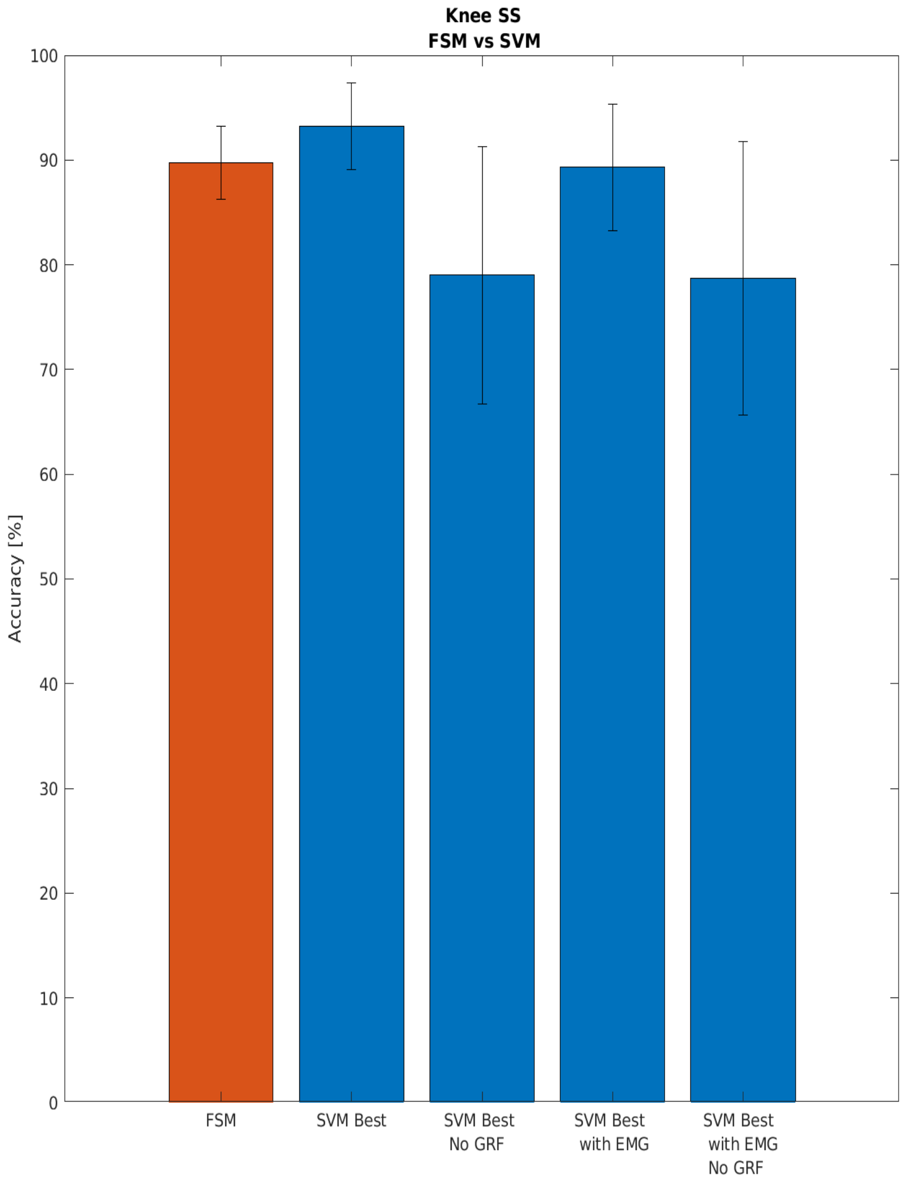


Figura 2.8: Knee Single Subject, Torque equations accuracy

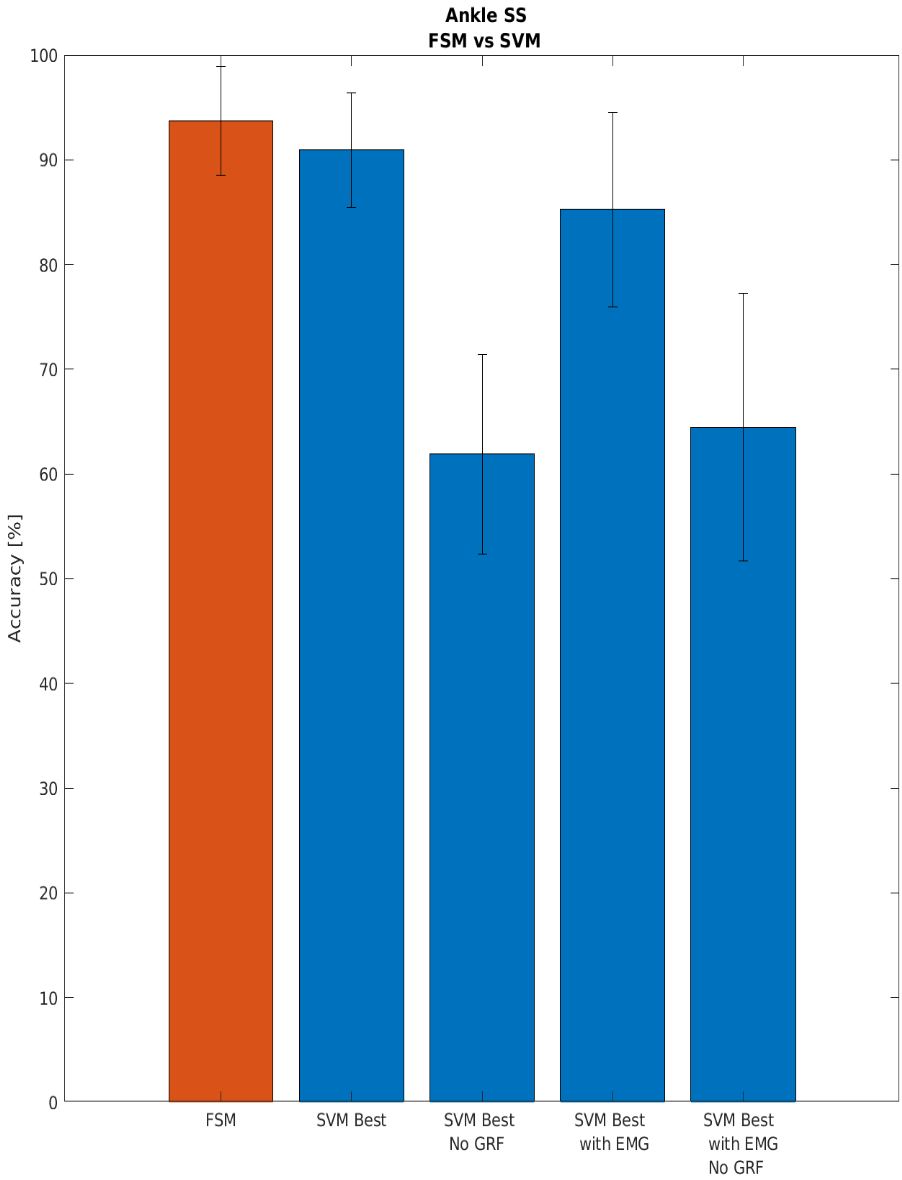


Figura 2.9: Ankle Single Subject, Torque equations accuracy

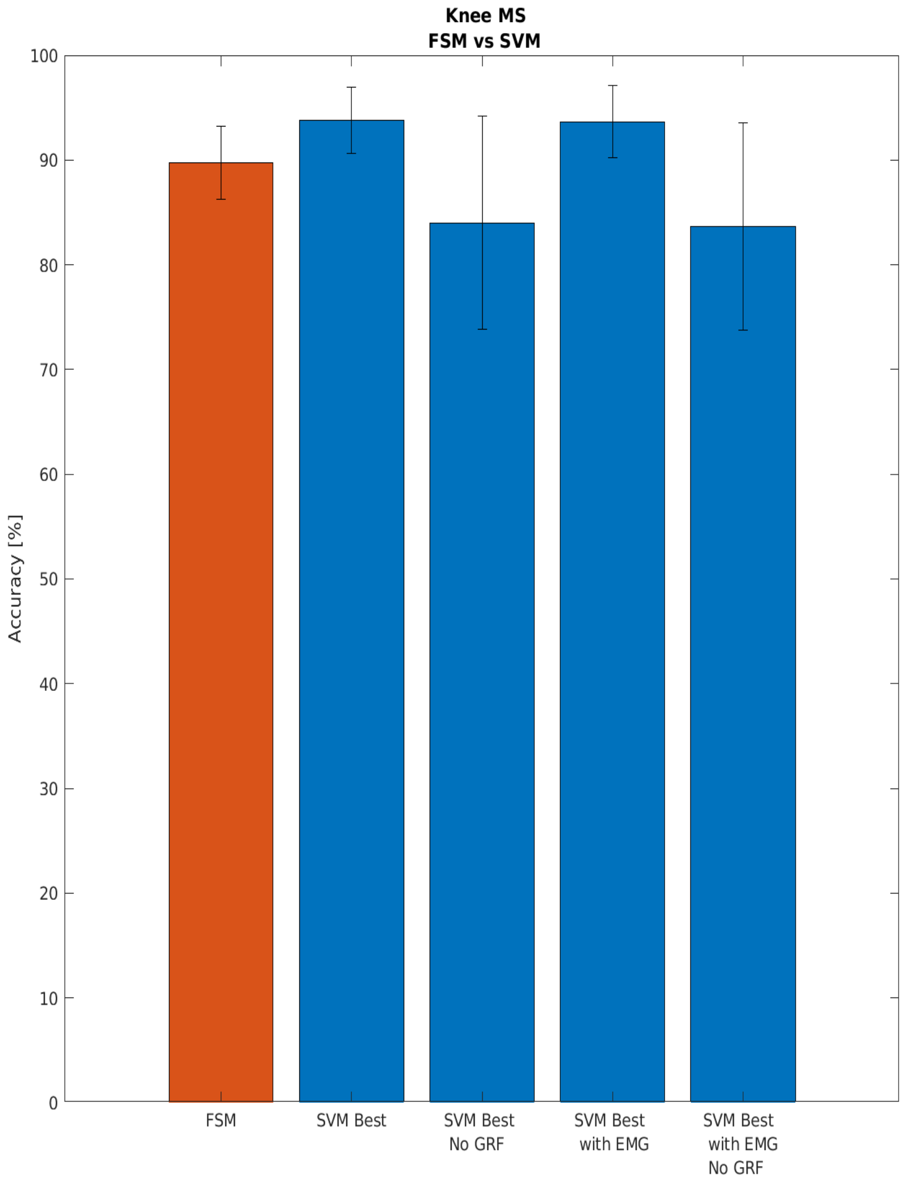


Figura 2.10: Knee Multi Subject, Torque equations accuracy

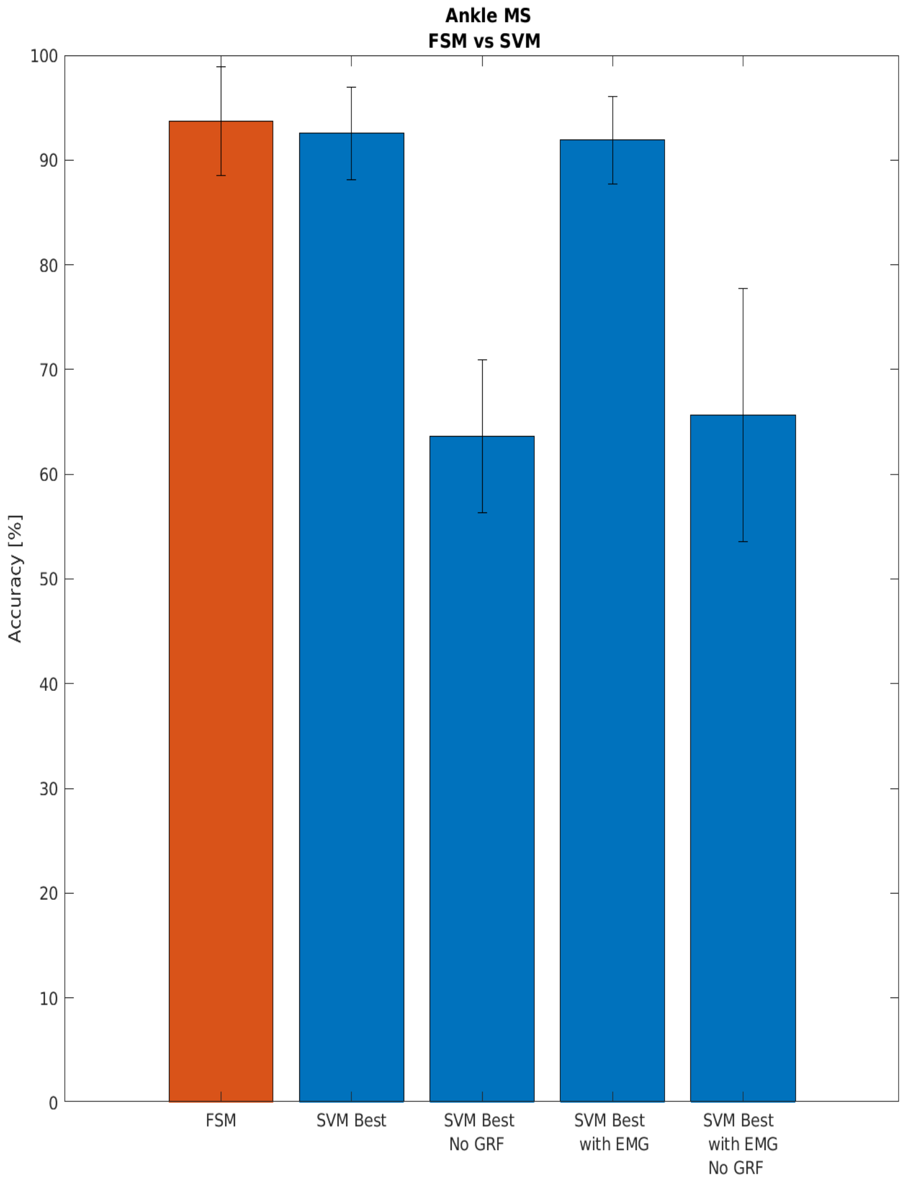


Figura 2.11: Ankle Multi Subject, Torque equations accuracy

		FSM vs SVM							
		KNEE				ANKLE			
		SVM		FSM		SVM		FSM	
		Accuracy	Std dev	Accuracy	Std dev	Accuracy	Std dev	Accuracy	Std dev
SS	Best	93.2	4.1	89.7	3.5	90.9	5.5	93.7	5.2
	Best No GRF	79.0	12.3			61.9	9.5		
	Best With EMG	89.3	6.1			85.3	9.3		
	Best With EMG No GRF	78.7	13.1			64.5	12.8		
MS	Best	93.8	3.2	89.7	3.5	92.6	4.4	93.7	5.2
	Best No GRF	84.0	10.2			65.7	12.1		
	Best With EMG	93.6	3.5			91.9	4.2		
	Best With EMG No GRF	83.7	9.9			65.7	12.1		

Tabella 2.3: Gait Cycle Analysis, FSM vs SVM

		TRUE LABEL							
		KNEE				ANKLE			
		Linear Regressor		Gaussian Process		Linear Regressor		Gaussian Process	
		RMSE	Std dev	RMSE	Std dev	RMSE	Std dev	RMSE	Std dev
SS	3param	6.8	2.6	8.5	3.3	8.9	4.3	17.6	17.2
	2param	6.7	2.4	2.4	1.0	9.7	4.5	3.8	2.4
	6param	7.2	3.1	1.1	0.8	9.4	3.5	19.3	30.4
	8param	7.8	3.3	1.1	0.8	11.5	5.2	6.9	5.1
	12param	12.5	5.9	1.1	0.9	15.9	8.7	7.6	5.3
MS	3param	6.4	2.3	7.0	2.9	11.9	3.4	14.3	2.4
	2param	6.4	2.3	6.1	2.3	10.8	3.2	11.9	3.3
	6param	7.9	1.7	8.2	3.1	12.8	3.9	13.4	3.3
	8param	7.6	1.8	8.1	3.2	12.3	4.1	12.7	3.3
	12param	8.6	2.7	7.9	2.8	13.7	4.7	13.2	2.9

Tabella 2.4: True Label Torque Curve Regressor, Linear vs Gaussian Process

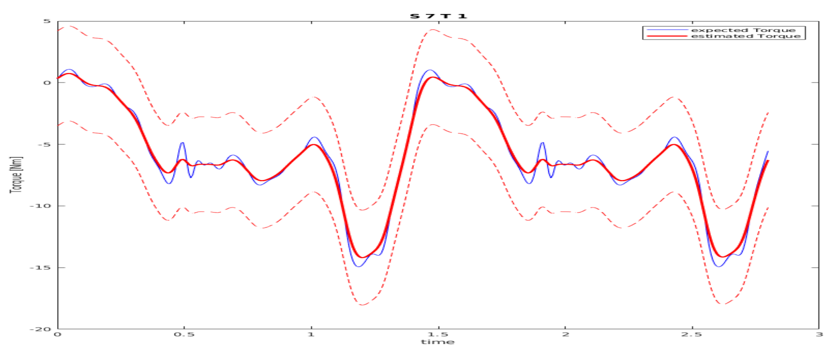


Tabella 2.5: Torque Curve representation for a Single Subject Test Trial

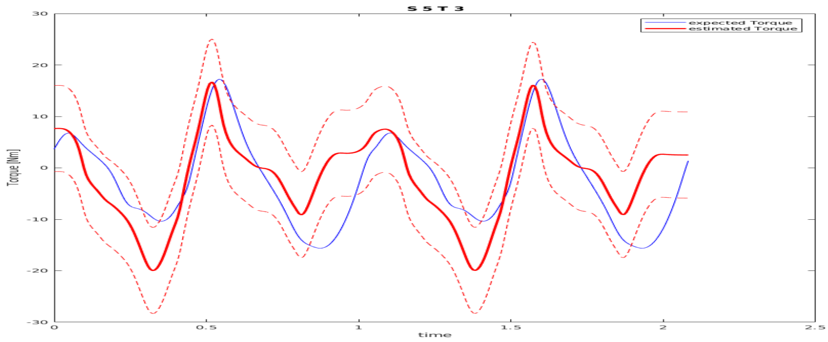


Tabella 2.6: A good Torque Curve representation for a Multi Subject Test Trial

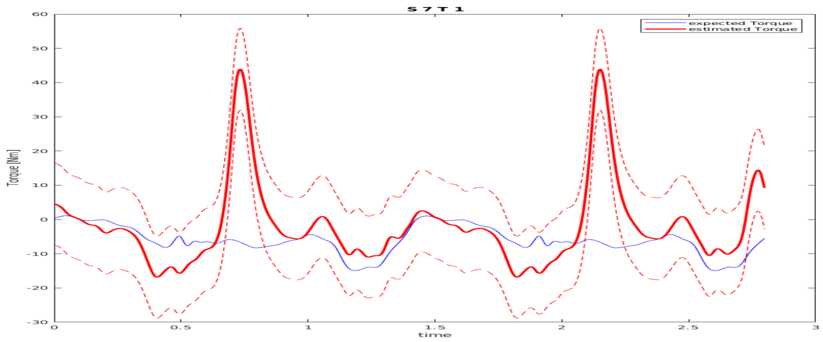


Tabella 2.7: A bad Torque Curve representation for a Multi Subject Test Trial

			RMSE			
			KNEE		ANKLE	
			LR	GP	LR	GP
SVM N. 1	SS	3param	6.8	8.3	8.9	2.6
		2param	6.7	2.8	9.7	3.9
		6param	7.2	1.4	9.4	7.3
		8param	7.8	1.4	11.5	2.4
		12param	12.5	1.6	15.9	2.6
	MS	6param	7.9	8.0	12.8	13.1
		8param	7.6	8.0	12.3	12.3
		12param	8.6	8.0	13.7	12.9
SVM N. 2	SS	3param	6.8	9.1	8.9	10.7
		2param	6.7	5.3	9.7	9.4
		6param	7.2	4.9	9.4	10.0
		8param	7.8	4.7	11.5	10.7
		12param	12.5	5.1	15.9	12.4
	MS	6param	7.9	8.6	12.8	18.0
		8param	7.6	8.7	12.3	16.7
		12param	8.6	8.8	13.7	17.4
SVM N. 3	SS	3param	6.8	8.5	8.9	4.3
		2param	6.7	3.1	9.7	4.7
		6param	7.2	1.9	9.4	10.0
		8param	7.8	1.8	11.5	3.3
		12param	12.5	2.4	15.9	4.0
	MS	6param	7.9	8.0	12.8	13.1
		8param	7.6	7.9	12.3	12.2
		12param	8.6	8.0	13.7	12.8
SVM N. 4	SS	3param	6.8	9.3	8.9	12.6
		2param	6.7	4.9	9.7	9.6
		6param	7.2	4.4	9.4	10.0
		8param	7.8	4.2	11.5	9.9
		12param	12.5	4.8	15.9	11.1
	MS	6param	7.9	8.7	12.8	17.4
		8param	7.6	8.7	12.3	16.4
		12param	8.6	8.8	13.7	17.0

Tabella 2.8: RMSE summary of all torque curve input parameters combination applied to each SVM

Abstract

In the following section are linked the five torque equations used to estimate the joint torque at the knee and ankle joint. To a better understanding, below is shown for what each parameter stands for:

θ - joint angle
ω - joint angular velocity
ϵ - coefficient linking joint stiffness and dampness
a_{shank} - shank acceleration
θ_{EMG} - EMG angle
K_{EMG} - EMG stiffness
EMG - EMG signals from the rectus femoris and medial and lateral hamstring muscles
x - parameters to be estimated

Torque curve equation including three parameters:

$$\tau = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} \begin{bmatrix} 1 \\ \theta \\ \omega \end{bmatrix}^T$$

Torque curve equation including two parameters:

$$\tau = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \begin{bmatrix} 1 \\ \theta + \epsilon\omega \end{bmatrix}^T$$

Torque curve equation including six parameters:

$$\tau = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \\ x_6 \end{bmatrix} \begin{bmatrix} \theta \\ \omega \\ a_{shank} \\ \theta(\theta + \epsilon\omega) \\ \omega(\theta + \epsilon\omega) \\ a_{shank}(\theta + \epsilon\omega) \end{bmatrix}^T$$

Torque curve equation including eight parameters:

$$\tau = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \\ x_6 \\ x_7 \\ x_8 \end{bmatrix} \begin{bmatrix} \theta \\ \omega \\ a_{shank} \\ \theta_{EMG} \\ \theta(\theta + \epsilon\omega) \\ \omega(\theta + \epsilon\omega) \\ a_{shank}(\theta + \epsilon\omega) \\ K_{EMG}(\theta + \epsilon\omega) \end{bmatrix}^T$$

Torque curve equation including twelve parameters:

$$\tau = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \\ x_6 \\ x_7 \\ x_8 \\ x_9 \\ x_10 \\ x_11 \\ x_12 \end{bmatrix} \begin{bmatrix} \theta \\ \omega \\ a_{shank} \\ EMG_{rf} \\ EMG_{mh} \\ EMG_{mh} \\ \theta(\theta + \epsilon\omega) \\ \omega(\theta + \epsilon\omega) \\ a_{shank}(\theta + \epsilon\omega) \\ EMG_{rf}(\theta + \epsilon\omega) \\ EMG_{mh}(\theta + \epsilon\omega) \\ EMG_{lh}(\theta + \epsilon\omega) \end{bmatrix}^T$$

Next up, are the bar graphs of each SVM combination summarizing the RMSE performance for each parameter combination:

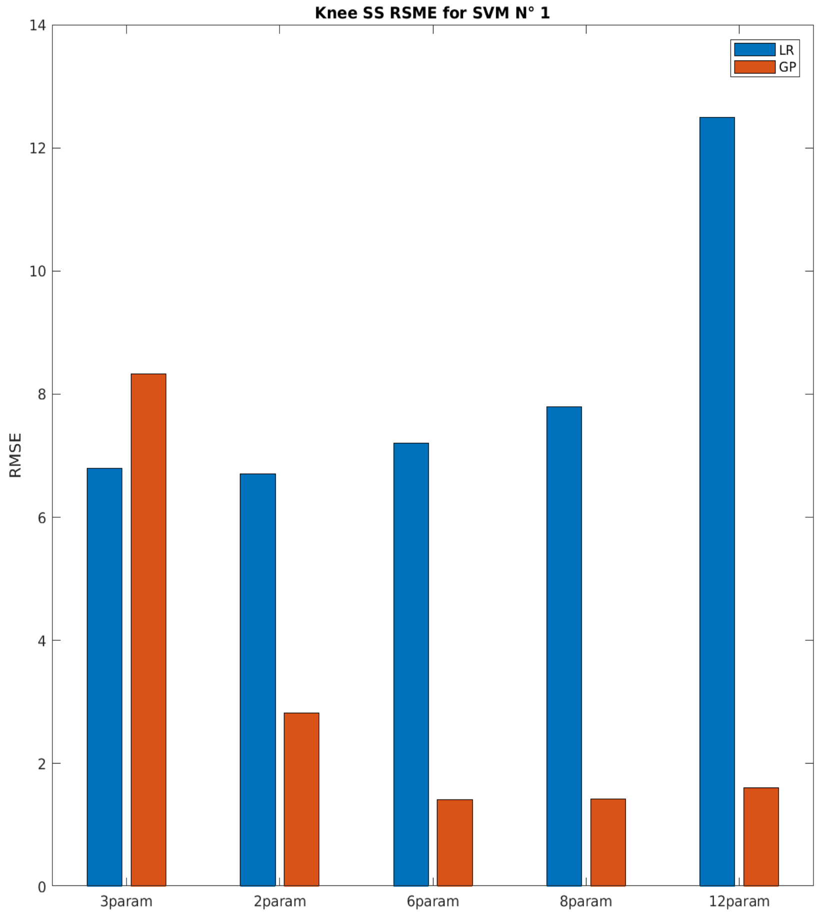


Figura 2.12: First SVM combination for the Knee joint - single subject wise

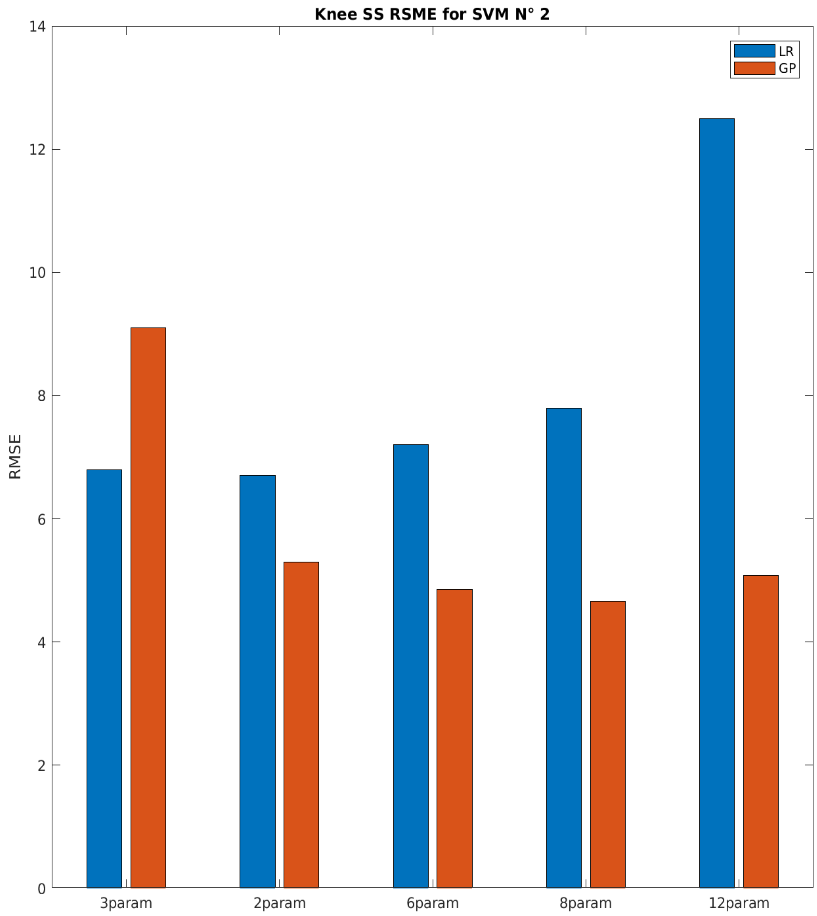


Figura 2.13: Second SVM combination for the Knee joint - single subject wise

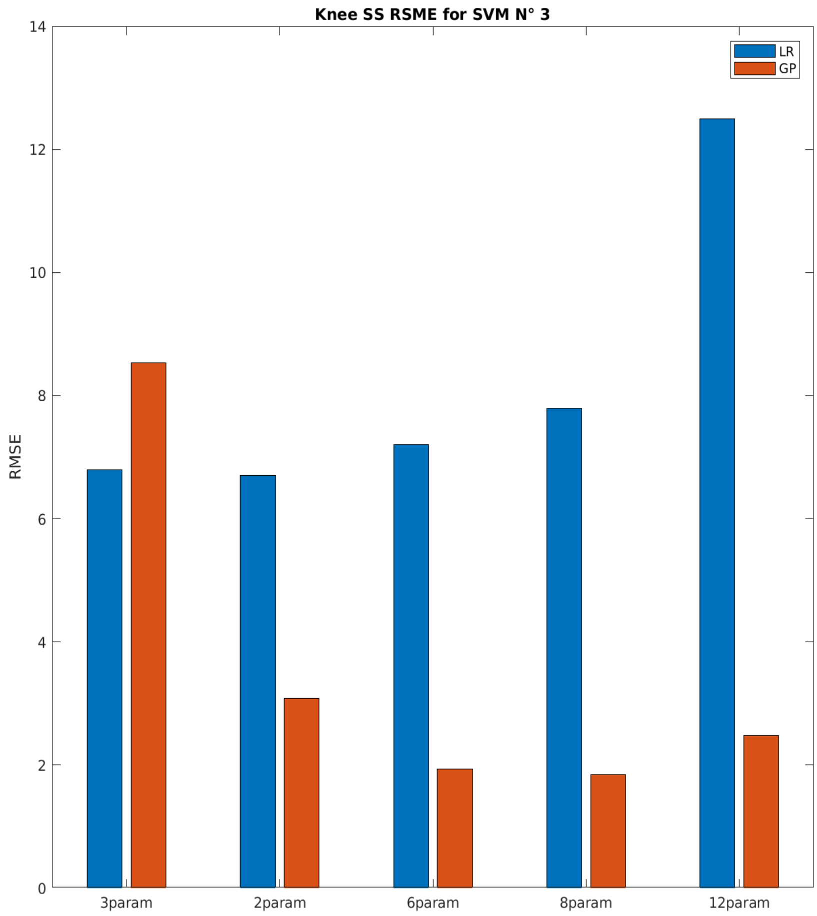


Figura 2.14: Third SVM combination for the Knee joint - single subject wise

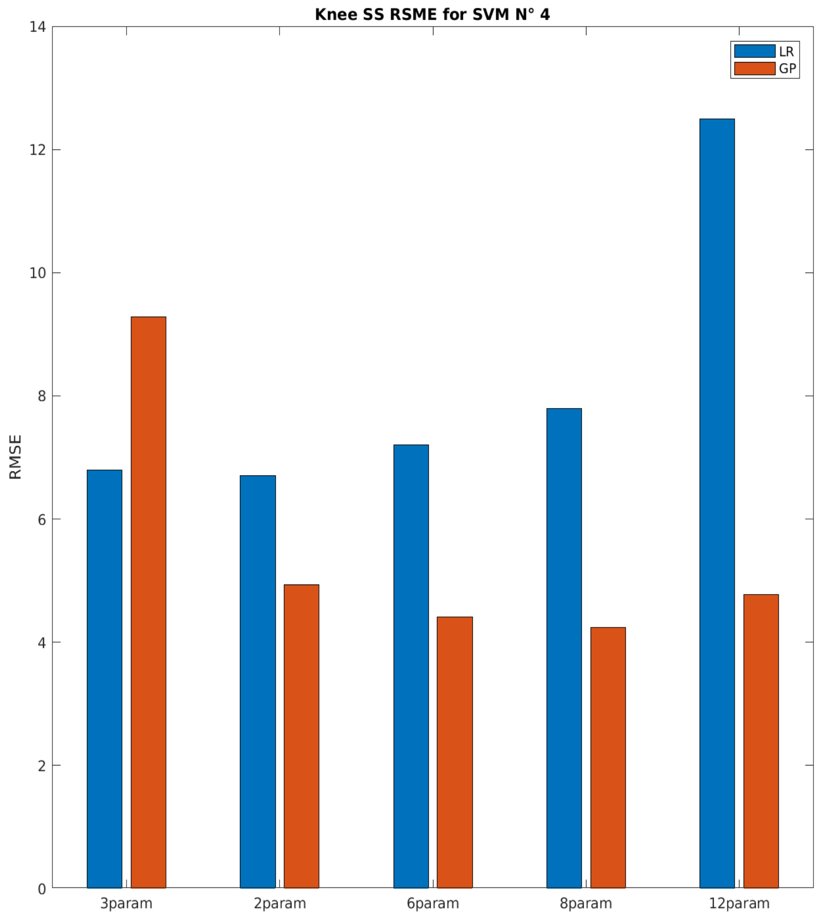


Figura 2.15: Fourth SVM combination for the Knee joint - single subject wise

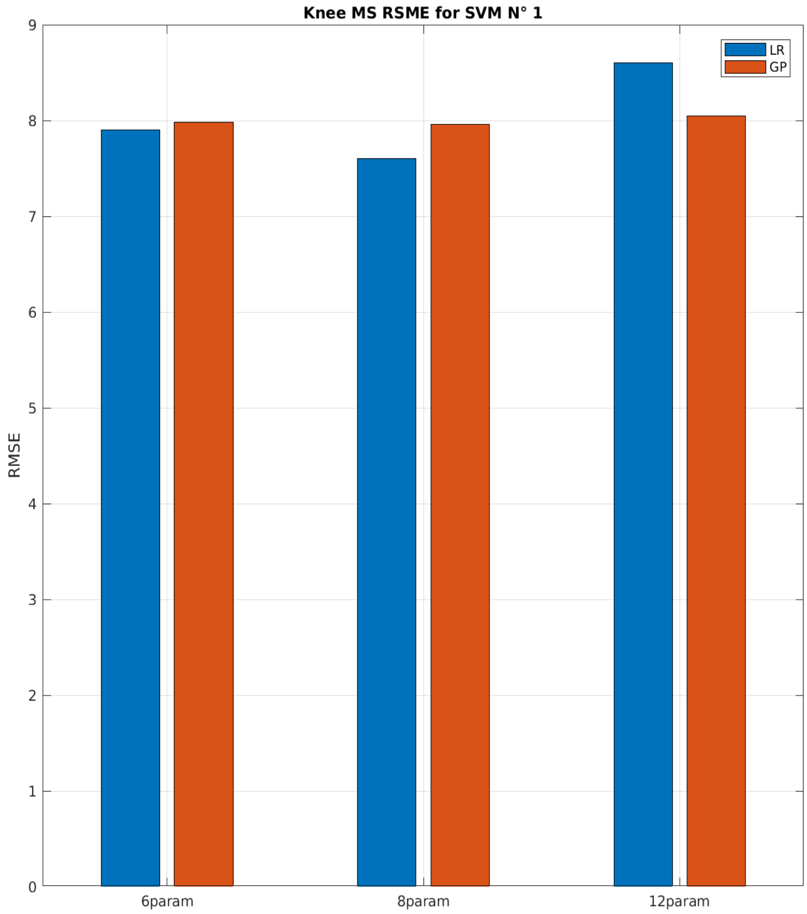


Figura 2.16: First SVM combination for the Knee joint - multi subject wise

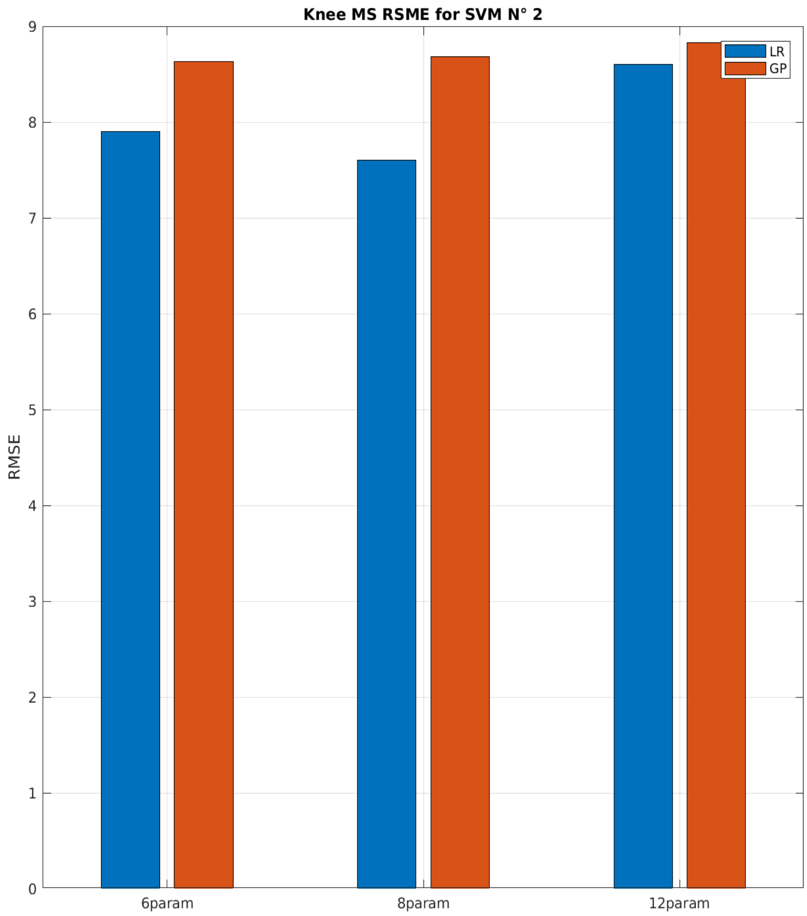


Figura 2.17: Second SVM combination for the Knee joint - multi subject wise

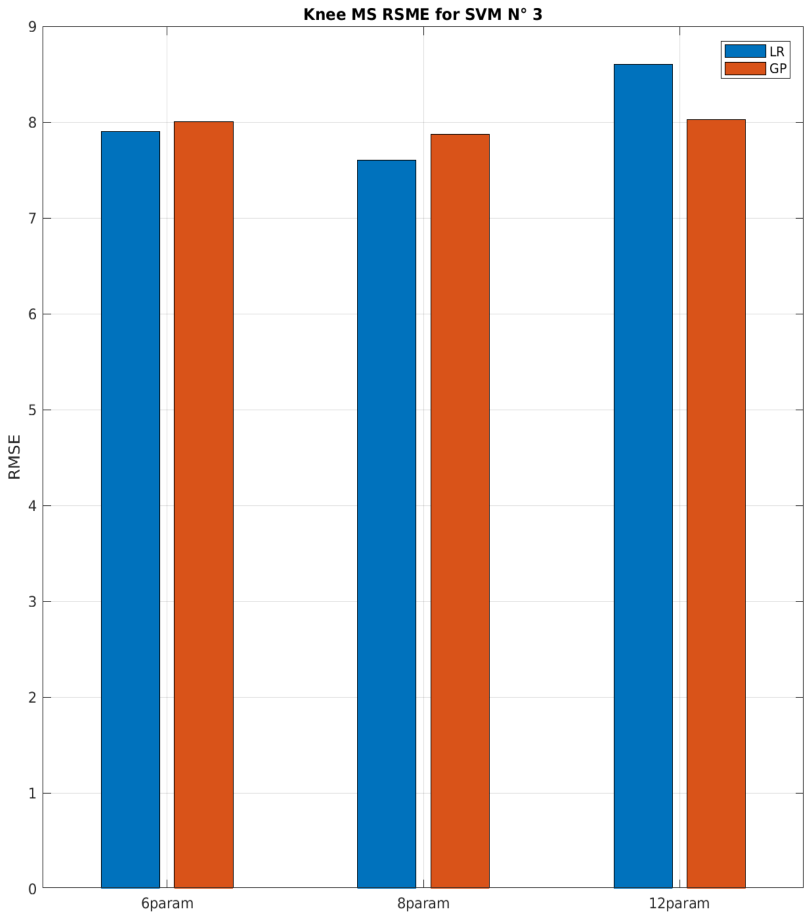


Figura 2.18: Third SVM combination for the Knee joint - multi subject wise

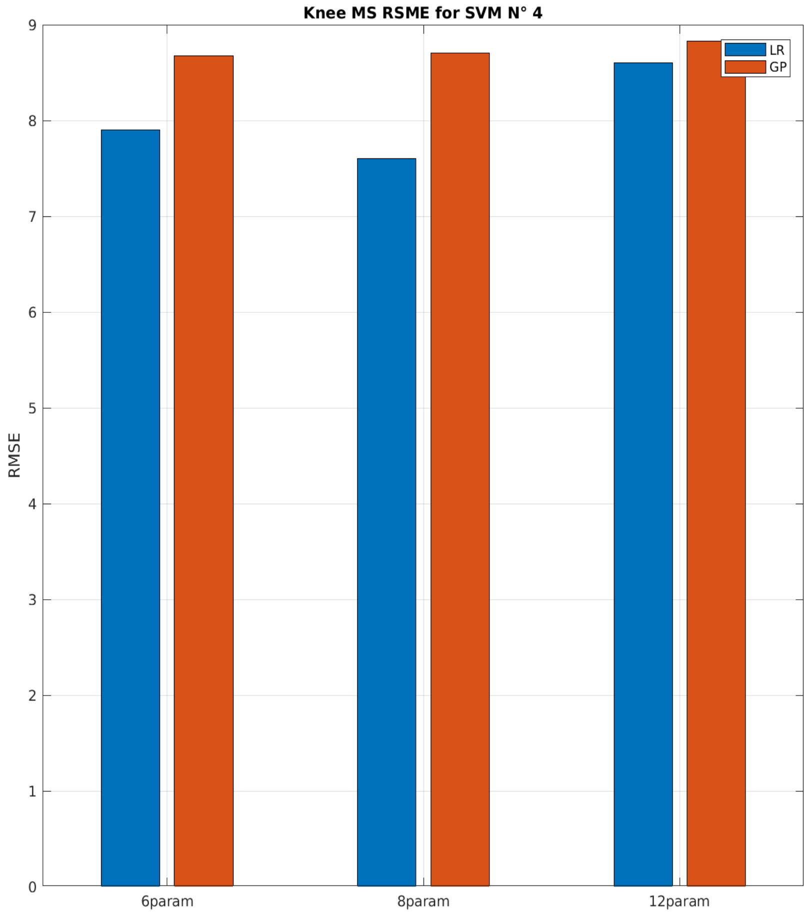


Figura 2.19: Fourth SVM combination for the Knee joint - multi subject wise

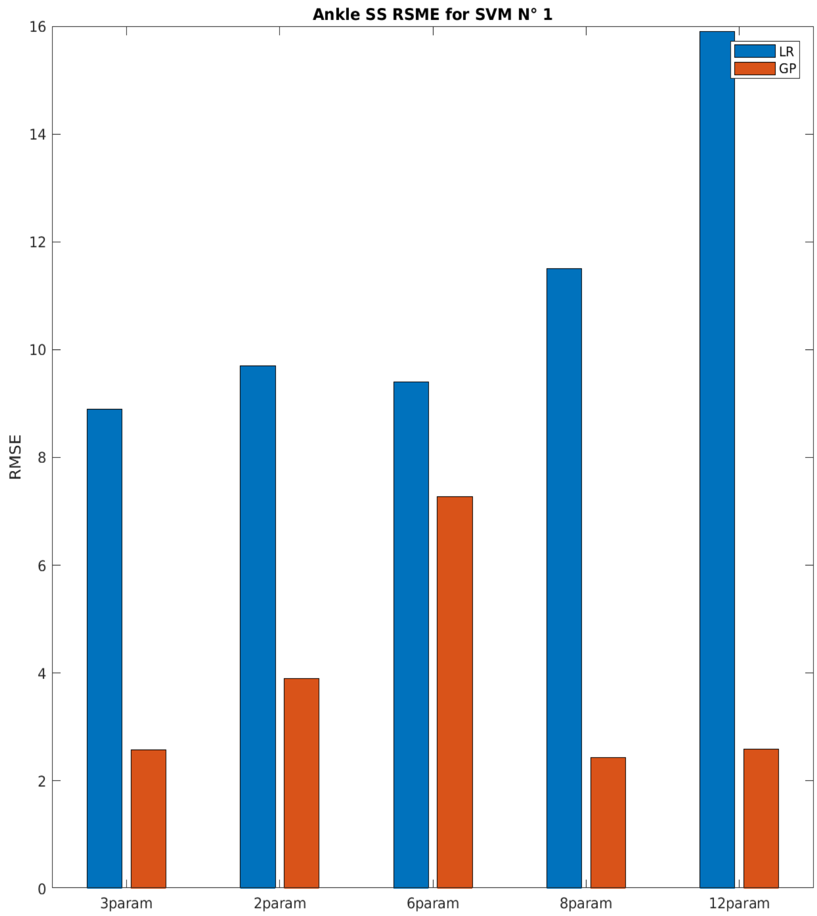


Figura 2.20: First SVM combination for the Ankle joint - single subject wise

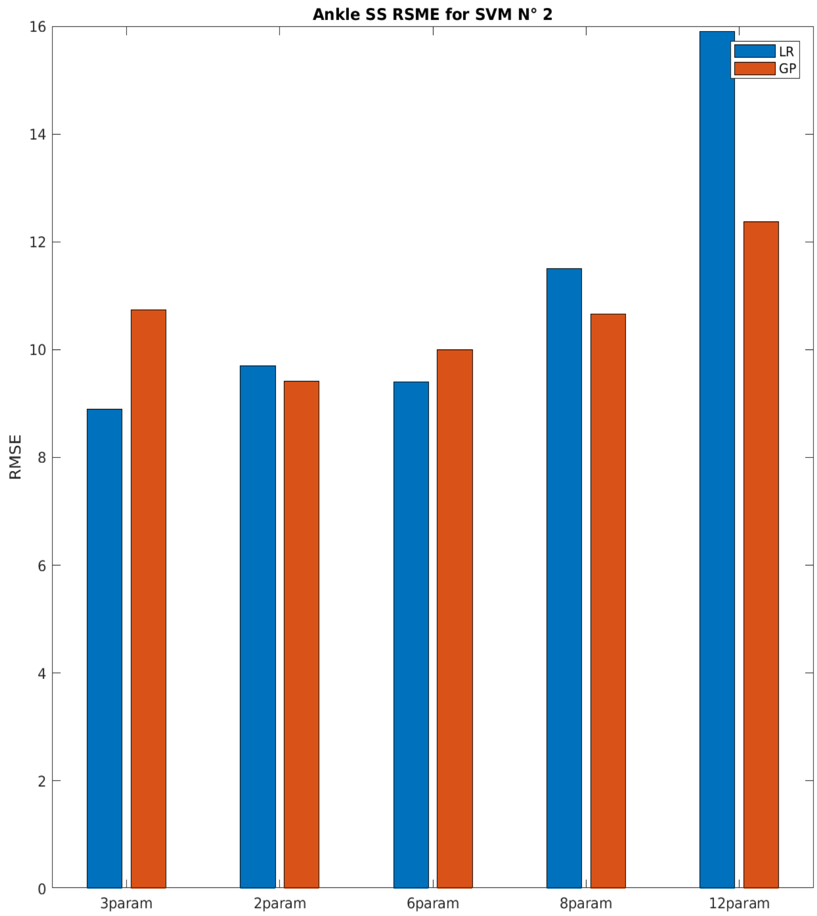


Figura 2.21: Second SVM combination for the Ankle joint - single subject wise

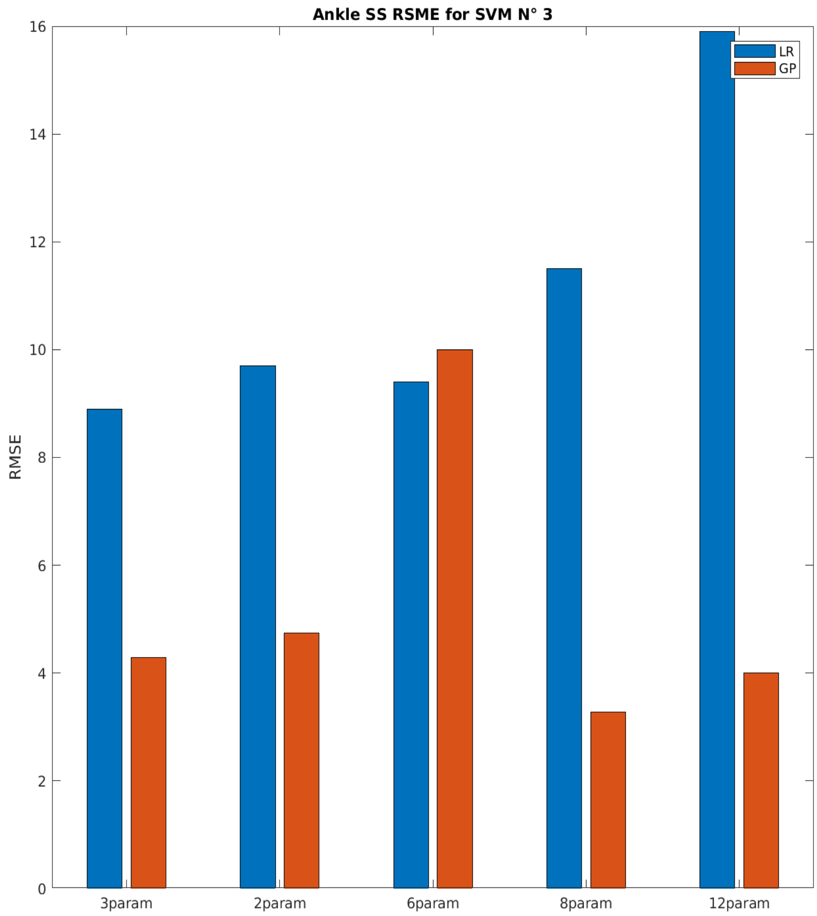


Figura 2.22: Third SVM combination for the Ankle joint - single subject wise

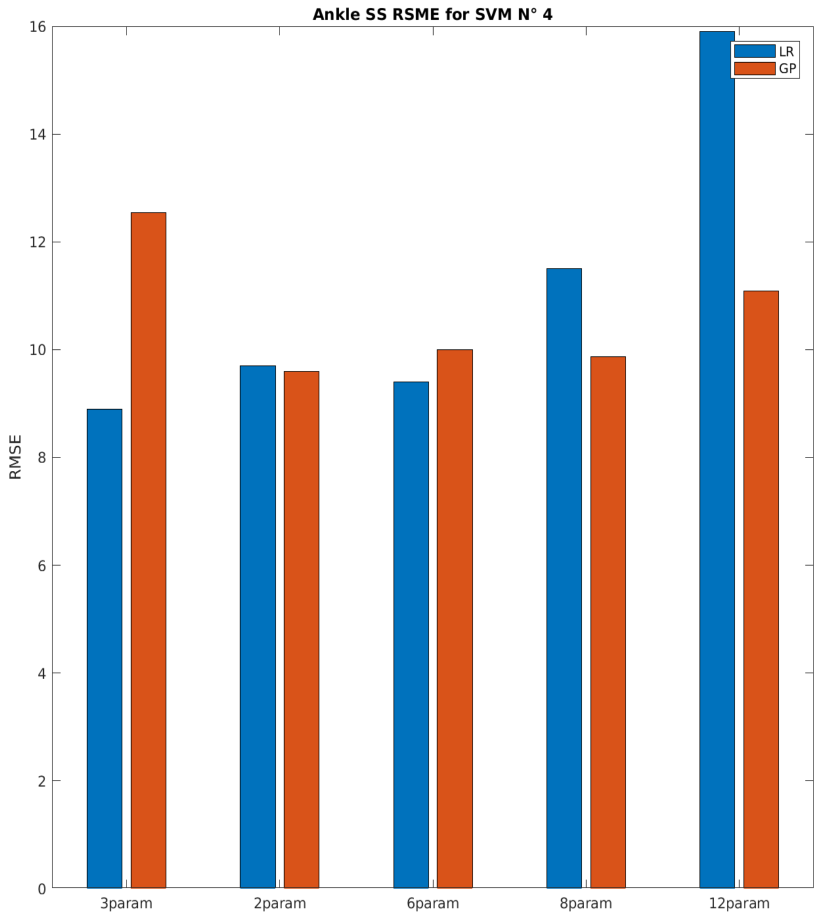


Figura 2.23: Fourth SVM combination for the Ankle joint - single subject wise

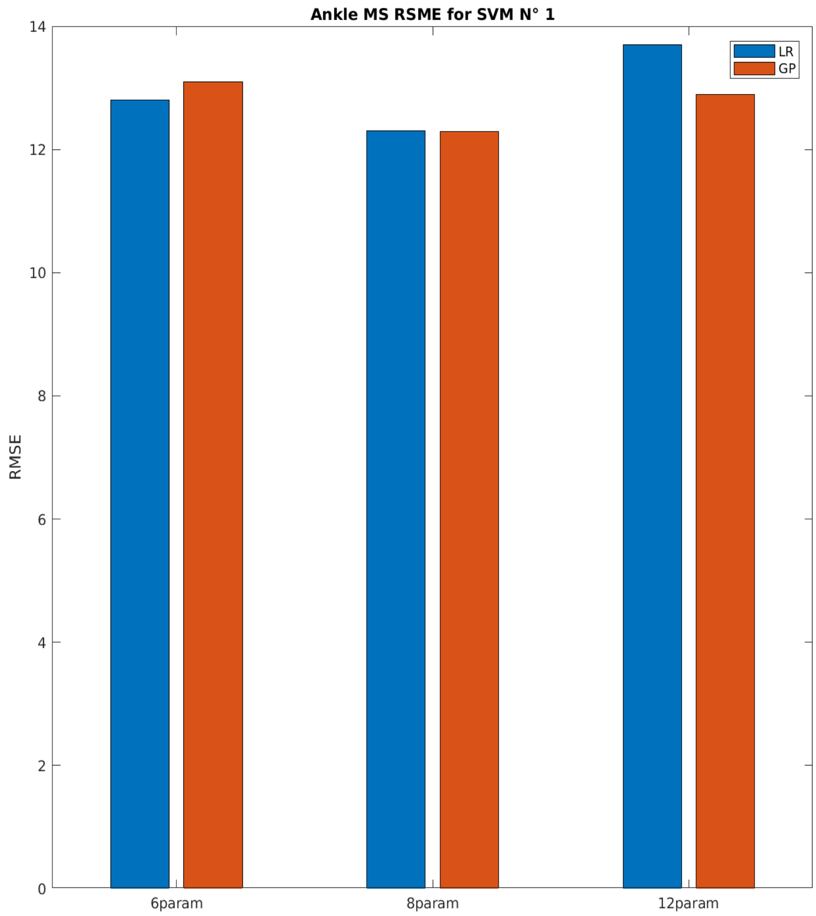


Figura 2.24: First SVM combination for the Ankle joint - multi subject wise

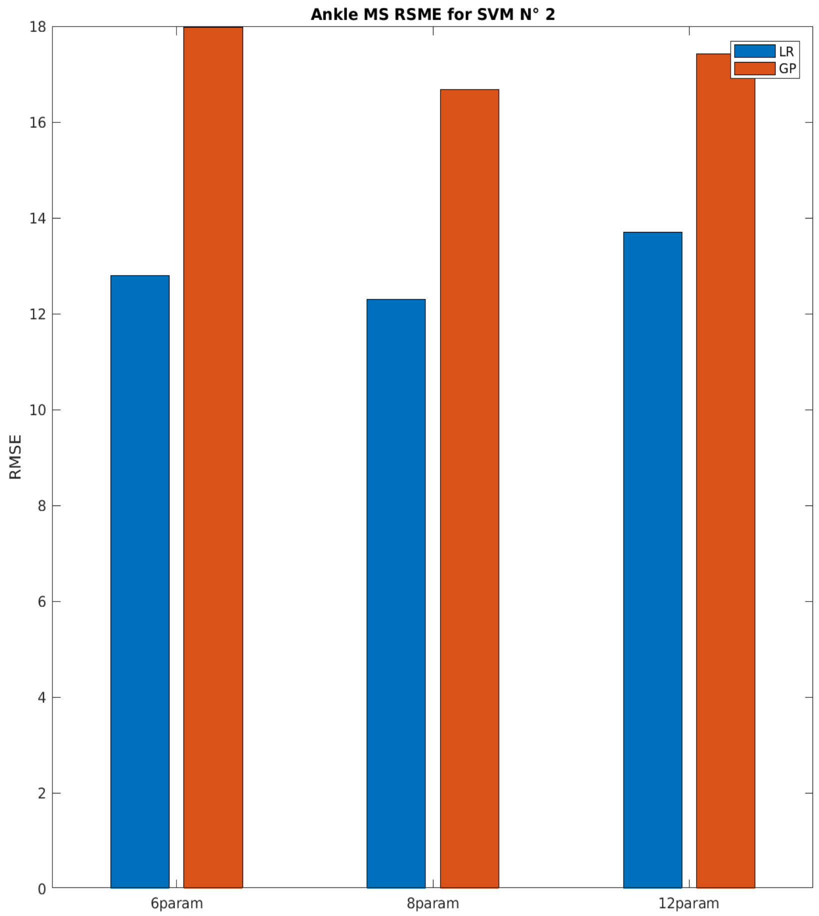


Figura 2.25: Second SVM combination for the Ankle joint - multi subject wise

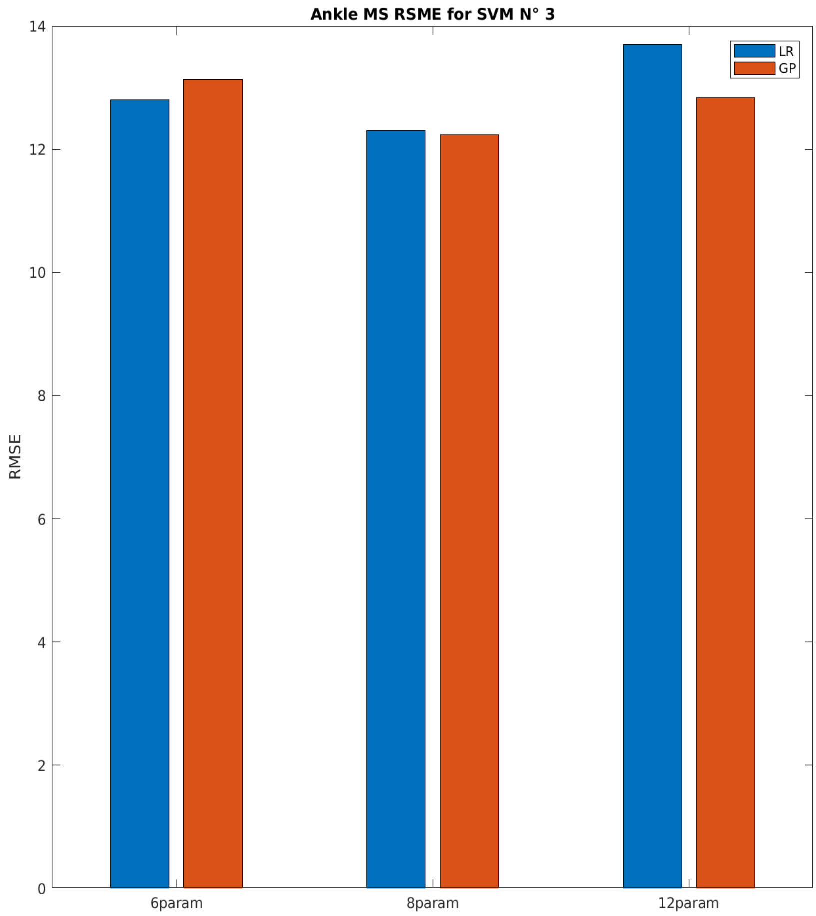


Figura 2.26: Third SVM combination for the Ankle joint - multi subject wise

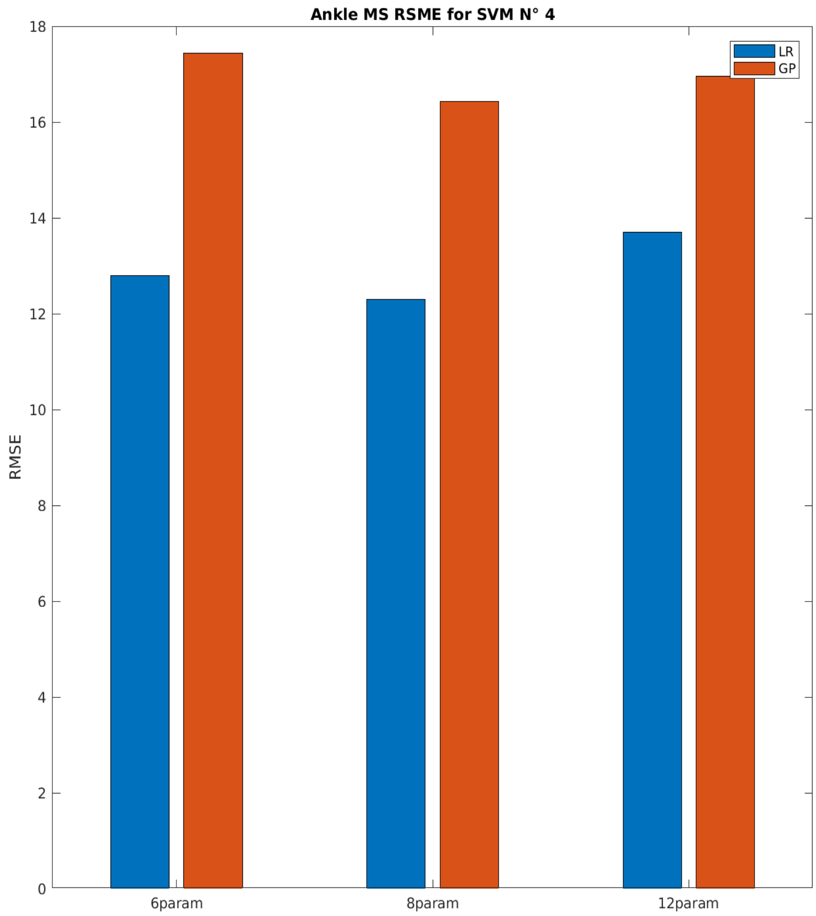


Figura 2.27: Fourth SVM combination for the Ankle joint - multi subject wise

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