Politecnico di Torino
Department of Mechanical and Aerospace Engineering
(DIMEAS)
Master of Science in Biomedical Engineering

Ecole Polytechnique Fédérale de Lausanne
Translational Neural Engineering Laboratory
(TNE Lab)

Master Thesis

Instrumented Fugl-Meyer to assess upper limb motor impairment and recovery after stroke: reliability and association with clinical scores.

Author: Bibiana Mangia (Student ID: 244122)
Supervisor: prof. Gabriella Olmo
Head of laboratory: prof. Silvestro Micera
Co-Supervisor: PhD Camilla Pierella

December 2019

To my mother, my father and my brother

Intelligence is the ability to adapt to change.

Stephen Hawking

Abstract

Stroke is one of the most common disease and the impairment in the world and its effects compromise daily living activities and quality of life. Clinicians assign score to pre-defined movements of the subjects according the use of standard clinical scales. The evaluation is less sensitive and less accurate due to clinician's judgment. The present study aimed to qualify and quantify motor movements of upper limb proposed to stroke subjects from a clinical scale, the most used in the rehabilitation after stroke, the Fugl-Meyer Assessment Upper Extremity (FMA-UE). Human movement analysis starts with the methods of mechanics used on human body to retrieve information about spatio-temporal parameters. Indeed, biomechanics is based on biomechanical model defined by segments position and joints position in which kinematic variables are expressed. Twelve exercise of FMA were analyzed and ten healthy subjects participated to the experiment. Inertial measurement unit and electromyography sensors were used to automate this clinical scale. Data analysis on kinematics retrieved quantitative and qualitative parameters to assessment the movement. The analysis on EMG data were focus on the extraction on muscle synergies to retrieve muscle activation patterns. The results provided a potential approach to the quantitative rehabilitation and a support medium to physicians' clinical decision about motor conditions of patients.

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Chapter 1

Introduction

Stroke is one of the most common disease and the impairment in the world and its effects compromises daily living activities and quality of life. The assessment of upper limb functions is relevant to contribute in the evaluation of the performance and to project a specific rehabilitation according the subject's conditions. Clinicians assign scores to pre-defined movements of the subjects according the use of standard clinical scales. In this way, the evaluation is subjective judgment of the clinician that influences the real score associated to the movement performed. The upper limb motor functions evaluation in an objective way increases the accuracy performance of the stroke patients.

1.1 Stroke percentage and its effects

Stroke is the second main cause of death and disability [1] and it is classified into four main types - ischemic stroke [IS], primary intracerebral haemorrhage [HS], subarachnoid haemorrhage, and undefined - on the basis of neuroimaging findings such as Computed Tomography (CT), Magnetic Resonance Imaging (MRI) and autopsy [2]. Ischemic stroke occurs when an artery to the brain is blocked and this obstruction causes the lack of nutrients and oxygen and also the accumulation of cellular waste in the area supplied by blood. As a result, the neurons stop working and in a few minutes they die. Intracerebral hemorrhage is caused by damage of blood vessels following a bursting of vessels in the brain. At the end, subarachnoid hemorrhage is similar to the previous one, but the blood vessel inundates the area of the skull, which is called subarachnoid space.

The Global Burden of Disease, Injuries, and Risk Factors Study (GBD) quantified incidence and mortality by stroke from 1990 to 2016 analyzing data from the World Health Organization (WHO) in 199 countries and took them from extensive literature with review articles published from 1980 until 2016. Stroke burden is reported in terms of incidence, prevalence, mortality, and disability-adjusted life-years in children (0-19 years), young to middle-aged (20-64 years) and old age. Incidence and mortality variability are different between countries and regions, probably due to different environmental and risk factors, genetic and lifestyle factors. In 2016,

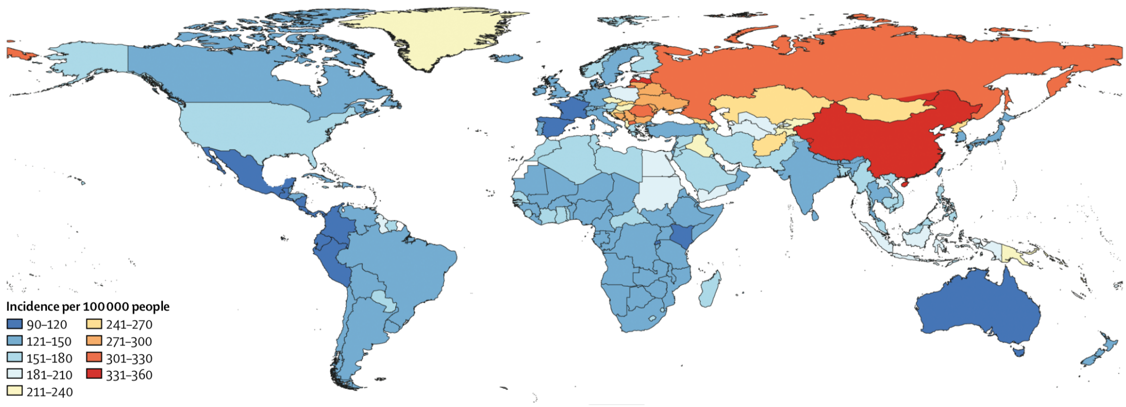


Figure 1.1: Stroke incidence per 100 000 people from lower (cold color) to higher (hot color).

stroke was the second most common cause of deaths after ischemic heart disease with fewer deaths in women than man.

In 2016, globally 80 million of people were affected by stroke [3], of which 41 million women and 39 millions men; 84% were ischaemic and 13.7 millions were new strokes. Stroke incidence was similar between men and women younger than 55 years; the difference in age between women and man starts at ages 55-75 years. Countries in east Asia, China, Russia, and eastern Europe present the highest age-standardised incidences of stroke. Central Latin America has the lowest incidences Fig 1.1. Over the last four past decades stroke incidence in high-income countries decreased of 42% but there was a hug increasing of 100% in low to middle income countries [2]. Reliable data on stroke burden help care planning to be more effectively reducing costs of treatment and help politicians in development of national strategies to deal with.

Common effects of stroke are impaired balance, partial or full paralysis, and spasticity problems. The remission of upper-extremity function disability takes place in the first three months after stroke and subjects increase day by day motor dysfunction with significant contributor to the loss of independence in activities of daily living and quality of life. They start to reduce speed, coordination, range of motion or strength implementing control strategies to perform the desired movement. Other effects, linked to muscle activity, are muscle weakness, contracture, changes in muscle tone, impaired motor control and joint laxity.

1.2 Standard clinical scales

Subject assessment requires the identification and measurement of the impairment, handicap, disability and medical problems. Rehabilitation program after stroke is a common clinical practice enabling the patient to regain mobility and coordination and to reduce alterations by improving arm strength and manual dexterity. Clinicians and physical therapists use upper limb function measurement to quantify and retrieve the quality of motor impairment (e.g. smoothness of movement and intersegmental coordination), to evaluate efficacy of rehabilitation and to determine personal needs in stroke patients.

In clinical setting, upper limb function is generally assessed through clinical rating instruments such as ordinal scales and timed tests. Some of them and the most used are Fugl-Meyer Test (FMT) [4], the Wolf Motor Function Test (WMFT) [5], the Motor Activity Log (MAL) [6], and Action Research Arm Test (ARAT) [7]. Differing for movements types, during each test a trained therapist or a clinician asks patient to perform some pre-defined items and then gives him a score for each item. Timed tests are objective and less influenced by ceiling effect [8] but they not provide a whole assessment as rating scales. The ceiling effect occurs when test items are not challenging enough for a group of individual, thus the test score will not increase for people who may have clinically improved.

Briefly, the ARAT was constructed for assessing recovery of upper extremity function following cortical injury and it measures the ability to handle and manipulate objects differing in size weight and shape. The ARAT includes four subscales – 'grap', 'grip', 'pinch' and 'gross movements' – and its counts 19 items. The patient is asked to grasp and then release object to the desired location, to pour water from one cup to the other and to touch the back and top of head and at the end to touch mouth. This study is an easy and quick measure about grasping abilities and some fine finger manipulation tasks.

The WMFT consists of 21 simple tasks involved joints (shoulder to fingers) and level of difficulty (gross to fine motor skill) of which 12 timed-based and 2 strength-based tasks. The time-based tasks explore the functional activities from basic movements such as placing the forearm onto a table, to complex such as stacking checkers. Strength-based tasks includes weight-lifting task and maximal grip-strength.

The MAL provides information about motor function in life situation. Fourteen common daily living activities within the area of feeding, grooming, and dressing are explored in this test. Each item is evaluated with six-point scale and is reported by the patient during a specific period. Motor activity information are collected in the year before the subject's participation, during and after the end of treatment.

Due to its feasibility in clinical application, sensibility, reliability, validity and responsiveness, the Fugl-Meyer Assessment (FMA) scale is the most frequently used outcome measure for qualitative and quantitative assessment of upper and lower limb functions in stroke subjects. The correct selection of perfect outcome measure can improve the diagnosis and lead to more efficient rehabilitation for the patient group [1].

1.3 Fugl-Meyer Assessment

Fugl-Meyer Assessment consists of 33 items for upper-limb, where the clinical asks a patient to perform pre-defined movements. It takes at least 30 minutes for each patient. In the 1975, the introduction of this scale was due to the lack of an existing instrument for monitoring the development of recovery from hemiplegic stroke. The FMA examines 5 domains - motor function, sensory function, balance, joint range of motion, and join pain - of the movement while a subject performs selected tasks. Upper and lower extremity movements and reflexes are rated on a 3 point ordinal scale (0 = *cannot perform*, 1 = *performs partially*, 2 = *performs fully*). The maximum score for the entire motor scale is 100 and it is split in 66 points and 34 points for upper and lower extremity motor function respectively. In the greater part of stroke studies, the upper and lower limb section is often used separately. In this study some upper limb motor functions are explored.

1.4 Aim of the thesis

The assessment accuracy, though ordinal scales, is less sensitive and less accurate due to clinician's judgment. In addition, it has been noted that stroke patients perform to try assessment tasks in the clinic better than they do at home. For both stroke subjects and therapists these standardized scales represent a time-consuming process and influenced by ceiling effect. At finally, the number of therapists is being outpaced by the number of individuals who suffer from stroke, following a gap between the rehabilitative interventions that are need and the amount being provided.

As a solution to the problems above, clinical assessments need to be automated. Instrument of a clinical scale is possible though the study of human movements with biomechanical analysis and methods and tools, result of the progressive and evolution of new technologies such as wearable technologies. The present study aimed to qualify and quantify motor movements of upper limb proposed to stroke subjects to perform specific and pre-established tasks from a clinical scale, the most used in the rehabilitation after stroke. Inertial measurement unit and electromyography sensors were used to automate this clinical scale. Data analysis on kinematics retrieved quantitative and qualitative parameters to assessment the movement. The analysis on EMG data were focus on the extraction on muscle synergies to retrieve muscle activation patterns.

Chapter 2

Human Movements Analysis

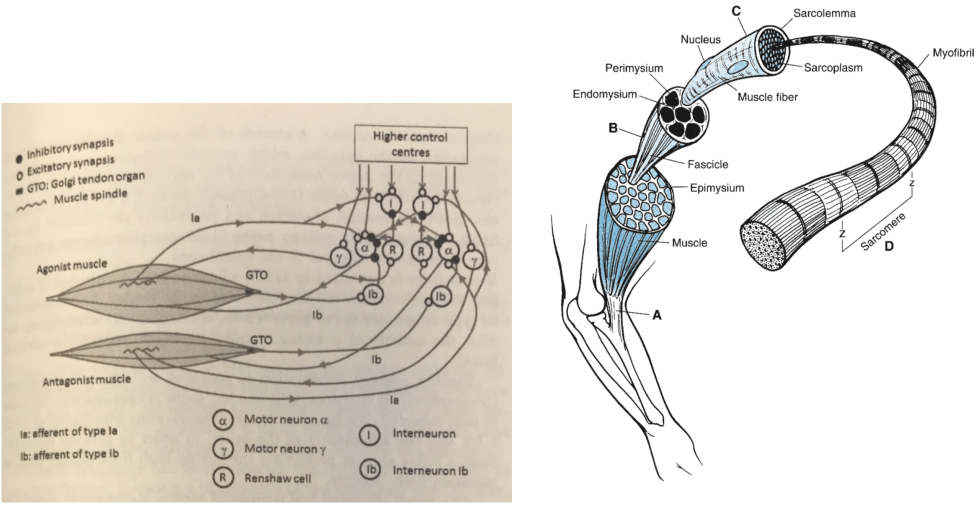
Musculoskeletal system and nervous system work together to perform limb movements. Methods of mechanics are used on human body to retrieve information about spatio-temporal parameters, called kinematic data, to quantify motions in the same way for all subjects. A biomechanical model defined by segments position and joints position is supportive to the reference system in which kinematic variables are expressed. At the end of the Chapter, a short description of target tasks is provided.

2.1 Musculoskeletal and nervous system in short

Skeletal system, muscle system, and nervous system control and perform the human movement. The skeleton is composed of bone tissue and joints, or articulations, are the intersections between bones and some main functions are support of body and protection of the vital organs. The muscular system is made up of muscles and tendons, and the nervous system is made up of subsystems, the center nervous system (CSN) and the peripherical system (SNC).

The CSN is made up of brain and spinal cord, and the SNC is made up of nerves and ganglia outside the CSN. First, the nervous system identifies the muscles responsible for performing the movement and then generates the stimulus to develop the force required from that muscle. Each branch of the nervous system innervates a specific muscle fiber, then the information exits, and the brain receives the feedback to provide another stimulus, creating a loop.

The movement is the motor result of the electric signal propagation generated by excitable cells of the brain. The anatomic-functional unit of the nervous system is the neuron, constituted by a cell body, a great number of dendrites and an axon. The neuron unit performs excitability and the electric-pulse is transmitted in the neuron network though the synaptic junctions. The neurons are excitable cells and maintain ion concentration gradients across the membrane using ion pumps. Ions such as Na^+, K^+, Cl^-, and Ca^{2+} at the membrane sides, equipped with ion channels, affects the trans-membrane voltage. The voltage change generates the so-called ac-



(a) (b)

Figure 2.1: Efferent and afferent pathways in the control of muscles (a); Tendon connects muscle to bone.

tion potential, which has the origins in the soma and is propagated though the axon. Three types of neurons permit the electrical signals to travel from sense organs to the Central nervous system (CSN) (afferent way) and from the CNS to the effector organs (efferent way). The afferent transmission is carried by sensory neurons and the efferent transmission is carried by motor neutrons; in the middles there are the interneurons Fig 2.1(a).

The smallest functional unit in the muscles is called motor unit (MU) and the muscle contraction is induced by the propagation of action potentials along the muscle fibers. The action potential is the first bioelectric command and it determines an extracellular electric field that can be recorded (electromyography). The acquired signal depends on the spatial and temporal recruitment strategy of the motor units (MUs) and on the detection system. Skeletal system and muscular system are connected though tendons which attach muscle to bone Fig 2.1(b). When a muscle fiber receives a signal from the nervous system the muscle contracts, the tendon acts the bone and the movement is performed [9]. The musculoskeletal system supports the body and protects the vital organs. The nervous system sends signals to muscle to perform functions in life, thus they work together for all performance in life.

2.2 Biomechanical analysis

Structures and functions of biological systems are studied by means of the methods of mechanics, an area of physics that concerns of the study of motion and the effect of forces on an object. The study of the movement of living things though the science of mechanics has been defined the concept of biomechanics. Biomechanics provides the tool for the study of motion (effect) and the effect of the forces (causes) in a living organism [10] in qualitative and/or quantitative terms. In the qualitative

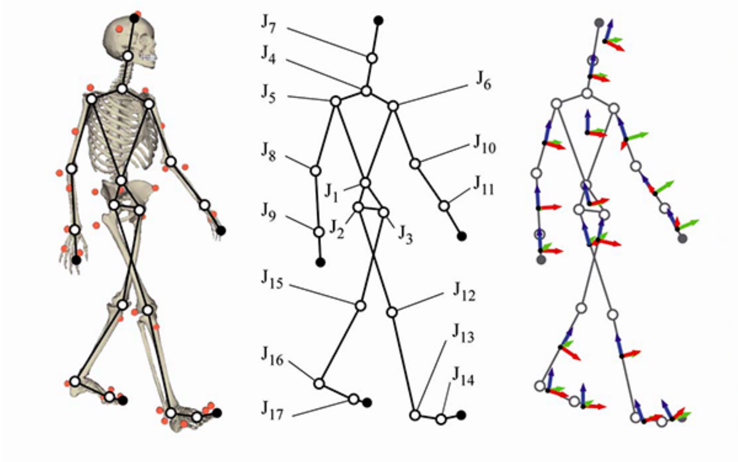


Figure 2.2: Biomechanical model used in biomechanics analysis.

approach the movement is directly observed and described, while in the quantitative approach some aspects of the movement are measured. These approaches belong to the concept of kinematics and kinetic.

Kinematics-based biochemical analysis describes the characteristics of the motion without reference to the force causing the motion. Position, velocity, and acceleration are the interesting components in a kinematic analysis, applied for understanding of human movement such as golf swing, high jumper, or ball launch. The study of the range of motion can be not applied in push or pull between two objects. Kinetics-based biochemical analysis is another approach for describing the motion in terms of the forces acting on the system. The forces producing the human movement are responsible for creating all movement and for maintaining positions and postures. All aspects of a movement can be understood investigating of both the kinematic and the kinetic components.

2.3 Biomechanical model

Biomechanics analysis is conducted on a specific model from which kinematic data are retrieved. Thus, the anatomy of skeletal system is the base for joint coordinate systems and the definition of anatomical landmarks for locating other segmental reference frames. The skeletal system is modelled as actuated articulate system Fig 2.2 in which motor moments are generated by muscle system's models; this model was designed by International Society of Biomechanics as a guide for standardization in the reporting of kinematic data [11].

Body segment names are the terminology for conducting and describing movement analysis. For example, the shoulder flexion is the lifting of the arm identified as the segment between the shoulder and the elbow. The description of the segmental position is relative to a starting position which is when the body is in an erect stance with the head facing forward, arms relaxed posture at the sides, and the legs together with the feet pointing forward. The joint angle, namely the relative angle between two segments, is defined to discuss the joint position. For description of joint angle, the starting position is called zero position since the rotation of each segment is a parameter to evaluate while performing a movement.

In joint of the body basically six movements occur. Flexion is a movement in which the relative angle of the joint between two segments decreases, and this angle decreases when the extension occurs. Abduction is a movement away from the midline of the body: raising an arm is an example of it. Adduction is the movement of the segment back toward the midline of the body. Supination is the movement of the forearm in which the palm from the fundamental starting position rotates to face forward. Pronation is the movement in which the palms face backward. Supination and rotation are referred also to as external and internal rotation respectively. Plantarflexion is the movement in which the hand moves up and the angle at wrist joint increases; this movement is also referred to as volar flexion. Dorsiflexion is the movement in which the hand moves down and the angle at wrist joint decreases. The circumduction is a final specialized movement in which the segment moves in a circular path drawing an imaginary circle.

2.4 Target FMA tests

As mentioned before some motor tasks of Upper Extremity Fugl-Meyer Assessment are analyzed in this study. A brief description of motor functions are reported in Table 2.1 and some motor functions illustrations in Fig 2.3.

The flexor synergy in a voluntary action of the muscles to bring the forearm supinated starting near the contralateral knee to the ear of the ipsilateral ear, the elbow is flexed, and the shoulder abducted to at least (90°). The extensor is a voluntary action of the muscles to internally rotate the shoulder and extend the arm until the contralateral knee, with the forearm pronated; pectoralis major and/or the triceps are activated while performing this motion. Flexor and extensor synergy are considered movement within synergies. Hand to lumbar spine consists in the actively position of the hand on the ipsilateral lumbar spine. In the flexion of the shoulder to (90°) the elbow must be fully extended until the range of motion, the forearm in the midposition between pronotation and supination; shoulder abduction or flexion elbow brings to bad evaluation of the motion. Elbow must be flexed to (90°) while performing the pronation-supination of the forearm, in the meanwhile the shoulder must be at (0°); the max scores is assigned if active prono-supination is in a limited range of motion. As well as shoulder flexion, the elbow is extended in the pure shoulder abduction motion, and the forearm is pronated; flexion of the elbow is not tollared. The characteristics in shoulder flexion from (90°) to (180°) are quite the same of shoulder flexion to (90°). The prono-supination of the forearm with elbow completely extended, requires a shoulder angle between (30°) degree and (90°) degree. Repeated movements from maximum dorsiflexion to maximum volar flexion of the wrist require the forearm pronated and the shoulder in flexion and/or abduction; this motion is texted with elbow in the both (90°) degree and (0°) degree. The maximum quality of the movement is reached when in the circumduction of the wrist is well performed. In the finger-to-nose test the patient is instructed to bring the finger from the starting position to the noise five times as fast as possible; this test highlight tremor, dysmetria and speed [4]. ID number is reported in Chapter 5 in the Table 2.1.

Motor task	**Description**
Flexor synergy	Hand from contralateral knee to ipsilateral ear. Shoulder retraction, elevation, abduction (90°), external rotation; elbow flexion, forearm supination
Extensor synergy	Hand from ipsilateral ear to contralateral knee. Shoulder abduction, internal rotation; elbow extension; forearm pronation
Hand to lumbar spine	Shoulder hyperextension
Shoulder flexion 0°-90°	Maintains 0° in elbow. Shoulder flexion, extension; hand pronation
Pronation-supination (elbow at 90°)	Maintains position in elbow. Hand pronation, supination
Shoulder abduction 0°-90°	Maintains extension and pronation. Shoulder abduction, adduction; hand pronation
Shoulder flexion 90°-180°	Maintains 0° in elbow. Shoulder flexion, extension; hand pronation
Pronation-supination (elbow at 0°)	Maintains elbow extension. Hand pronation, supination
Repeated dorsi/volar flexion (elbow at 90°)	Full active range of motion, smoothly. Elbow at 90°; hand pronation, flexion, extension
Repeated dorsi/volar flexion (elbow at 0°)	Full active range of motion, smoothly. Elbow at 0°; hand pronation, flexion, extension
Circumduction (elbow at 0°)	Complete and smooth circumduction. Wrist abduction, adduction, flexion, extension
Coordination/Speed	Index finger from knee to nose, 5 times as fast as possible. Shoulder flexion, extension, abduction; Elbow medial and lateral rotation; hand pronation

Table 2.1: Set of selected tasks from FMA-UE.

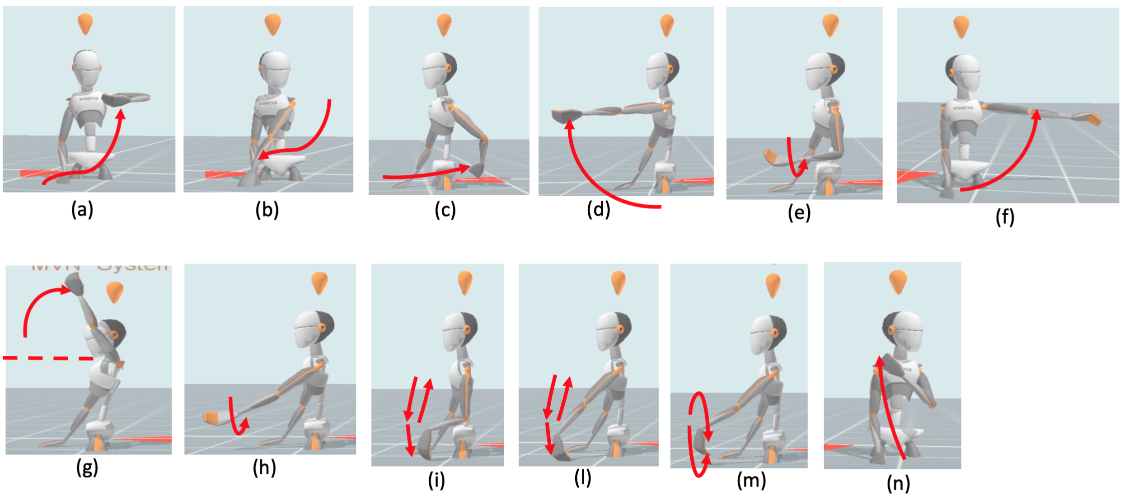


Figure 2.3: Flexor synergy (a); extensor synergy (b); hand to lumbar spine (c); shoulder flexion (0°)-(90°) (d); pronation-supination (elbow at (90°)) (e); shoulder abduction (0°)-(90°) (f); shoulder flexion (90°)-(180°) (g); pronation/supination (elbow at (0°)) (h); repeated dorsifexion/volar flexion (elbow at (90°)) (i); repeated dorsifexion / volar flexion (elbow at (0°)) (l); circumduction (elbow at (0°)) (m); index finger from knee to nose; 5 times as fast as possible (n).

Chapter 3

Automated assessment in previous studies

As introduced in Chapter 2, the efficiency of standard clinical scales can be augmented and/or supported by automated assessment in order to determine accurate rehabilitative interventions and to document outcomes of rehabilitation programs. Between the benefits, an instrumented approach for upper-limb function measurements can take less time and be more frequent, can be performing also as in-home assessment resulting in better quality of patient care. Observation errors of the physician combined to the subjective evaluation cannot explain the biomechanical characteristic of the motor function deficits. The evolution of the technology and methods based on the processing of data retrieved from these technologies brought the researchers to create new shapes of upper limb assessment which tried to overcome the limit of the standard clinical scales. This science was applied to different pathologies and fields, some studies are reported in this chapter.

3.1 New technologies and methods to assess upper limb movements

In the last years, one popular technique to capture and to assess upper limb movements consists in video cameras and special markers attached to patients' bodies [12]. Even if optical based sensing technology is sensitive and precise, it is expensive, it needs complex set up and it can't quantify the strength of the patient's movement. Wearable inertial sensing technology is cheap and tiny: accelerometers and gyroscopes are used to detect movement's acceleration and rotation. Quite frequent is also the electromyography (EMG) technique which is becoming an advanced tool to classify upper limb movements though machine learning methods [13] or as an assessment too for spasticity after stroke. Use of robotics arms and motion capture system combined with EMG sensors to monitor and evaluate upper limb function is also tested but for it is not so convenient for clinical practice. Other system uses more than one sensor, creating a wireless body sensor network system using two accelerometer sensor nodes and one collecting node to automatically estimate shoulder-elbow movements [14]. Also confirmed by [1], there is a growing trend for the use of novel technology to provide instrumented upper limb function assessment after stroke. In the following lines some previous studies are described.

3.2 Previous studies

The authors in [15] proposed a platform to collect and to classify data from FMA movements with a score. A machine learning algorithm was used for data classification. In this project Microsoft Kinect sensor was used to track joint positions of a patient in 3D space. Since Kinect had some limitations such as inaccuracy for twisting motions, it didn't distinguish a patient's arm from the armrest or inaccuracy for finger tracking, the researchers used a Shimmer inertial measurement unit, a glove sensor for finger motions and a pressure sensor for patient grip strength. From Kinect data, limb orientations and joint angles were the features extracted to give as input for classification method. For IMU features were supination and pronation. Summary, the feature extracted were limb orientation, joint angle, supination and pronation, movements smoothness, grip strength, amount of movement, and finger flexion and extension. Two machine learning algorithms were tested with the same features and these methods were the Support Vector Machine (SVM) and the Backpropagation Neural Network (BNN) since they were tested in the past with a similar sensor dataset. The results on healthy subjects showed an accuracy about 93.1% for the BNN and 86.1% for the SVM; the automated FMA had less accuracy from stroke patients probably due to the training data collected from healthy subjects' movements.

In [16] the researchers by using the Function Ability Scale (FAS) presented an approach to assess six upper limb movements on the analysis of accelerometer data. The scores obtained by this approach were compared with the one provided by the clinician. Healthy and stroke subjects participated in the study. Accelerometers were place on thumb, index, forearm, upper arm, and trunk. From the accelerometer data, some feature were extracted such as the mean value of the accelerometer time series, root mean square value of the accelerometer time series, and signal energy. The ReliefF feature selection algorithm was used to perform the feature selection. As classification method a Random forests was used to estimate the FAS scores associated with each of the motor tasks. Well-separated classes were obtained selecting data features, in particular the most relevant feature were the mean value of the accelerometer data and the correlation coefficient of pairs of accelerometer time series.

Using only one inertial measurement sensor on the wrist, scientists in [17] estimated scores related to 15 Wolf Motor Functions though automated tool. These scores were compared with those by the clinician. Several features were extracted for Bayes classifier such as skewness, mean, variance, RMS of jerk, time of the task, and kurtosis. Affected arm gestures were compared with those of the unaffected arm of the same subject. Scores assigned by the therapist were compared with those obtained from the classification algorithm and the results showed that the automated system was able to compute the FA score with a good level of accuracy.

Authors in [18] to estimate automatically four shoulder-elbow movements of the FMA used two accelerometers and one receiving node to retrieve a dataset using it as input for the Support Vector Regression (SVR). Some statistical features such as max, standard deviation, root mean square, mean, entropy, velocity, energy, and angle of movement were retrieved. ReliefF algorithm helped the scientist to rank in descending order of importance the feature to obtain the optimal feature set for each task. The results showed that the feature selection was valid since the RMS errors decreased for all tasks, increasing the accuracy of the model.

The researchers in [19] used two types of wearable sensors, accelerometer and flex sensors, to propose a quantitative Fugl-Meyer assessment system. Focus on the shoulder, elbow, wrist, and fingers, seven training upper limb motor function were considered, specifically four of them were used to monitor movement of upper limb while the last three to monitor movements of the fingers. Feature extraction from sensors data consisted in amplitude of sensor data, root mean square value of sensor data, mean value of sensor data, root mean square value of the derivative of sensor data, and the approximate entropy of sensor data. For each exercise the authors created a weak regression model, and then they ensembled them to build a quantitative FM assessment model. A mapping model was established adopting the extreme learning machine (ELM) algorithm a single layer feedforward network. For each exercise, the optimal features were selected though the RRelief algorithm, thus the number of features have reduced a lot and the generalized performances were improved a lot. The results showed that no statistical difference between the clinical FMA scores and the predictive results of quantitative assessment model. In addition, also a Support Vector Machine (SVM) was tested and the performance were improved after the feature selection.

The scientists in [20] developed a method to process movement data into metrics for the quality movements evaluation of upper limb in both daily life and clinic setting. The upper extremity metrics were associated with shoulder, arm, and trunk movements. These metrics gratified movement requirements, a result of a specific analysis conducted on care-professionals, health insurance companies, and researchers. For example, the requirement related to hand position relative to pelvis was satisfied by the following requirements: hand-pelvis distance, covered work area, and maximum reaching distance for both hands. Another metric quantified the range of motion of the elbow and shoulder, in order to satisfy the requirement of flexion and extension in the elbow and the abduction of the shoulder. The change in acceleration of the hand was used for smoothness of motion metric. The number of reaching movements that a patient can performs in a selected time period was a metric for representing the frequency of activities. Different activities could be distinguished by different metrics: the choice of these metrics was done by an activity classifier.

Inertial measurement was not the only one outcome for quantify motor functions of the upper limb, several previous works used the surface electromyography signals for upper-limb motion pattern recognition method. Researchers in [?] tested own performance model in five motions which involved shoulder flexion, abduction, internal rotation, external rotation, and elbow flexion by five healthy subjects. After data preprocessing phase which includes baseline correction, network interference removing, and signal-to-noise improving, the signal was divided into frames due the short-term stationary of sEMG signals. The variance, the root mean square, the fourth-order autocorrelation factor, wavelength, and short-term energy of each frame were calculated representing the features of the signal. sEMG signals were used as input of the Support Vector Machine which detected and classified these signals recognizing the movement in order to permit the ReRobot, the rehabilitation robot platform, to assist the impaired arm with that movement. The classification of each motions had a mean accuracy of $93,21 \pm 4,14$; there was a low accuracy in shoulder abduction recognition due to the muscles involves in the motions which they have a high coincidence.

Some studies were conducted also on Multiple Sclerosis (MS) subjects such as [21] during the execution of the Action Reasearch Arm Test (ARAT). The study recruited healthy subjects too. Subjects executed all ARAT tasks wearing only one inertial measurement unit on the wrist. An optoelectronic motion analysis system was assumed as a ground truth. Some parameters were calculated from IMU signals after segmentation which consisted in identify the reaching, transport, and the return phase of the movement. Some features extracted were the duration of the task, the jerk index, and the Z-score used to quantify the deviation of each parameter from normative data. This method was able to discriminate motor performances of healthy from that MS subjects controls, even if according the authors' opinion the small number of subjects was a limitation. From the results MS subjects were split into sub-groups according to mild, moderate, or severe impairment. It has been clearly shown that MS patients executed ARAT tasks slower and less smooth with respect to controls.

Chapter 4

Material and Methods

In this Chapter materials and methods used in the experiments are described. Experiment set up and experiment produce are explained. IMU sensors were widely used in human movements analysis, focus on quantitative and qualitative parameter from the study of the kinematic. Data from EMG sensors give additional and complementary information, focus on the extraction of muscles synergies.

4.1 Subjects

The experiment was carried out in Translational Neural Engineering Laboratory (TNE Lab) of Ecole Polytechnique Fédérale de Lausanne (EPFL) in Campus Biotech in Geneva. The subjects were recruited following a homogeneous age with no neurological, or sensorimotor impairments. Ten healthy subjects (5 women and 5 man) were engaged, 9 right-handed and 1 left-handed, and had a mean age of $23,36 \pm 0,64$. The subjects signed an informed consent to the analysis of their data for research purpose. Demographic data of subjects recruited in the experiment are reported in Table 4.1.

Subjects	**Gender**	**Age**	**Lateralization**
Subject 1	Female	23	Left-handed
Subject 2	Female	23	Right-handed
Subject 3	Male	23	Right-handed
Subject 4	Male	24	Right-handed
Subject 5	Male	24	Right-handed
Subject 6	Male	23	Right-handed
Subject 7	Female	23	Right-handed
Subject 8	Male	23	Right-handed
Subject 9	Female	23	Right-handed
Subject 10	Female	25	Right-handed

Table 4.1: Demographic data of subjects recruited in the experiment.

(a) (b)

Figure 4.1: Some components of the Xsens MVN: a) Wireless Motion Tracker (MTw); b) Awinda Station.

4.2 Experimental equipment

4.2.1 Kinematic hardware system

The hardware used for tracking inertial measurement was the Xsens MVN, a tracking product for capture full human body motion [22] based on Xsens' state-of-art miniature inertial sensors and wireless communication solutions.

The Wireless Motion Tracker (MTw) Fig 4.1(a) is a miniature wireless inertial-magnetic motion tracker for accurate 3D kinematic applications. All motion trackers transmit their data to the PC, via the Awinda Master station Fig 4.1(b) connected to a recording PC. Specifically, the MTw is a measurement unit containing 3D linear accelerometers, 3D rate gyroscopes, 3D magnetometers, and a barometer. 3D gyroscope is an inertial sensor that senses angular velocity and 3D accelerometer is an inertial sensor that measure linear acceleration. The Awinda Station controls the reception of synchronized wireless data from all wirelessly connected MTw devices. The Awinda Station is the interface between the Awinda host, typically a PC running Xsens-based software, and MTw devices and ensures the data from each MTw are synchronized. The Awinda Master send data to Awinda Host though a USB connection. The trackers are placed at strategic locations on the body though straps, headband and gloves, to measure motion of each upper body segment.

Data from the accelerometer and gyroscope is captured at a sampling frequency *fs* of 1000 *Hz*. The signals are processed at the *fs* by the Strap-Down Integration (SDI), an algorithm that guarantees high accuracy in dynamic conditions of the output data rate developed by Xsens. From each tracker the data are send at output rate of 60 *Hz*.

The MTw is a great measurement unit for orientation measurement of human body segments. Body segment orientation and position changes are estimated by integration of gyroscope and accelerometer signals, continuously updated by us-

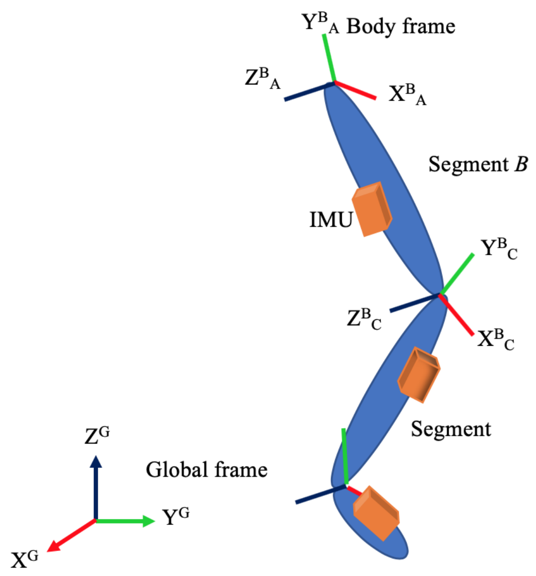


Figure 4.2: Body segment coordinate systems in global coordinate system.

ing a biomechanical model of the human body. In this model a subject's body is view as body segments linked by joints, and sensors are attached on subject's body segments [23]. When attaching sensors to body, segments positions and orientation are unknown and a reference pose is used while subject stands in N-pose, namely upright with arms along the side. Though a sensor-to-segment calibration procedure, data trackers are translated to body segment kinematics. The position and orientation, and other kinematic data of each body segment, are calculated respect to an earth-fixed reference co-ordinate system, G, Fig 4.2. The earth-fixed reference coordinate system is defined, by default, as a right-handed Cartesian co-ordinate system:

- X positive when pointing to the local magnetic North
- Y according to right-handed co-ordinates (West)
- Z positive when pointing up.

The output segment kinematics are the position, velocity, acceleration, orientation, angular velocity and angular acceleration of each body segment, with respect to the earth-fixed reference coordinate system.

Based on the standards of the International Society of Biomechanics (ISB) an extra frame of reference is used to define body frame and it is an intermediate frame to calculate joint angles:

- Origin, center of rotation
- X, forward in sagittal plane

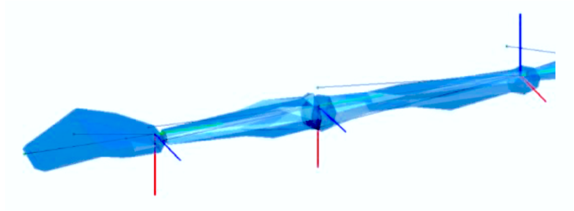


Figure 4.3: Right arm and shoulder.

- Y up, from joint center to joint center, pointing vertical
- Z, right in the frontal plane.

Joint origins are related to function movements. For example, flexion/extension of the knee is described by the rotation about the Z^B axis of the lower leg with respect to the upper leg. All joint angles follow the extraction order of Z for flexion/extension, X for the abduction/adduction and Y for internal/external rotation. The parameterization of the joint rotation describing the joint angles is the Euler representation; the Euler angles describe the orientation of a rigid body with respect to a fixed coordinate system. In Fig 4.3 the segment coordinate system at right arm and shoulder's joints is illustrated. The Xsens motion capture is able to provides 3D position, linear and angular acceleration and velocity of 23 segments and 3D joint angles of 22 joints. This biomechanical model was created though the calibration system. The sensor-to-segment calibration estimates the dimensions/proportions of the person being tracked, as well as the orientation of the IMUs respect to the corresponding segments.

4.2.2 Electromyography hardware system

TeleMyo Direct Transmission System (DTS), a 16-Channel EMG system was used as hardware for electromyography signal, a product of Noraxon U.S.A, Inc. The Noraxon DTS directly transmits wireless data from the electrode to a Receiver. A USB cable connects the Receiver to the PC running Noraxon-based software.

The EMG sensor is a small and lightweight individual radio transmitter, wireless connected to the Receiver Fig 4.4(d). The EMG probes are applied to the measurement site using Noraxon supplied double-sided adhesive tape with the reference electrode pad on the bottom side directly contact with the skin. The 2-pin lead Fig 4.4(b) wire connect is inserted into the EMG Sensor Fig 4.4(a) and though a pair of pliers is attached to the surface electrodes Fig 4.4(c). The electrode type used was H124SG Covidien, it has a pre-gelled adhesive side and its foam is latex free and therefore suitable for every skin type.

After starting the recording, the data are captured and stored within the sensor. Once the recording is finished, this data is transferred back into the recording. The sample rate was 1500 *Hz*.

(a)

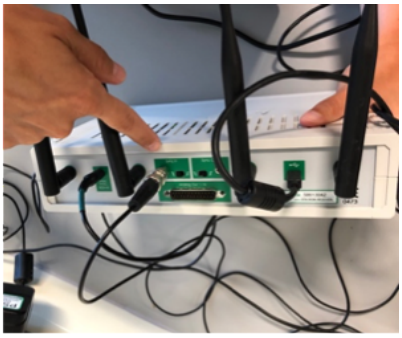
(b)

(c)

(d)

Figure 4.4: EMG Transmitter (a), EMG lead (b), EMG electrode (c), TeleMyo DTS Desk Receiver(d).

(a)



(b)

Figure 4.5: Xsens Awinda as Sync OUT (a), Noraxon TeleMyo as Sync IN (b).

4.2.3 Synchronizing Xsens Systems with Noraxon TeleMyo

The recording systems described before were able to synchronize own data and to retrieve information collecting and processing them. The information obtained from these analyses explored a limited space in which the upper limb motor function is expressed. The comprehension of the motor task cannot stay in only one environment. Combing data from kinematic model and biological model was a way to complete the framework of the arm task. Even if kinematic and EMG data can be taken out in the same time range starting the movement recording manually, the synchronization of Xsens and Noraxon systems though software settings opened the possibility to take kinematic and EMG data time accurately in time.

Xsens Awinda sends a starting signal and it acts as Sync OUT Fig 4.5(a), and Noraxon TeleMyo receives the signal and it acts as Sync IN Fig 4.5(b). The hardware component and connections are shown in Fig 4.6.

A cable with BNC and jack connector ends creates the connection between

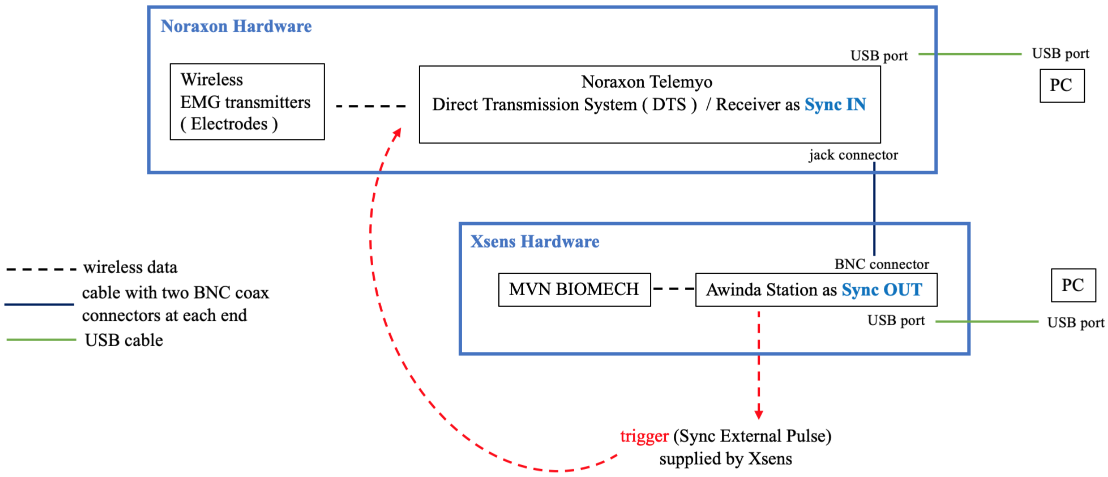


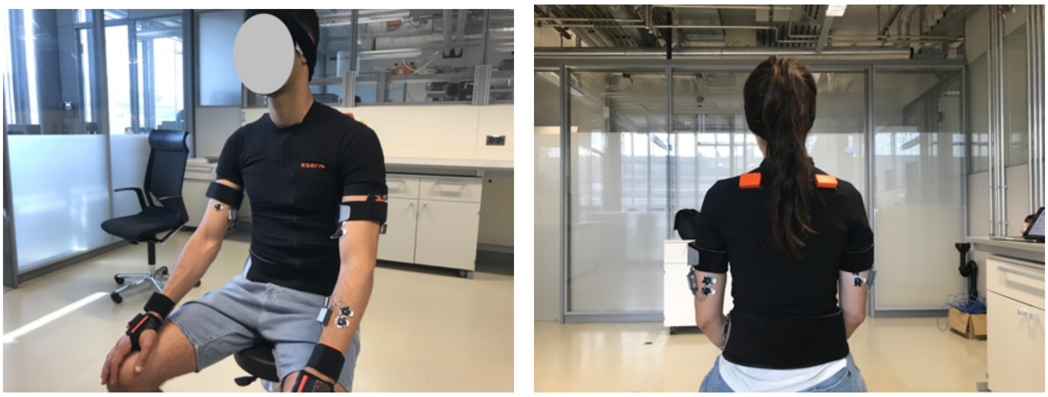
Figure 4.6: Connections between Xsens Awinda and Noraxon TeleMyo for synchronizing IMU and EMG signals.

the Xsens Awinda and Noraxon DTS. Xsens Awinda has Sync OUT port which enables the Xsens system to send a trigger pulse via the Awinda Station to third party hardware. Channel 9 in the Noraxon MyoResearch Software is selected as the synchronization line: this choice is done only for the lack of the probe of that channel, any channel is possible to use as synchronization channel. To initialize recording, first the Record button in the Xsens software is pressed and after visualizing the trigger in the EMG channel, the Record button is Noxaron Software is pressed too.

4.3 Experimental protocol and procedure

Upper limb movements were measured with wearable sensory system of eleven wireless IMU sensors and fifteen EMG sensors. The IMU sensors were attached on the dorsal side of each hand, wrist, upper arm and forearm and on both shoulders, neck, sternum, and sacrum using straps and the Lycra suit provided by Xsens. The IMU probes we placed following the tutorial video on Xsens web page. The set-up configuration is showed representing the front view Fig 4.7(a) and the back view Fig 4.7(b).

Since the movements to analyze were mainly related to shoulder, elbow and hand joints, the muscles selected for EMG analysis were pectoralis, deltoid, trapezius, latissimus dorsi, biceps long head, triceps long head, pronator teres, extensor carpi radialis, flexor ulnaris of the arm performing the task and all muscles mentioned before except for pronator, extensor and flexor of the contralateral arm were selected for the same task. For the EMG placement, the application site was clean with soap and water plus dry with a dry cloth. For IMU placement was necessary to to input body height, shoe length, arm span, ankle height, shoulder width, and shoulder height for computing segment lengths by Xsens. The placement of IMU and EMG probes were done carefully and aiming to not create conflict between them. Equipped with wearable sensory system, the participant is asked to stay in N-pose



(a) (b)

Figure 4.7: IMU and EMG sensors on two subjects's bodies: front view (a) and back view (b).

with both arms along the sides few seconds and to walk few meters back and forward for a short period of time while the calibration.

Each subject is asked to perform twelve exercise of the Fugl-Meyer Assessment Upper Extremity (Table 2.1) with each arm per time. The starting position of each exercise is sitting with both hands on the legs and the exercise is repeated five times. In order to maintain stability and balance in all directions while sitting, their feet were placed on the floor. The whole experiment was recorded in one time since it was possible to split each exercise in data-processing phase. The subjects were asked to perform the exercise after seeing it performed by the responsible of the experiment.

4.4 Kinematic data analysis

Kinematic data were first recorded and stored using the XSENS environment as well as EMG data using Noraxon software. So, data were moved in a local drive (e.g. PC) for data analysis. All procedures on IMU data and EMG data were implemented using MATLAB software (The Mathworks Inc., Natick, MA, USA). Data analysis in the end-point space was conducted using the 3D position (m), linear (m/s) and angular velocity (rad/s) of all segments, while in the joint space the data analysis was conducted using the joint angles (deg) of all joints in terms of Euler angle.

4.4.1 Synchronization

All motion tasks performances were recorded in one unique recording. The advantage of the synchronization of Xsens and Noraxon systems consisted in the recording both IMU and EMG data in the same time. The start of recording in Xsens software sent a signal though the synchronization channel to Noraxon software; after

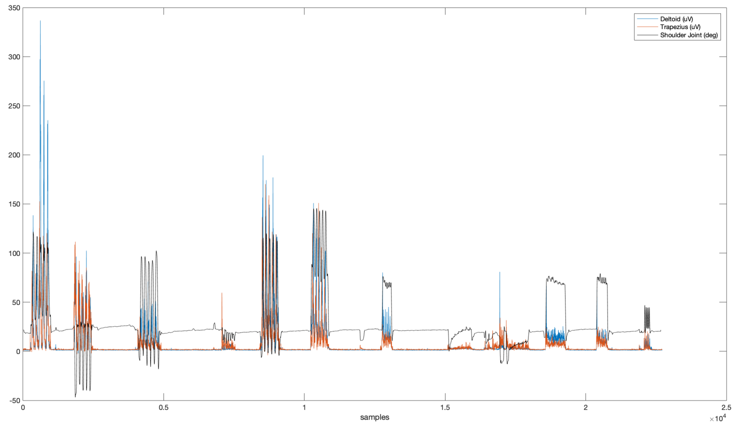


Figure 4.8: Muscle activation represented by deltoid and trapezius muscles and motor function represented by shoulder joint while a subject performed the whole experiment using the right arm.

this trigger, the operator pressed manually the recording botton in the Noraxon software. Thus, before the trigger, the EMG data had some samples that must be removed. Since the IMU data and EMG data were sampled at two different frequencies, 60 Hz and 1500 Hz respectively, it was necessary to subsample EMG data taking into account one sample each 25 samples according with this proportion:

$$\frac{fs_{emg}}{fs_{imu}} = \frac{1500}{60} = 25Hz$$

After the synchronization, the IMU and EMG recording were perfectly overlapped in time. The synchronization result was confirmed plotting the shoulder joint and muscle signals (deltoid and trapezius muscles) of a subject while performing the whole experiment Fig 4.8.

4.4.2 Pre-processing and movement segmentation

For statistical distribution, the subject performed the movement five times, and as first step the movement onset and ending were identified. According to the movement performed, the segmentation algorithm was based on IMU linear velocity or IMU angular velocity of the hand segment:

- linear velocity was used for flexor synergy, extensor synergy, hand to lumbar spine, shoulder flexion, shoulder abduction, and coordination/speed tasks;
- angular velocity was used for wrist pronation, wrist repeated dorsiflexion, and circumduction tasks.

According to the fact that the hand was the most distal portion of the body while performing the task, the linear or angular velocity associated to the hand

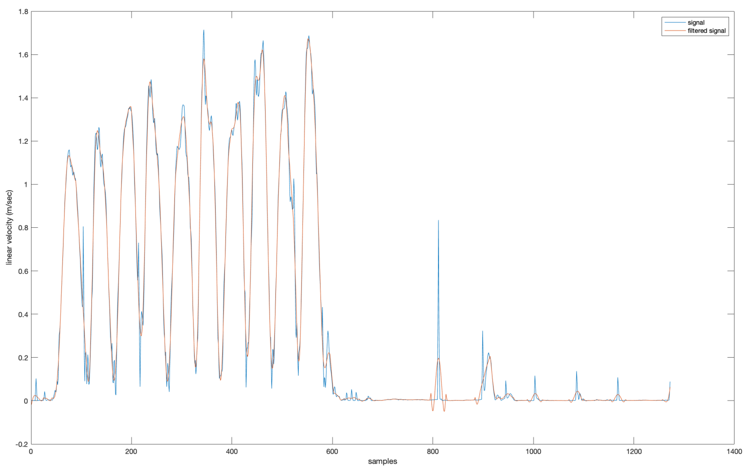


Figure 4.9: Linear velocity profile of left arm while performing hand to lumbar spine task: row data is shown in blue while the filtered signal is shown in orange.

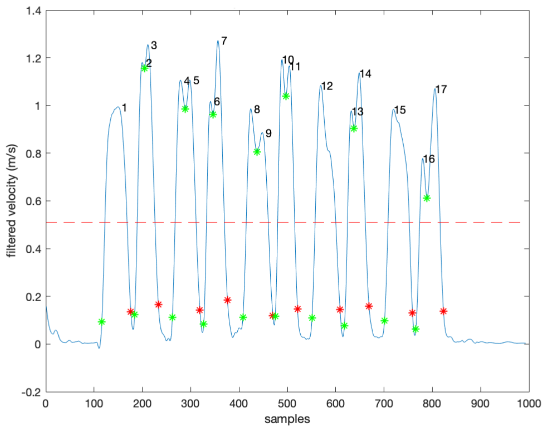
was considered for the identification of each motion inside the recording, and in specifically, the hand can be imagined as the end-effector of a robotic arm. Raw data were affected by environment conditions in which the experiment was recording. The Savitzky-Golay filter Fig 4.9, a polynomial filtering method for smoothing, was used to increase the signal-to-noise ratio: the filter length was set on 31 frames, the filter order was set on 4th [24]. The absolute value of linear or angular velocity of the hand [25], as shown in:

$$v = \sqrt{v_x^2 + v_y^2 + v_z^2}$$

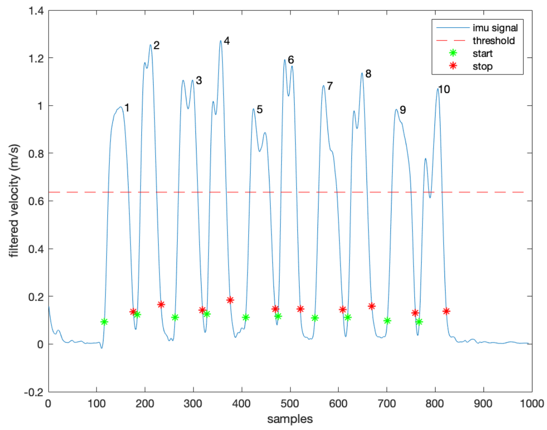
was computed and a segmentation algorithm was applied on it.

Each motion can be considered as the composition of a going movement and a back movement. Looking the speed profile, each its peak is a movement performed by the hand in the space. Each motion was viewed in a speed profile as two peaks in total. A simple algorithm was developed to find the time instance of onset and ending of both going and ending movements. The Matlab function *findpeaks* first found the peaks inside speed profile and sorted them from the higher to the lower. A threshold based on value equal to 50% of max peak was selected (red dotted line in Fig 4.10(a)) imposing the algorithm to consider only the peaks higher than this threshold. It might happen that more than 10 peaks were selected over this threshold Fig 4.10(a), so a second parameter imposed the algorithm to consider only the first 10 highest peaks Fig 4.10(b). A second threshold based on the 10-15% [26] of each peak was considered to find the onset and the ending of the movement. The limitations of this algorithm are discussed in the last chapter of this study.

The identification of onset and ending movement was improved though joints trajectories since each movement is characterized with a specific joint. This step is explained in the Appendix.



(a)



(b)

Figure 4.10: Segmentation on speed profile of subject number 10 while performing hand to lumber spine task with the left arm; segmentation on the same signal changing segmentation parameters such as the threshold related to the max peak and the number of peaks above the threshold to consider.

4.4.3 Metrics

After signals segmentation, some metrics were obtained to describe the motion in quantitative and qualitative terms. The identification of the kinematic metrics that best evaluate impairment of upper-extremity motor function depends on what kind of movement category that subjects are asked to realize. Reaching movements (point to point reaching), path drawing and activities of daily living (ADL) are some movement categories in kinematic analysis. Kinematics metrics related to upper-extremity point to point reaching movement includes two categories: end-point (hand) kinematic metrics and joint kinematic metrics. End-point kinematic metrics are calculated by 3D Cartesian coordinates of the hand's components such as position, velocity, and acceleration and can be considered as a motor performance of the movement. Joint kinematic metrics can be considered as a movement quality and they include inter-joint coordination and joint range of motion [27]. For all metrics, it should be emphasized that each metric value is retrieved average all repetitions related to the repeated movements, thus the metric value is obtained in terms of mean and standard deviation.

Kinematics metrics were defined either in the endpoint space, obtaining movement performance kinematics, and the joint kinematic metrics in the joint space, obtaining movement quality metrics.

In the endpoint space the following spatial-temporal metrics were retrieved from the segment of the hand of the arm which performed the task:

- duration: time interval between the movement onset and ending;

- average speed: according to the tasks, the mean value of the absolute value of linear or angular velocity;
- top speed: according to the tasks, the max value of the absolute value of linear or angular velocity;
- jerk: known as spectral arc-length, the movement's speed profile Fourier magnitude spectrum.

The metrics listed before are explained better in the following lines. Duration is the most simple and obvious parameter to observe since it is a simple movement indicator. As expose at the beginning of this study, one parameter that cannot be measured using clinical scale is the duration that employs a subject to perform a task. In some cases, it is measured using a stopwatch, but measurement accuracy is low. Time testes are considered objective and less influenced by ceiling effect, and it is the reason why it is chosen as metric. This metric is obtained though:

$$t_m = t - t_0$$

where $\mathrm{t_m}$ is the movement time computed as the difference between the ending time t and the onset time $\mathrm{t_0}$. Approximately the time for the execution of the exercise should be quite the same for all subjects.

Average speed is often used as an outcome metric and it is correlated to the level of impairment. Hand speed profile that prior and after the movement should be zero. During the movement the speed profile should be bell-shaped. The average speed is correlated to the time metric since if the movement is performed quickly, the duration of the task is low. Generally, a subject without motor deficit is able to perform a task quickly. Previous studies reported that in stroke subjects, hand speed profile is not so smooth such that the speed profile have several peaks. Their hand changes direction before realizing the reaching task and the tasks is realized by a series of small consecutive movement. The average speed may be considered a measure of smoothness; several papers have shown that the movement during a motor task is the combination of a sequence of submovement with a bell-shaped velocity profile.

Spectral arch-length, also called jerk, was used as a metric to quantify movement smoothness in [28]. This metric uses the movement speed profile's Fourier magnitude spectrum and it was tested on experimental data from stroke and healthy subjects. The results indicated that the spectral arc-length is a valid measure of movement smoothness. Healthy subjects showed smooth and well-coordinates movements, and these movements can be considered as a composition of a few submovements closely spaced in time. Instead, stroke patients have a choppy movement and smoother, these motions are the results of the superposition of a large number of submovements with loose temporal packing. According to this study [28], respect to other metrics, the spectral arc-length is more sensitivity to modifications of motor behavior and robustness to measurement noise. This metric satisfies the requirements such as dimensionless, it means the jerk is independent of its amplitude and duration, and monotonic response, it means that if the number of movements increases so the smoothness measure decreases. More negative is the value obtained, the jerkiness increases.

Since each movement is characterized by one or more degree of freedom, joints angle of the arm were retrieved to check the orientation of the arm in the space. Joint angle was also useful to evaluate the repeatability of each exercise, specifically in the segmentation phase signal. The importance of the join angle in the segmentation step of the signal into single movement repeated is explained in the Appendix. So, in the joint space the following metrics were retrieved:

- angle of shoulder joint
- angle of elbow joint
- angle of wrist joint

During the execution of the exercise, according to the Fugl Meyer assessment, each joint angle has an own range of motion. The measurement of joint angles is extremely important since each movement is described in the scale in terms of joint angles. In order to the have the initial position at 0° the offset, associated to the initial instant of time, was removed from raw data of joint angles. Since each joint has three degrees of freedom, depending in which plane the movement is performed, one or more degrees of freedom were taken into account. Each exercise was performed in one of the three planes, which were sagittal plane, frontal plane, and transverse plane. For this reason, since each joint had three components, that was x-component, y-component, and z-component, the following components were considered: for the shoulder joint z-component was chosen for all tasks except for the shoulder abduction/adduction and in flexor and extensor synergies; for the elbow joint z-component was chosen for all tasks; and for the wrist joint y-component was chosen for all tasks except for the dorsi/volar flexion in which the z-component was chosen. For a easy understanding of the component considered for each exercise, here the abstract:

- adduction/abduction (x-component)
- pronation/supination (y-component)
- flexion/extension (z-component)

Each exercise can be expressed in terms in going movement and back movement. Both going movement and back movement had the starting instant and the ending instant in time. The angle of each joint was retrieved considering the ending instant in time of the going movement.

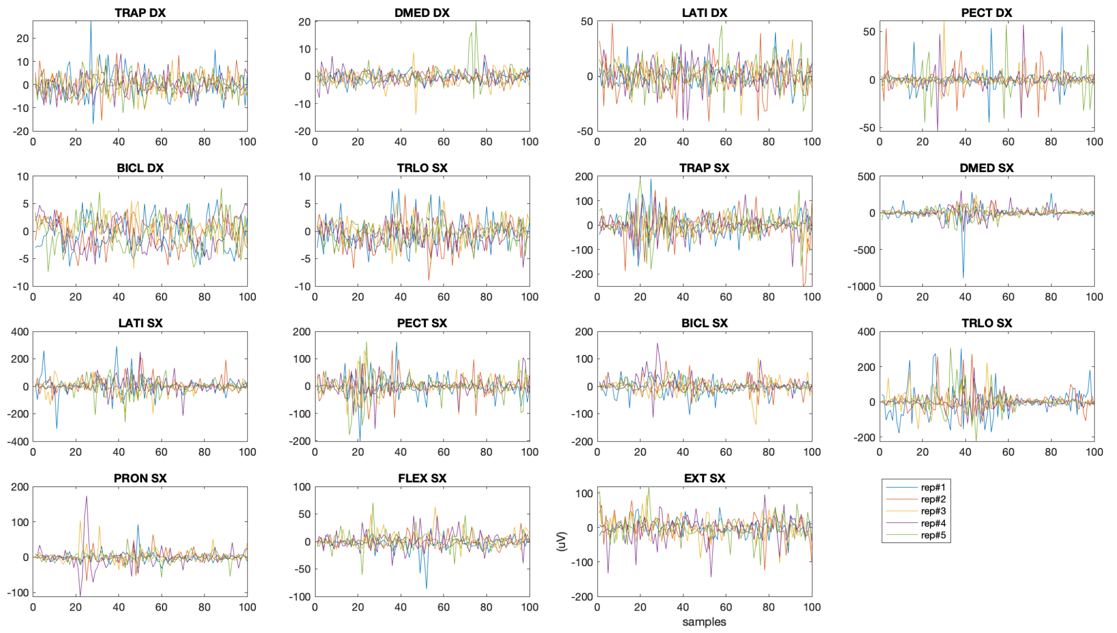


Figure 4.11: Each subplot represents row EMG signals, all repetitions are overlapped. These signals are recorded performing shoulder flexion 90° with left arm.

4.5 EMG data analysis

4.5.1 EMG preprocessing

For each subject, arm and task, all row EMG data of all repetitions were plotted in order to identify wrong signal such as those with high amplitude due to interference of the system or environment disorders. In Fig 4.11 the repetition number 1 in left deltoid is an example of the problem explained before since its amplitude was about four times higher than the averaging of the others. The repetitions were removed in accurate way, taking care to remove at maximum one repetition looking each subject, arm and task. If a repetition was removed, the same repetition was removed from IMU data as well.

EMG data pre-processing consisted in removing the mean value (detrending), band pass frequency filtered (50-500 Hz) Butterworth 7th order, rectification that is the computation of the absolute value, and low pass frequency (10 Hz cut-off frequency) to obtain the EMG enveloped. For each trial, a time window of 400 ms before the movement onset was considered to observe the muscle activation. The result of the pre-processing is showed in Fig 4.12, taking into account the EMG signal of the left deltoid performing the task Shoulder Adduction with the left arm of the subject number 1, using the repetition number 1.

The Xsens software setting permitted to save the time instance frames in which each motion function was started in the recording: these frames were used

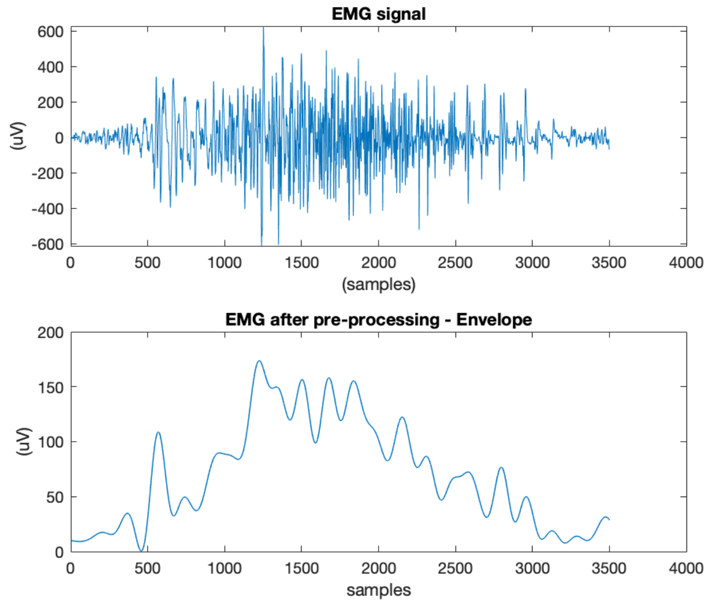


Figure 4.12: EMG signal of the left deltoid performing the task Shoulder Adduction with the left arm of the subject number 1, using the repetition number 1. On the top the row EMG signal, down the EMG signal after the pre-processing.

to obtain sub-recordings related to all upper limb motor functions. The EMG enveloped was normalized on the median value in order to correct the inter-arm EMG-amplitude differences due to electrode placement. A median value was obtained for each muscle averaging all repetitions of all tasks, using both arms, and of all subjects. Also, the mean and median value were calculated but the median value was chosen for its robustness to outliers.

4.5.2 Analysis of muscle activity

The surface electromyogram reflects the activity of the muscle fibres and it has an amplitude of 50-1000 μV and bandwidth of 0.1-400 Hz. The Root Mean Square (RMS) method is commonly used as a metric since it represents the energy of the original signals. So, the RMS value was the first metric extracted for each muscle, arm, subject, and task.

Mainly the analysis of muscle activity was done though the factorization algorithm, that was able to decompose the myoelectric activations patterns into their principle building blocks [29]. A muscle synergy represents a group of muscles activated together and then it is activated by a time-varying coefficient. All individual synergies were summed together, after their activation by the activation coefficients, in order to obtain a muscle activation patterns Fig 4.13.

Muscle synergies took place in the description of muscle coordination related to motor impairments. Small number of parameters, small numbers of building block,

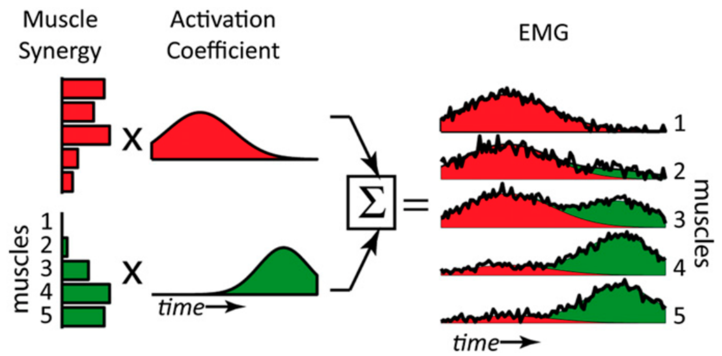


Figure 4.13: Muscle patterns recorded as electromyographic signals (EMGs) are generated by linear combination of muscle synergies (red and green bars) activated, through multiplication, by a time-coefficient. After the activations, the waveforms of individual synergies are summed together in order to reconstruct the recorded EMGs (black lines). Each waveform contributed in different weight to the reconstruction of the model.

made a muscle synergy which controlled a task. A muscle synergy is based on a set of muscles activated together in the same time and of course can be some differences in terms of set of muscle synergies performing the same task between unaffected and affected arms. A normal motor control may be based on the use of a limited set of muscle synergies, each representing a muscle activation pattern with a specific organization and temporal profile. Muscle synergies can be thought as reproducible modules organized by the central nervous system (CNS) to take the role of "basis functions".

A muscle synergy can be seen as a set of muscles, which are simultaneously activated by a single temporal command. It can be view as a profile activation across all muscles and activated though multiplication, by a time-dependent coefficient. This model creates an EMG waveform which is summed together to other EMG waveforms coming from different individual synergies, activated by their activation coefficients, in order to reconstruct the recorded electromyographic signals EMGs. The linear combination of each synergies explains that each of them has as a different contribute to the final result of the EMG reconstruction.

Basically, the extraction of muscle synergy consisting in the decomposition of a set of pre-processed EMG signals in linear combination of basic temporal components [30]:

$$E_{M\times t} = W_{M\times N} * C_{N\times t}$$

where:

- $E_M \times t$ is the matrix of normalized EMG enveloped average across the repetitions related to M muscles;
- $C_N \times t$ is the matrix of N (with N≤M) basic temporal components, called also activation coefficients;
- $W_M \times N$ is the matrix of weight coefficients representing the algebraic transformation between the temporal components and the EMG signals; it is refereed as the matrix of muscle synergy since it underlines which are the muscles working together and activated by a specific temporal component.

Both these matrix W and C explain the organization of the synergy in terms of contribution of each muscle and the temporal instant in which each muscle is activated.

The mathematical technique used to model a synergy is the non-negative matrix factorization (NNMF) [31] which tries to model complex data as linear combinations of a small set of basis vectors. The NNMF factors the nonnegative n-by-m matrix A into a nonnegative factors W (n-by-k) and H (k-by-m). The factorization is not exact, and the $W*H$ is only a lower-rank approximation to A. The iterative method starts with random initial values for W and H and calculate the root-mean squared residual D between A and $W*H$. Because the root-mean-squared residual D may have local minima, repeated factorizations may yield different W and H. The extraction is repeated fifty time and the solution explaining the highest overall amount of variance is chosen. The increasing number of elements when computing the synergies extraction minimizes the average muscle pattern reconstruction error across the repetitions of the movement. As mentioned before, different synergies can contribute to the final result of the EMG reconstruction and the number of muscle synergies to extract is also an input parameter of the algorithm. The extraction is repeated from one to the total numbers of the muscles.

Looking one task and one arm per time of each subject, not all synergies extracted are relevant to have a good representation of the original muscle activation. The minimum number of synergies is chosen though a method based on the inspection of the R^2 curve which indicates the fraction of total variation explained by the synergy. The number of muscle synergies necessary for an 95% R^2 EMG reconstruction is selected Fig 4.14.

To simplify the analysis the same number of muscle synergies, corresponding to the rounded average across subjects, was retrieved and used for each subject. This evaluation is done for both arms. A same number of synergies for both arms is useful to see the similarity between the muscle synergies of the dominant arm to those of the non-dominant arm in motor performance between the arms.

The order of muscle synergies as output of the NNMF can be different between subjects and arm. Since the number of muscle synergies is equal between

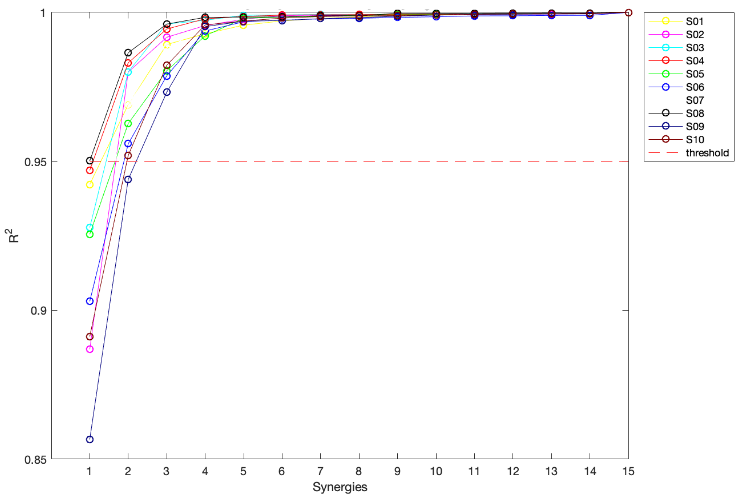


Figure 4.14: These trends show how many synergies should be considered for an 95% R^2 EMG reconstruction. Data retrieved from Flexor Synergy task using the Right arm were considered. Each curve represents a subject.

subjects and arms, a set of reference synergies is created to order all muscles synergies vectors respect to them for each task. First, a matrix obtained pooling all weights coefficients related to dominant (D) and non-dominant (ND) arm of all subjects is created. On that matrix, a hierarchical clustering procedure is done and it is based on the minimization of the Minkowski distance. The number of clusters was the same of the number of synergies extracted for each task. Consequently, a set of reference muscle synergies by averaging the synergy vectors with each cluster are obtained.

All synergies vectors of each subject and arm are ordered respect to the reference muscle synergies and herein we will only refer to ordered synergies. A DOT metric (the scalar product between pairs of weight synergy vectors) is used to see the similarity between the subjects and the max scalar product is used to rearrange the synergies to the one more similar. Indeed, $\cos\theta$ tells you the similarity in terms of the *direction* of the vectors (it is -1 when they point in opposite directions). This holds as the number in multi-dimensional space.

Chapter 5

Results and Discussion

In this chapter the analysis carried out on data from inertial measurement unit and electromyography is reported and it brought significant results though it was possible to quantify and qualify upper limb Fugl-Meyer Assessment Upper Extremity movements. The development of a kinematic assessment method of upper extremity motor impairment after stroke is relevant in rehabilitation and therapy phase. The first section presents the result on kinematic data, in the second section there are the results coming from the muscle analysis thought the EMG. Although there are no results related to stroke patients, there are some reflections about data analysis on stroke subjects found in the literature since this thesis would like to give a global information of the problem related to manual clinical scale.

Each movement was composed by a going movement and a back movement: for example, in Shoulder Flexion 0°-90°, the arm was prone from the initial position, which was sitting with both hands on the knees, to vertically beside the body in relax pose, and the going movement consisted of bringing the arm from the last position to shoulder flexion at 90°. Consequently the going movement was the movement of interest, while the back movement was performed only to repeat the exercise.

5.1 Kinematic results

Kinematic metrics obtained from the upper-extremity movements cab be classified into two categories; end-point kinematic metrics and joint kinematic metrics. The 3D Cartesian coordinates of only the inertial measurement placed on the wrist were calculated to retrieve the end-point kinematic metrics, since the hand is the most distal part of the arm from the body and it can be seen exactly as the end-point of an robotic arm. Joint range of motion was the metric retrieved for joint kinematics. Motor performance can be represented through the end-point kinematics, and the quality of the movement through the joint kinematics, since the value obtained from joint kinematics metric should be in a certain range of motion. Since each movement was repeated five times due to statistical reasons, the value of each metric was obtained though the mean and the standard deviation between the five repetitions. In the Table 5.1 all selected Fugl-Meyer motor functions are reported, and each task movement is identified through an identification number (ID number), since in the figures showing the results, the ID number helps to read and understand in east way the meaning.

ID task	**Motor task**
1	Flexor synergy
2	Extensor synergy
3	Hand to lumbar spine
4	Shoulder flexion 0°-90°
5	Pronation-supination
6	Shoulder abduction 0°-90°
7	Shoulder flexion 90°-180°
8	Pronation-supination
9	Repeated dorsi/volar flexion (elbow at 90°)
10	Repeated dorsi/volar flexion (elbow at 0°)
11	Circumduction (elbow at 0°)
12	Coordination/Speed

Table 5.1: ID task of selected tasks from FMA-UE.

5.1.1 End-point kinematic results

End-point kinematic metrics included mean and maximum of the hand, movement time, and jerk (smoothness). According to this study [27], mean and maximum of velocity of the hand, movement time, and smoothness were sensitive to change over time and these metrics can distinguish movement between healthy and stroke subjects specially in reaching-grasp movement.

Duration

Even though the duration of the movement is measured in the Fugl-Meyer assessment, for test concerning this type of test is an easy and valuable parameter to retrieve, and it can be considered as a complementary parameter to assess the movement. The unit of measurement of the duration of the movement was retrieved in seconds. The results of this metric are reported in Fig **??** and Fig 5.2. This metric was obtained for all tasks as can be seen from the figures. All subjects performed the exercise first with the right arm and then with the left arm, indeed the results, as can be seen easily in Fig 5.2, showed that approximately all subjects in all tasks performed in less time the exercises with the left arm. The exercises with the higher duration in time were the Wrist Flexion/Extension with both Elbow at 90° and 0°, since they were the most complicated exercises. In the Circumduction there are some value with high standard deviation, and this results is related to the fact that this kind of exercise is very difficult to segment starting from the speed profile. Less time to perform the exercise didn't mean that the movement was done in right way, indeed only the joint metrics kinematics can tell us the quality of the movement. The duration of the movement was reported looking all subjects to study the variability

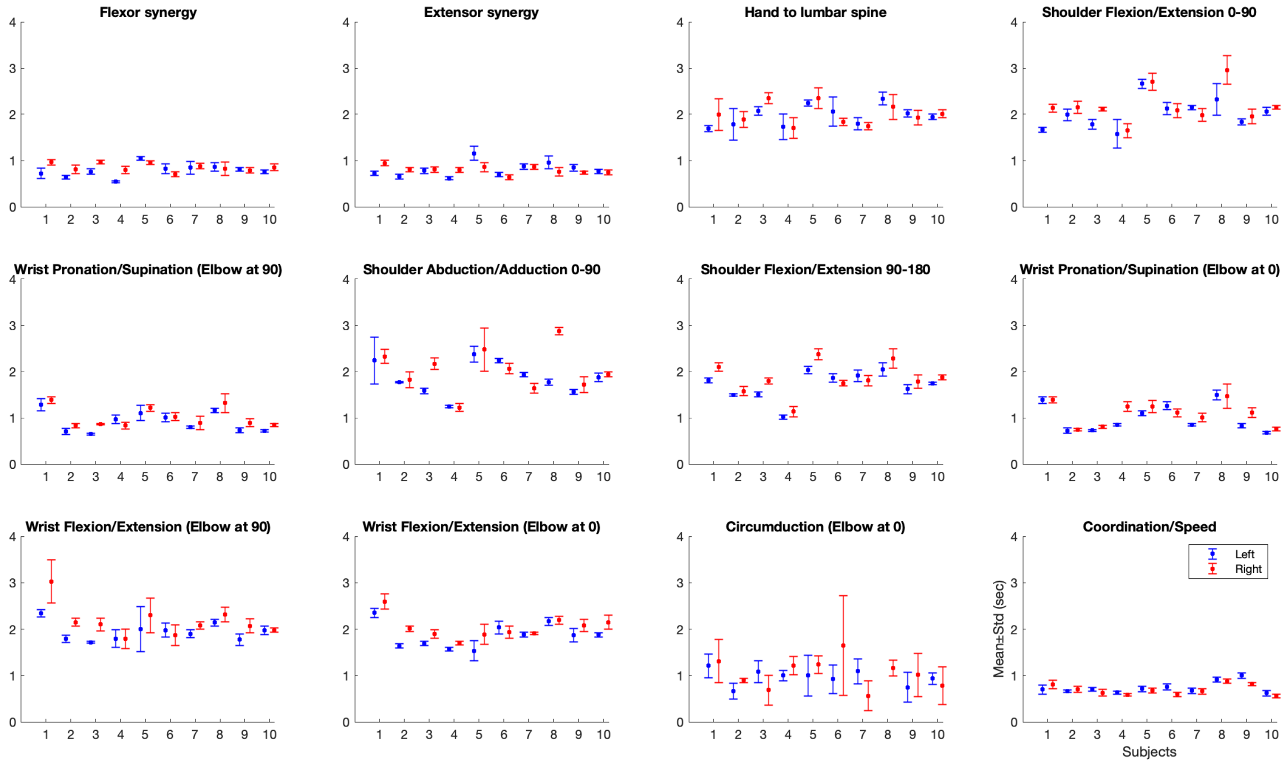


Figure 5.1: Mean and standard deviation of the metric of the duration of the movement for each healthy subject. Left (blue value) and right (red value) arms are compared.

inter-subjects, and the results showed that all subjects performed the movement mostly with the same duration.

Velocity

The velocity is a metric obtained for all tasks. The velocity is a complex capability, coordinated by the nervous system and muscle system. The velocity is the capacity to carry out motor actions in less time possible, this metric is strongly correlated to the duration metric. Highest is the velocity, lowest is the duration of the movement. The unit of measurement of the velocity depends on the task; indeed, for some tasks in which the trajectory was linear, the linear velocity was calculated, while in the task in which a rotation was evolved, the angular velocity was considered. The results of this metric are reported in Fig 5.3 and Fig 5.4. As expected, the value of velocity obtained from the left arm are higher than the value of velocity obtained from the right arm, since the subjects performed the exercises everytime first with the right and then with the left. As excepted, the higher velocity was obtained with the task Coordination/Speed. Except for the subject number 4, as can be seen in the task Shoulder Adduction and Shoulder Flexion 90°, all subjects performed the tasks with almost the same velocity. Since the task Wrist Flexion is more complicate, the lower values of speed were obtained with this task, and it

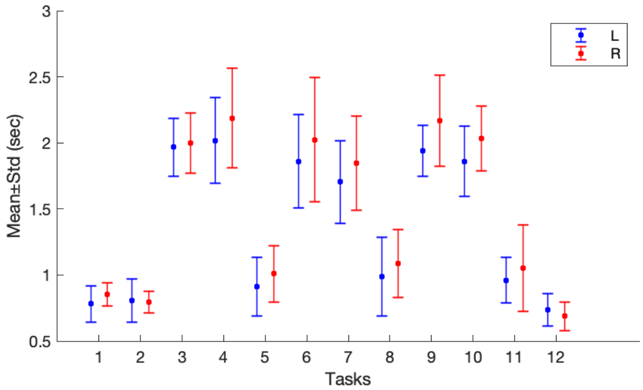


Figure 5.2: Mean and standard deviation of the metric of the duration of the movement for each task showing the average across the healthy population. Left (blue value) and right (red value) arms are compared.

was emphasized with a comparison with the task Wrist Supination. This metric provided a quantitative assessment of the movement but its quality is obtained with joint kinematics metrics.

Maximum of the velocity

The maximum of the velocity was obtained for all tasks. The unit of measurement of the maximum of the velocity depends on the task; indeed, for some tasks in which the trajectory was linear, the linear velocity was calculated, while in the task in which a rotation was evolved, the angular velocity was considered. The results of this metric are reported in Fig 5.5 and Fig 5.6. For this metric the same observation done for the velocity can be used for this metric.

Jerk

The jerk, that is the metric to qualify the smoothness of the movement, and it was obtained for all tasks. This metric has no an unit of measurement since it is a negative value with a specific meaning. The results of this metric are reported in Fig 5.7 and Fig 5.8. The negative value of this metric has the meaning of the smoothness of the movement. More the jerk is negative, so high in module, less smooth is the movement, and it is translated in the increasing of number of sub-movements. As excepted, the higher value of smoothness is in task Wrist Flexion/Extension since to perform this task the subject was asked to take a pause after the flexion and after the extension. The task of Coordination/Speed and Circumduction were more smooth respect to the other tasks since in the first the movement was very fast and there was no time to create some sub-movements, while in the second the task was performed as unique motion without going and back movement. Except for the tasks related to the synergies and Wrist Flexion, all tasks presented a value of jerk around [-2:-3], so the movements were smooth, typical of an healthy population.

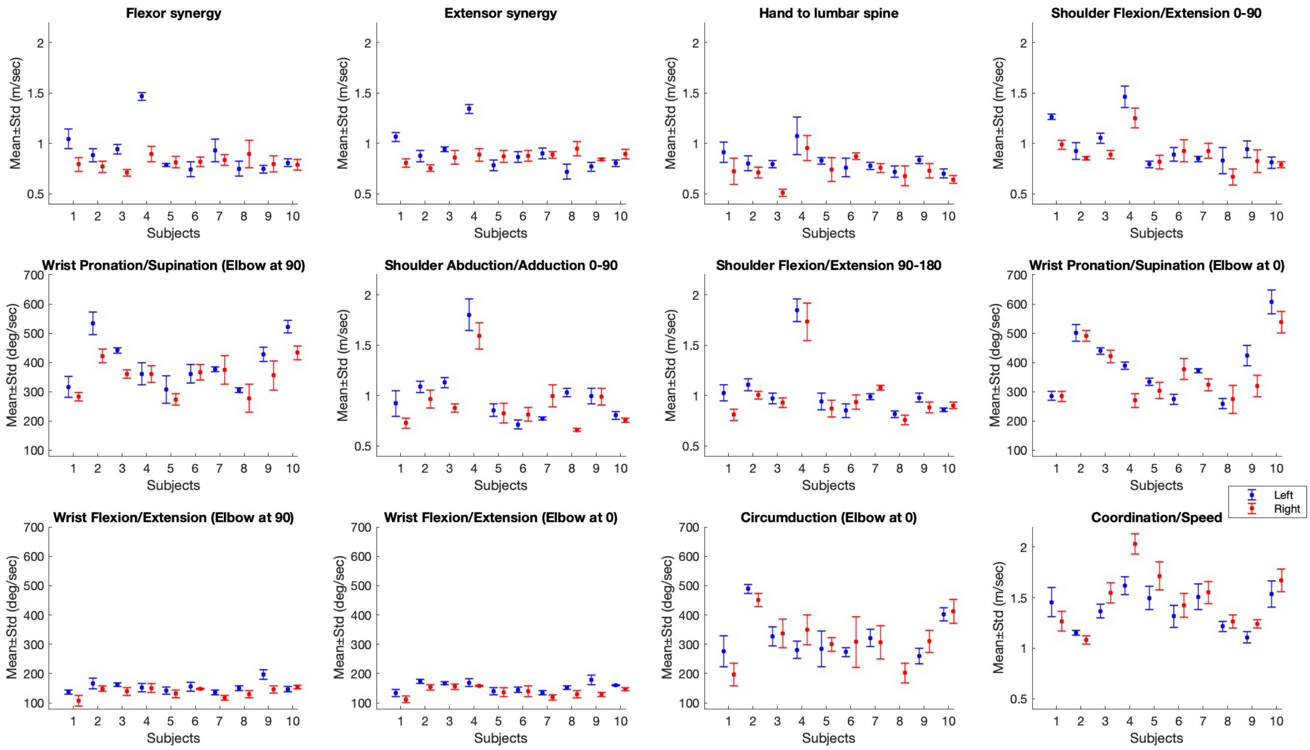


Figure 5.3: Mean and standard deviation of the metric of the velocity of the movement for each healthy subject. Left (blue value) and right (red value) arms are compared. Linear and angular velocity are considered based on the task.

5.1.2 Joint kinematic results

For joint kinematic metrics, the joint space was investigated to retrieve the accuracy of the movement in terms of quantity. In this part the range of motion of the shoulder, elbow, and wrist joint was explored in terms of degrees.

In healthy subjects the hand speed profiles were bell shaped and smooth. Other studies reported that in stroke subjects, hand speed profiles were not so smooth since their speeds have multiple peaks. Indeed, a stroke subject changes his hand several times during the movement, and consequently the movement is composed by a series of small consecutive movement [27]. Also in this case, as done for end-point kinematics metrics, the value of joint angle was retrieved in the time instance associated to the last of the going phase of the movement.

Shoulder angle

As explained in the Chapter before, each joint has an coordinate reference system, and the joint angle were retrieved in x-, y-, and z- components. For all tasks, except for the Shoulder Adduction and for those including the synergies in which the x- component was retrieved, the z- component was retrieved for the shoulder joint angle. The reason of this choice resided in which plane the movement was performed. Indeed, all tasks were performed in the sagitall plane, and the Shoulder Adduction,

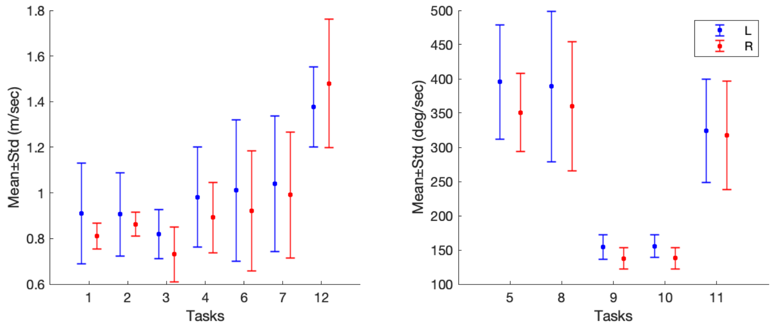


Figure 5.4: Mean and standard deviation of the metric of the velocity of the movement for each task showing the average across the healthy population. Left (blue value) and right (red value) arms are compared. Linear and angular velocity are considered based on the task.

and the Flexor/Extensor synergies were performed in the frontal plane. The results of this metric are in Fig 5.9 and Fig 5.10. The unit of measurement was the degrees. In contrast of what it has seen before in the end-point space, there are some differences in the results between the left and the right arm, but summary all subjects performed the tasks with approximately the same range of motion. As excepted, the shoulder angle is 0° in all tasks excepted in Shoulder Flexion and Adduction, Flexor synergy, and Coordination/Speed. Although in Shoulder Adduction and Flexion the subjects performed the tasks correctly reaching the angle of 90° in adduction in the first, and the flexion in the second, the value associated to the Shoulder adduction were lower than the value obtained in the Shoulder flexion, maybe misunderstanding was related to the intrinsic detection of data, a propriety of the sampling system.

Elbow angle

The z-component was considered for all tasks to retrieve the elbow angle. The results of this metric are in Fig 5.11 and Fig 5.12. The results in Shoulder Flexion both at 90° and 180° showed that probably, since the elbow angle was not at 0° but around 20°, the arm was not completely straight. In the task in which the elbow should be at 90°, as expected the angle was exactly at 90°. The results showed summary a good range of motion, and this metric represented a good indicator of performance.

Wrist angle

For all tasks expect in those in which the wrist performed a Pronation/-Supination, the z-component was retrieved, while in the pronation/supination the y-component was retrieved. The results of this metric are in Fig 5.15 and Fig 5.14. Except for some tasks, the results showed a high standard deviation, and this result was linked to the differences in the signals between the repetitions. Even though the value of the results were negative, for their understanding the module must be

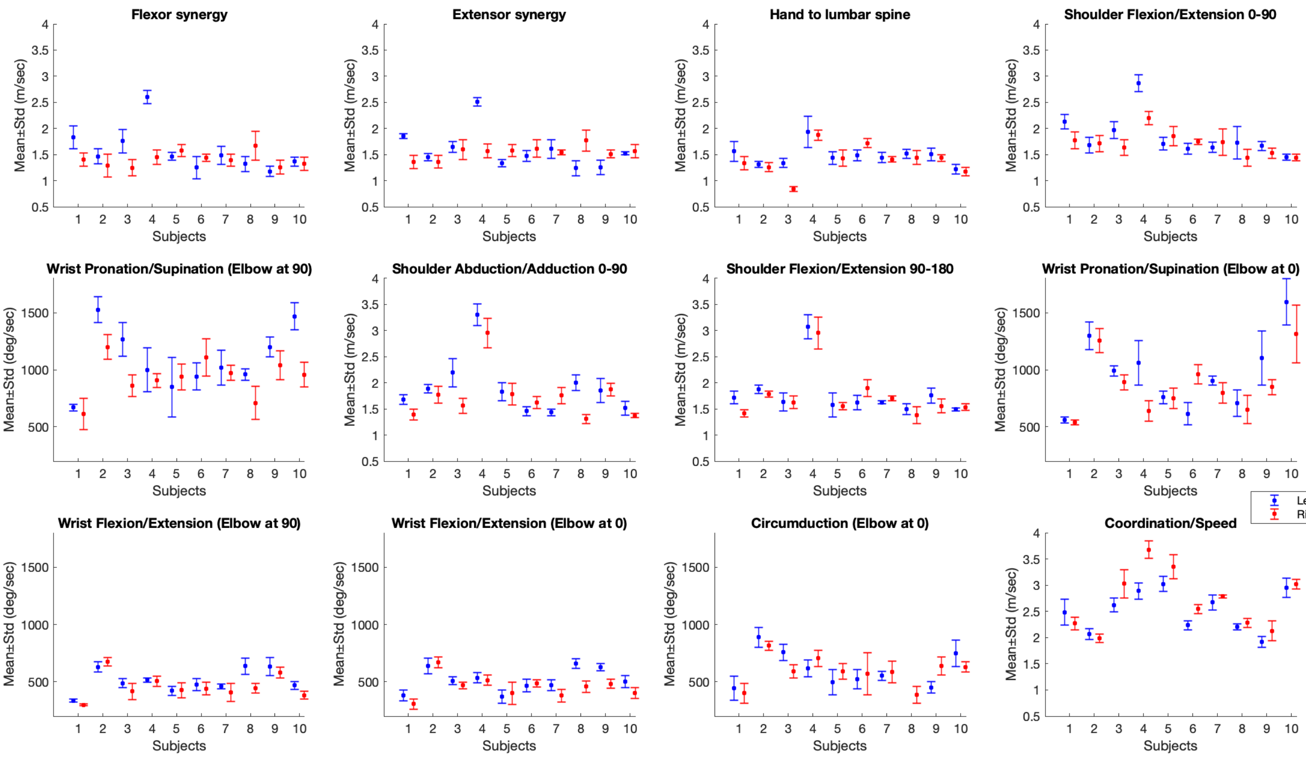


Figure 5.5: Mean and standard deviation of the metric of the maximum of the velocity of the movement for each healthy subject. Left (blue value) and right (red value) arms are compared. Linear and angular of the maximum of the velocity are considered based on the task.

considered. As excepted, the higher range of motion was in the tasks with Wrist Pronation/Supination, and also in tasks with Wrist Flexion the range of motion was high. There was a consistent inter-subjects variability which led to a not insignificant standard deviation.

Shoulder, Elbow, and Wrist angle

Since each joint had three degrees of freedom, for each task was important to consider in the same time two or more degrees of freedom. Indeed, for example, in the task Shoulder Adduction, all joint shoulde be at 0°, and the adduction angle should be at 90°; this example was chosen on purpose because we realized that inevitably this is also a flexion during the execution of this task, as can be seen in the results in Fig **??** and in Fig 5.16. For the shoulder angle the z-component, represented by the Shoulder Flexion, and the x-component, represented by the Shoulder Adduction, were considered; for the elbow the z-component was considered; at least, for the Wrist, the y-component, represented by the Wrist Pronation, and the z-component, represented the Wrist Flexion, was considered. In Fig 5.17 are showed the results on the healthy population.

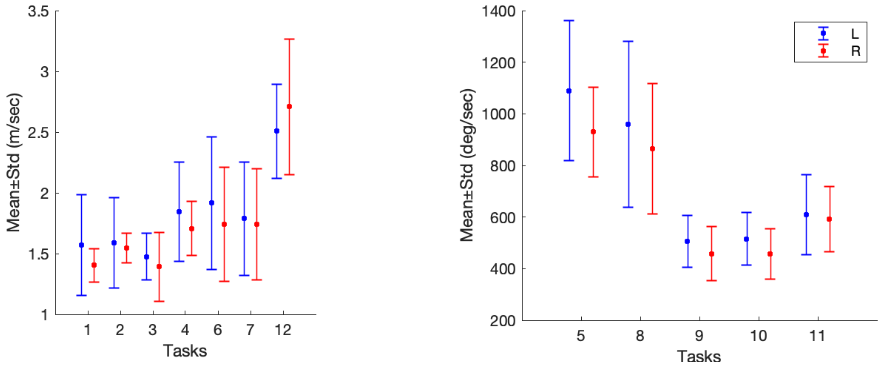


Figure 5.6: Mean and standard deviation of the metric of the maximum of the velocity of the movement for each task showing the average across the healthy population. Left (blue value) and right (red value) arms are compared. Linear and angular of the maximum of the velocity are considered based on the task.

5.1.3 EMG results

RMS

RMS value was obtained for all muscles (Table 5.2), all tasks, both arms, and all subjects. Since the movement was repeated five times, the RMS was computed as an averaging of the five repetitions obtaining the mean and the standard deviation. In order to simply the visualization of the results, in Fig 5.18 are reported the results on the healthy population with a comparison between the left and the right arm. As expected, for tasks such as Shoulder Flexion, and Adduction muscles of the shoulder and of the upper arm reached high intensity, while seemed to have the less or zero contribute muscles of the forearm. The tasks involved the synergies, such as Flexor and Extensor synergies, recruited the higher number of muscles. Even though the intensity is very low, in tasks such as Wrist Flexor, the flexor ulnaris and the pronator teres were involed.

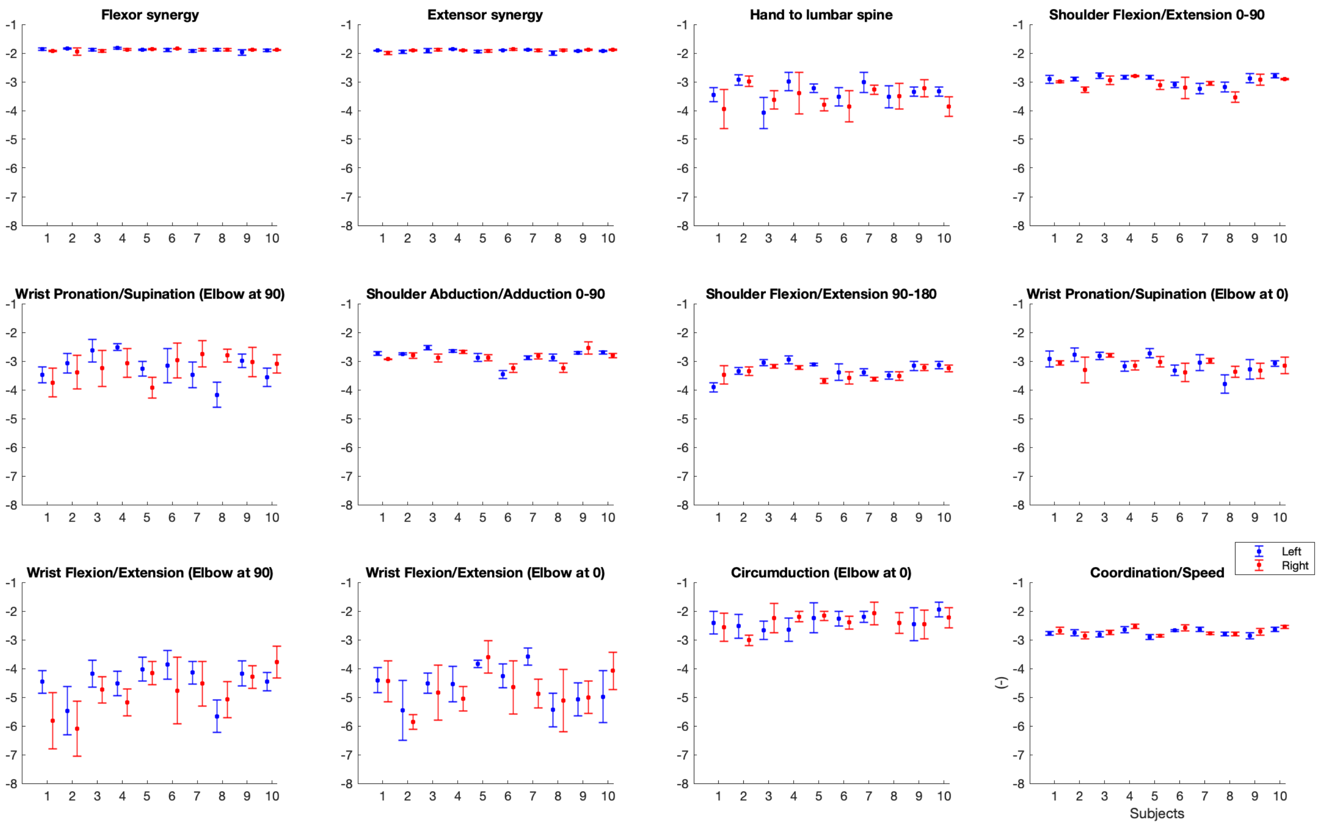


Figure 5.7: Mean and standard deviation of the metric of the jerk of the movement for each healthy subject. Left (blue value) and right (red value) arms are compared.

ID muscle	Muscle
1	trapezius left
2	deltoid left
3	latissimus dorsi left
4	pectoralis left
5	biceps long head left
6	triceps long head left
7	pronator teres
8	flexor ulnaris
9	extensor carpi radialis
10	trapezius right
11	deltoid right
12	latissimus dorsi right
13	pectoralis right
14	biceps long head right
15	triceps long head right

Table 5.2: Muscles for EMG recording.

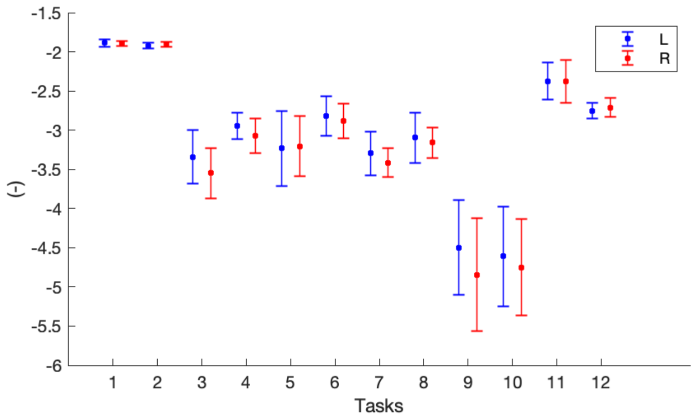


Figure 5.8: Mean and standard deviation of the metric of the jerk of the movement for each task showing the average across the healthy population. Left (blue value) and right (red value) arms are compared.

Muscle synergies

Muscle synergies were retrieved for all tasks from both left and right arm. The results are showed from Fig 5.19 until Fig 5.30: in each figure there are the muscle synergies extracted from both left and right arm, and the similarity inter-subject and intra-subjects of the synergies extracted of the corresponded task. The number of muscle synergies extracted were two for all tasks, expect for the task of Circumduction and the Wrist Flexion/Extension (Elbow at 0°).

As excepted, the muscles which were not involved in the movement, that were the muscles of the contro-lateral side, were not present in the subset of muscles that represented the synergy. Indeed, their values were not completely scratch since during the movement they had only the function of postural keeping. Sommary, for each task, there were no significat differences between the left and the right arm. Looking the Flexor synergy task Fig 5.19 in both the synergie, the muscles involved during the movement were the trapezius, deltoid, and biceps long head; it is possible to notice that the same muscles had the higher value of RMS in the same task, Fig 5.18. The same muscles were involed in the Extensor synergy but in less intensity, Fig 5.20. Some suspicious results were in the Wrist Prontation task Fig 5.19, in which the second synergy involved the pronator teres quite in the same intensity of the other muscles. The tasks such as Wrist Flexion, as excepted, the third synergy represented the task in the best way, since the pronator teres, and the flexor ulnaris were pronounced a lot. As can be seen from the results, each synergy contributed to the abduction, or/and flexion of some joints during the movements. In some subset of muscles, specific one or more muscles dominated the activity, and in some other cases all muscles of the active side were involved to perform the movement. At least, the DOT metrics, which in almost the tasks didn't reach the maximum value corresponding to the maximum similarity, underlined that subjects changed the organization of the muscle synergies in response the task.

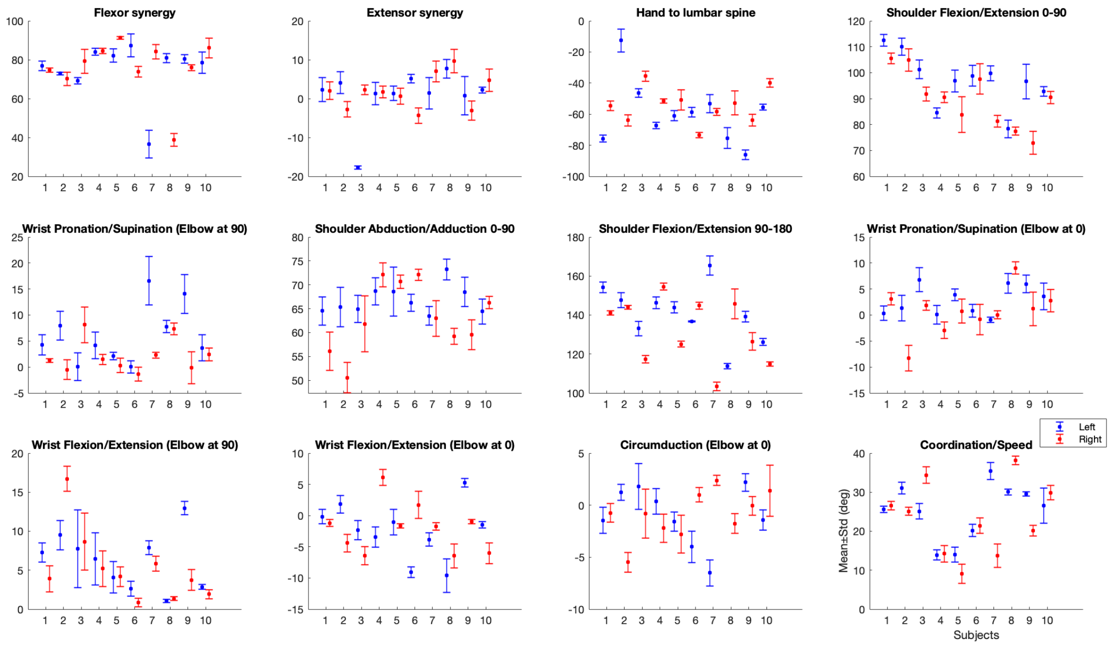


Figure 5.9: Mean and standard deviation of the metric of the shoulder angle of the movement for each healthy subject. Left (blue value) and right (red value) arms are compared.

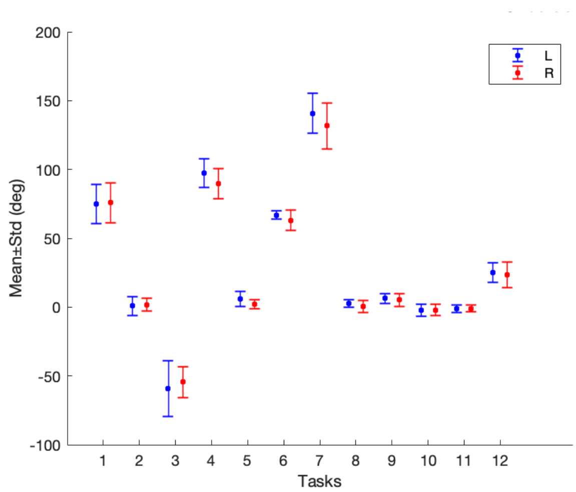


Figure 5.10: Mean and standard deviation of the metric of the shoulder angle of the movement for each task showing the average across the healthy population. Left (blue value) and right (red value) arms are compared.

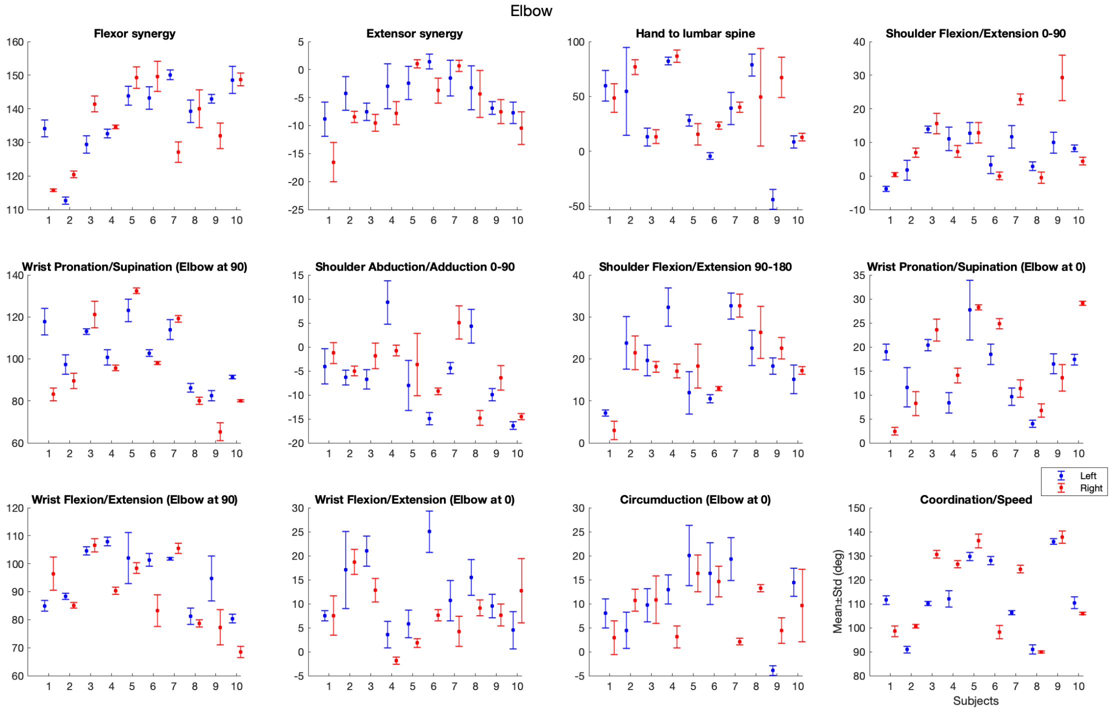


Figure 5.11: Mean and standard deviation of the metric of the elbow angle of the movement for each healthy subject. Left (blue value) and right (red value) arms are compared.

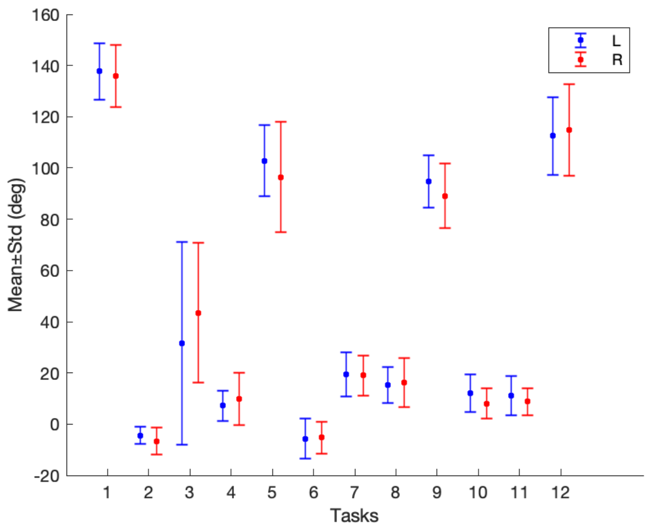


Figure 5.12: Mean and standard deviation of the metric of the elbow angle of the movement for each task showing the average across the healthy population. Left (blue value) and right (red value) arms are compared.

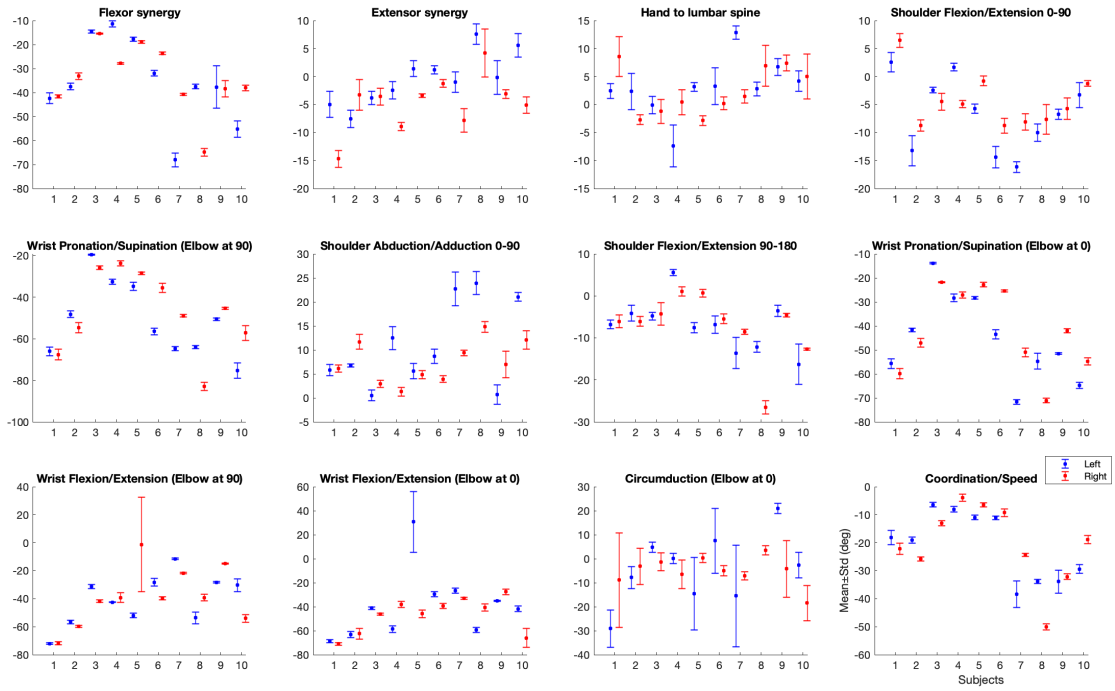


Figure 5.13: Mean and standard deviation of the metric of the wrist angle of the movement for each healthy subject. Left (blue value) and right (red value) arms are compared.

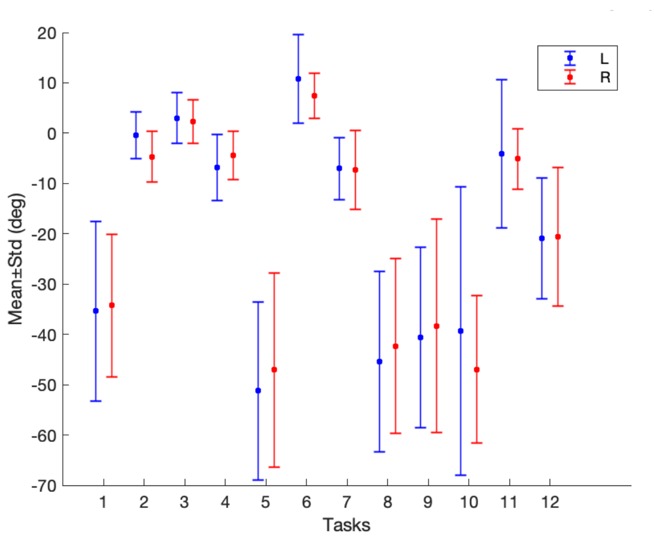


Figure 5.14: Mean and standard deviation of the metric of the wrist angle of the movement for each task showing the average across the healthy population. Left (blue value) and right (red value) arms are compared.

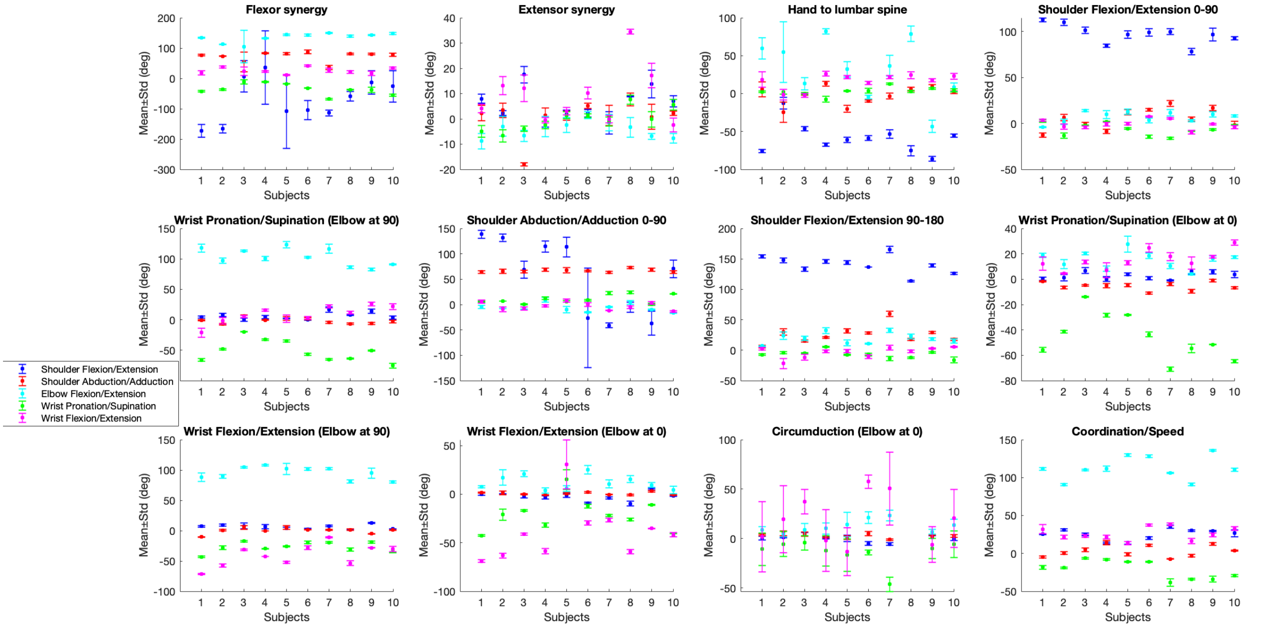


Figure 5.15: Mean and standard deviation of each joint angle of the left arm for each healthy subjects. More than one degrees of freedom were considered. The Shoulder Flexion is in blue, the Shoulder Adduction is in red, the Elbow Flexion is in ciano, the Wrist Pronation is in green, and the Wrist Flexion is in magenta.

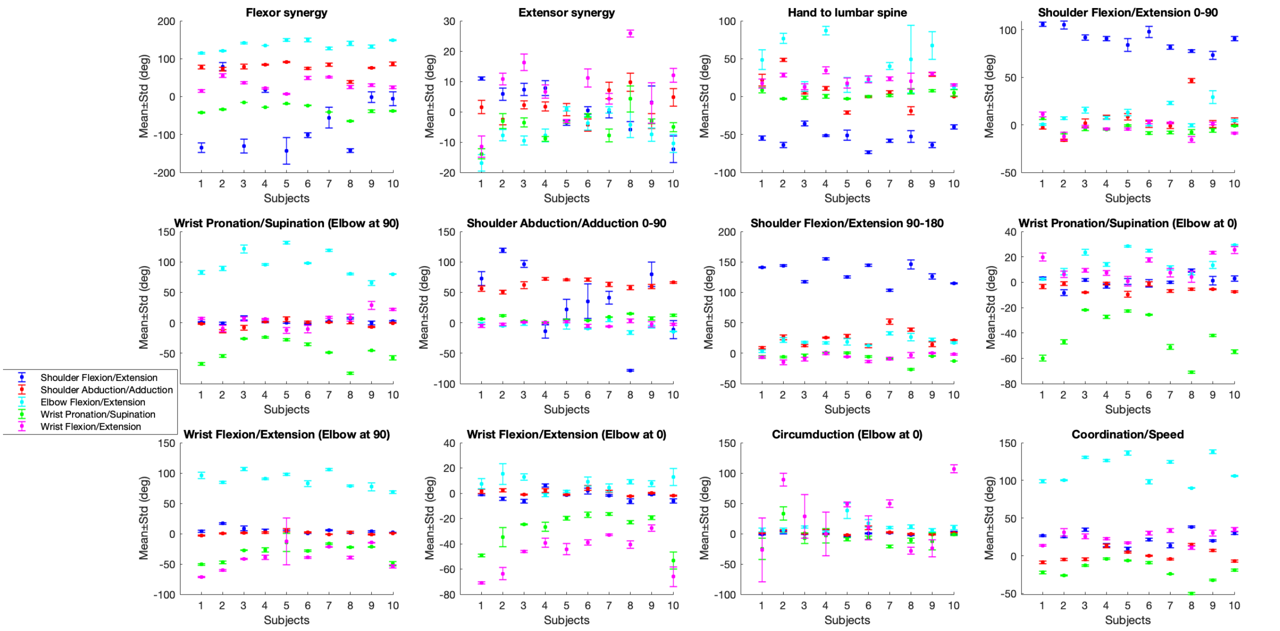


Figure 5.16: Mean and standard deviation of each joint angle of the right arm for each healthy subjects. More than one degrees of freedom were considered. The Shoulder Flexion is in blue, the Shoulder Adduction is in red, the Elbow Flexion is in ciano, the Wrist Pronation is in green, and the Wrist Flexion is in magenta.

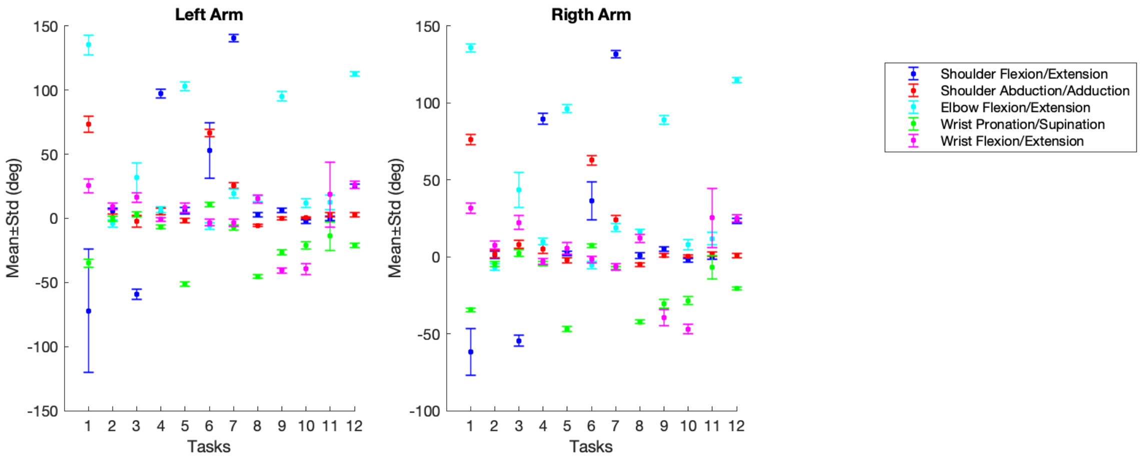


Figure 5.17: Mean and standard deviation of each joint angle of both left and right arm for tasks averaging the healthy poplation. More than one degrees of freedom were considered. The Shoulder Flexion is in blue, the Shoulder Adduction is in red, the Elbow Flexion is in ciano, the Wrist Pronation is in green, and the Wrist Flexion is in magenta.

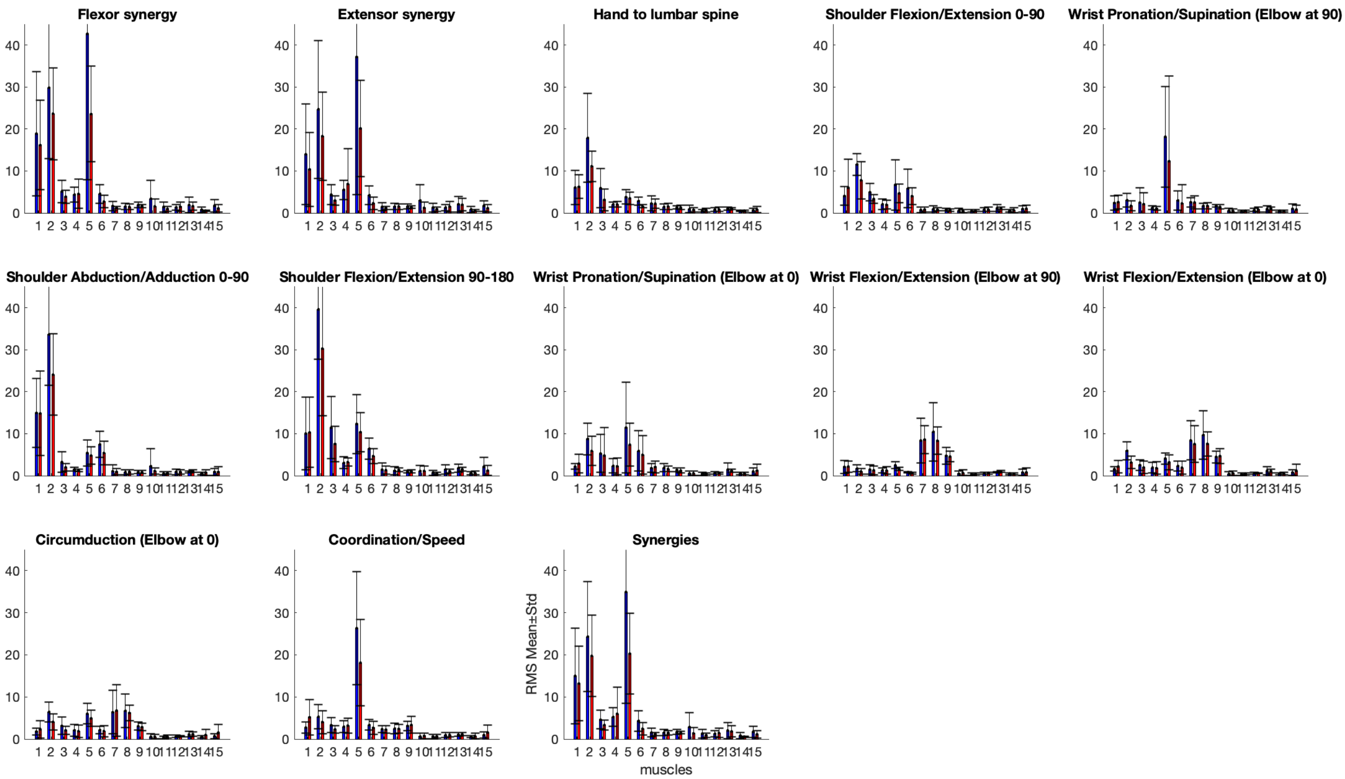


Figure 5.18: Mean and standard deviation of RMS value of all muscles of healthy population with a comparison between the left (in blue) and the right (in red) arm.

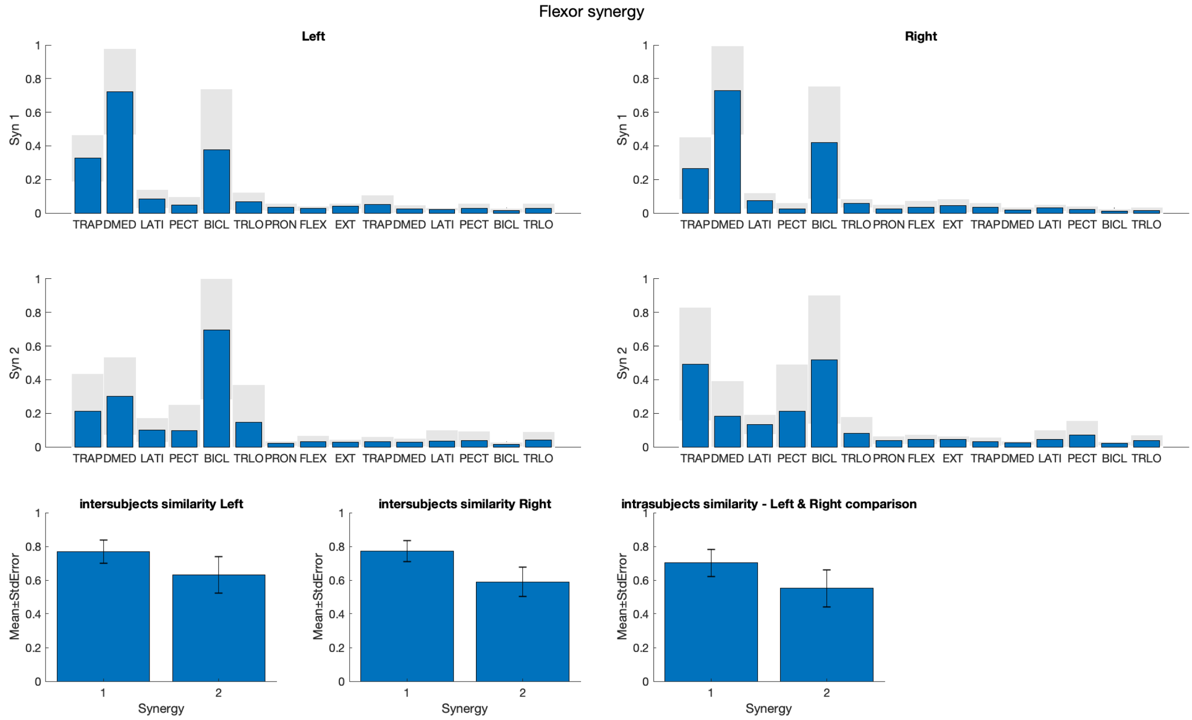


Figure 5.19: Muscle synergies of left and right arm in Flexor synergy task; similarity inter-subject and intra-subjects using the DOT product.

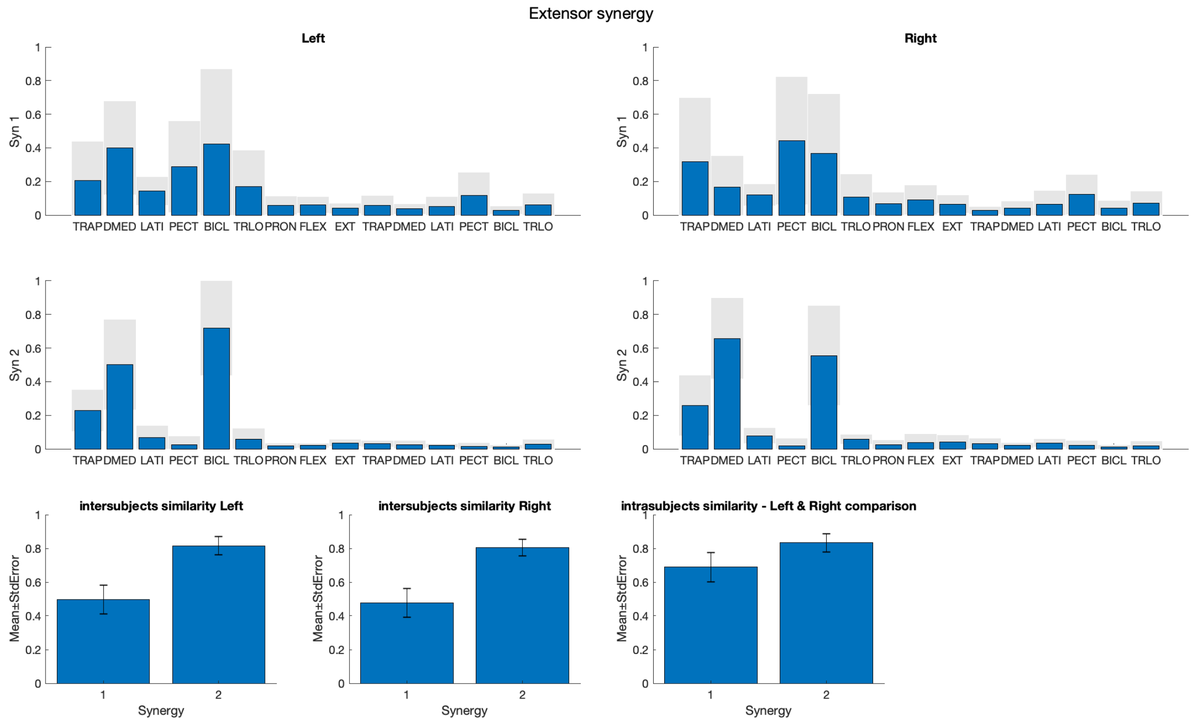


Figure 5.20: Muscle synergies of left and right arm in Extensor synergy task; similarity inter-subject and intra-subjects using the DOT product.

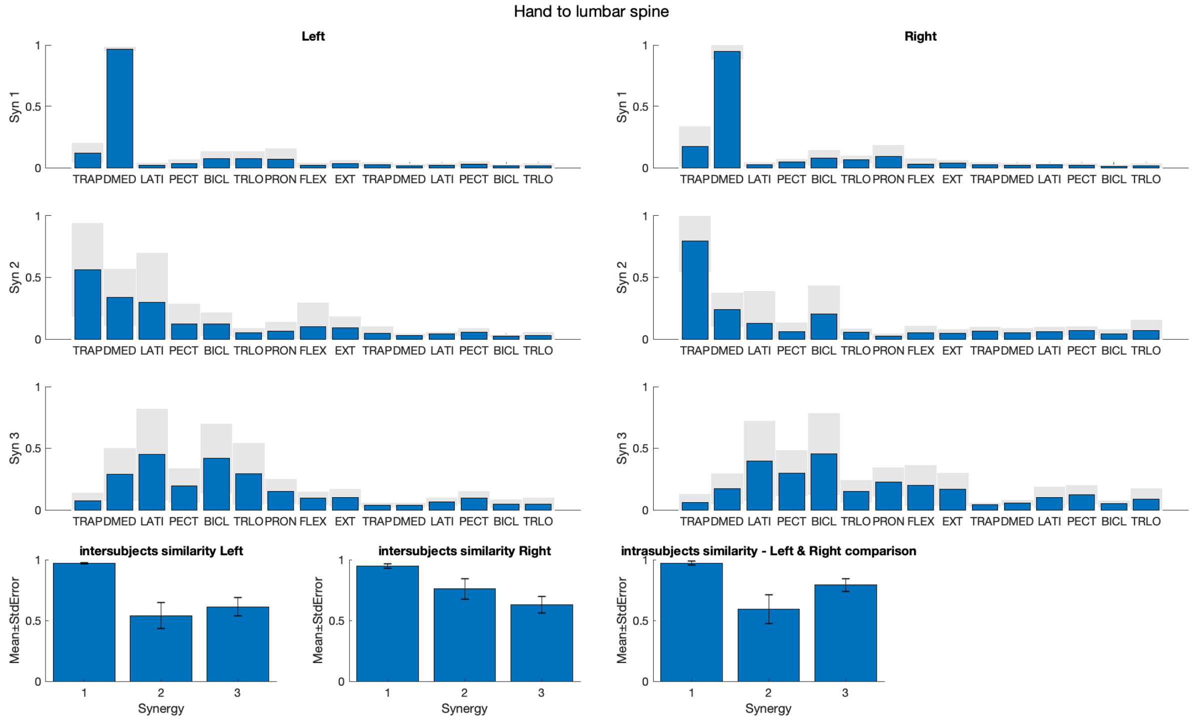


Figure 5.21: Muscle synergies of left and right arm in Hand to lumbar spine task; similarity inter-subject and intra-subjects using the DOT product.

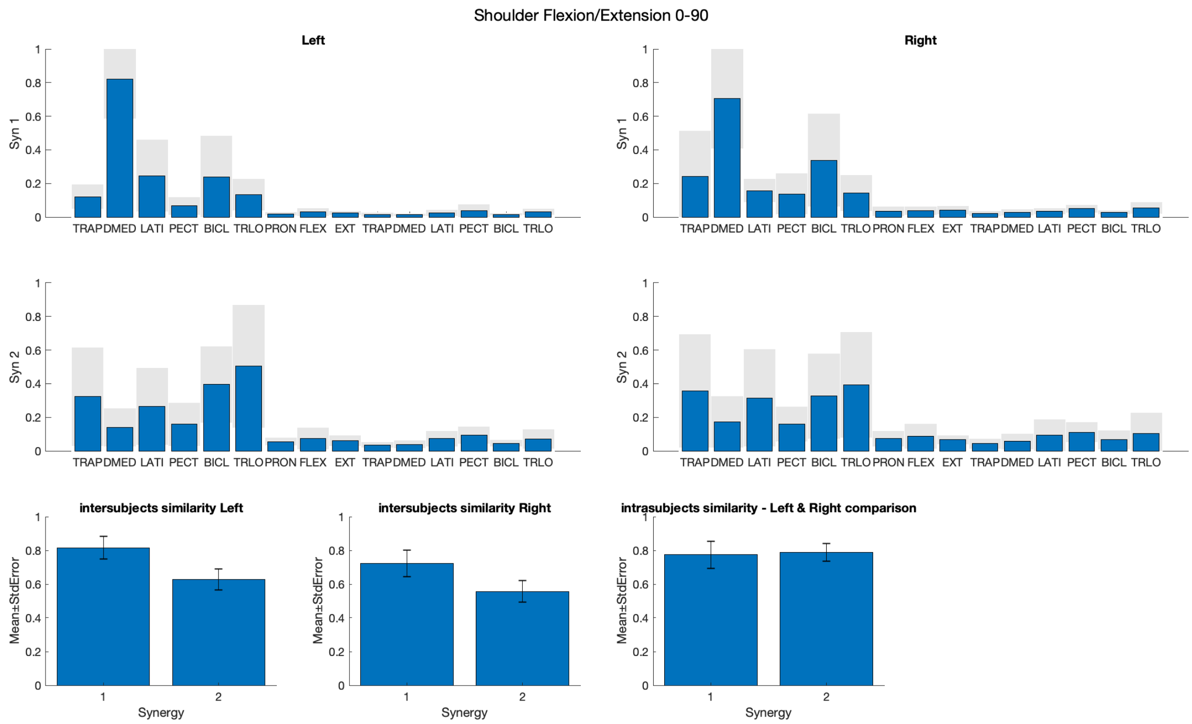


Figure 5.22: Muscle synergies of left and right arm in Shoulder Flexion/Extension 0°-90° task; similarity inter-subject and intra-subjects using the DOT product.

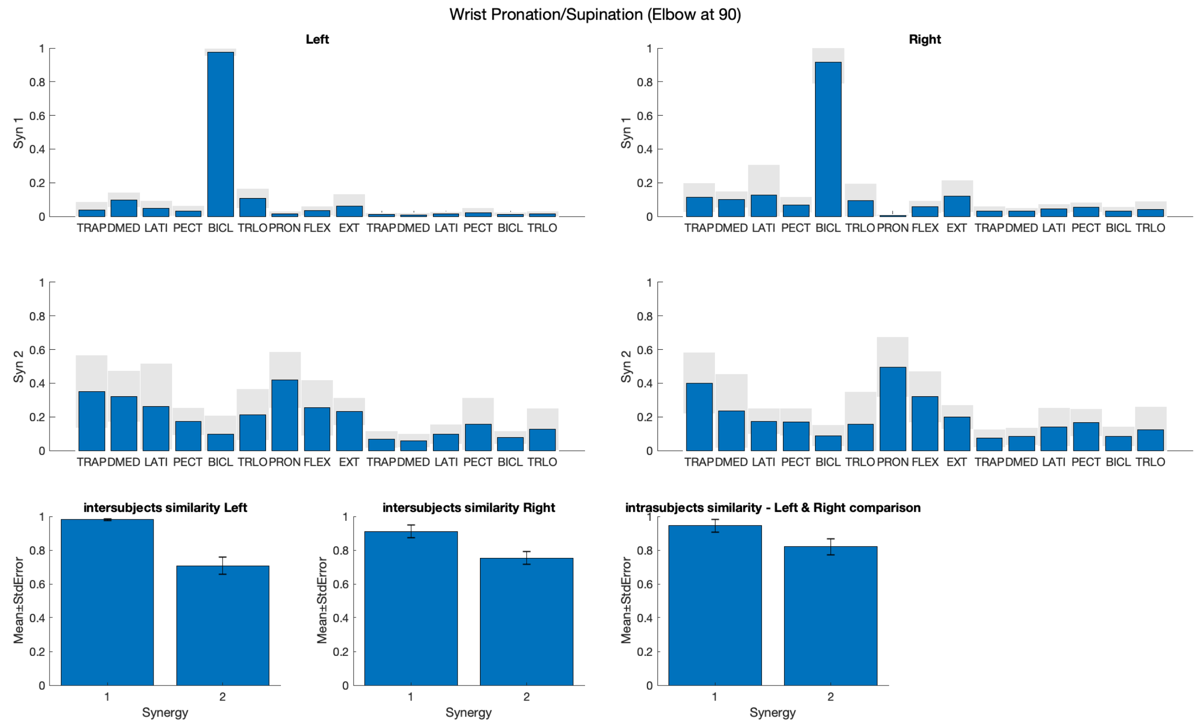


Figure 5.23: Muscle synergies of left and right arm in Wrist Pronation/Supination (Elbow at 90°) task; similarity inter-subject and intra-subjects using the DOT product.

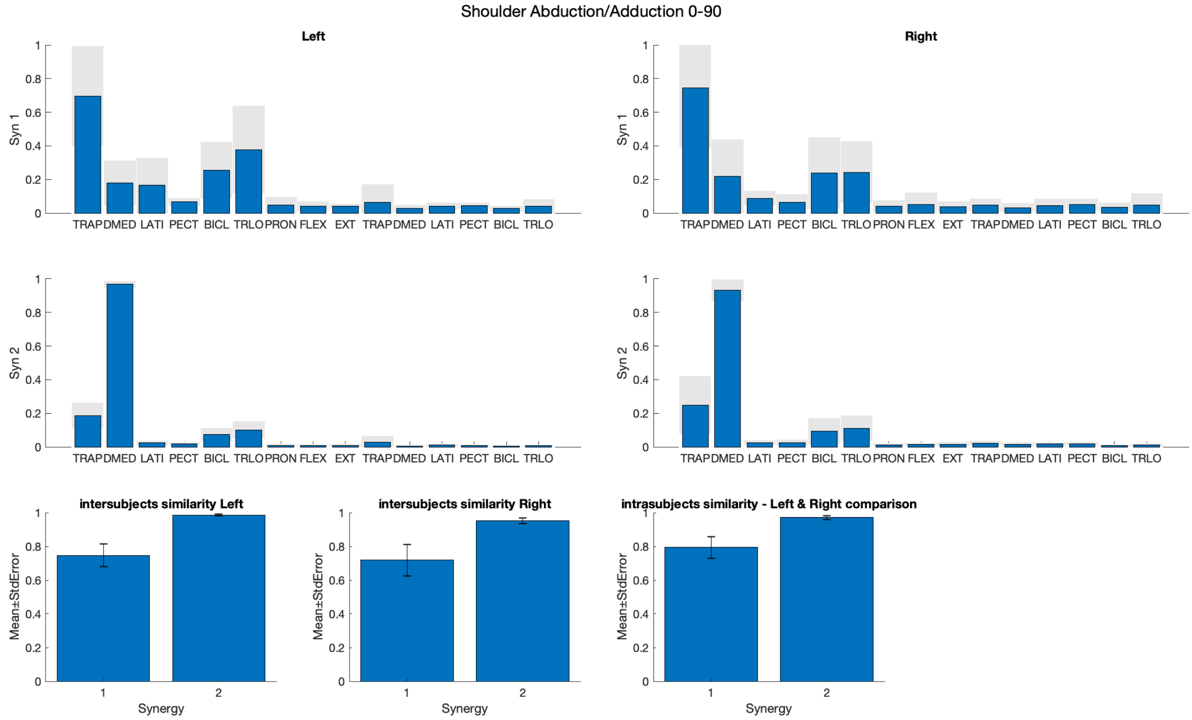


Figure 5.24: Muscle synergies of left and right arm in Shoulder Adduction/Abduction 0°-90° task; similarity inter-subject and intra-subjects using the DOT product.

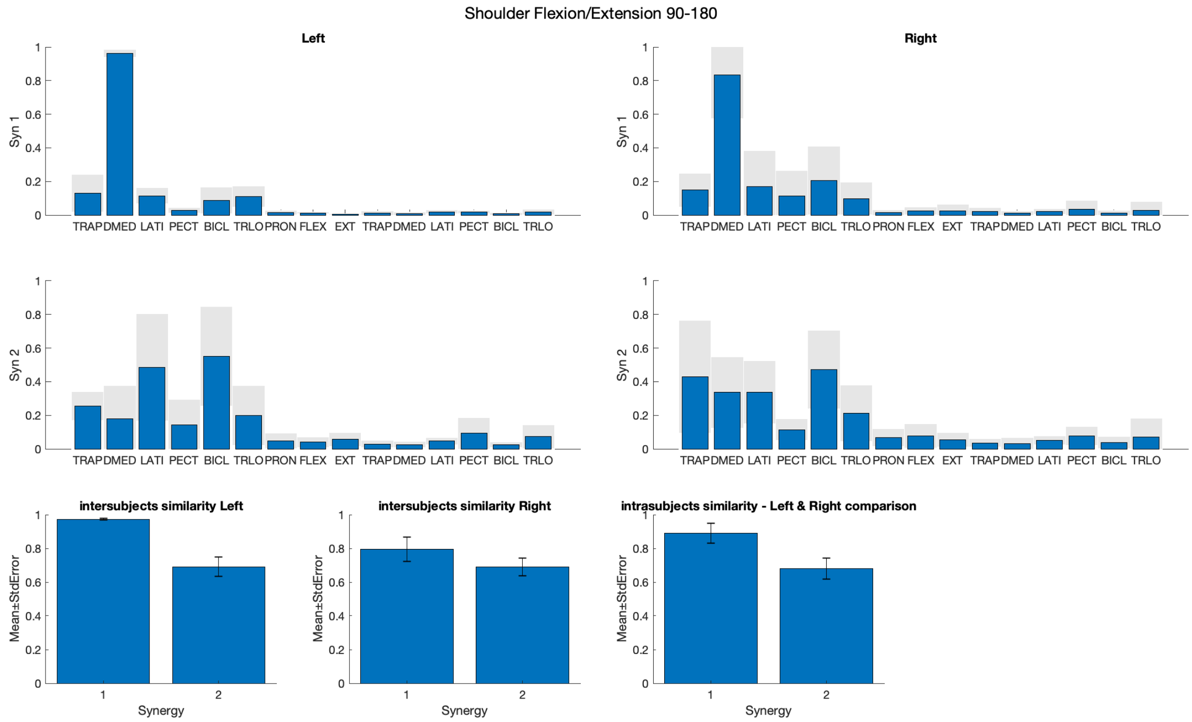


Figure 5.25: Muscle synergies of left and right arm in Shoulder Flexion/Extension 90°-180° task; similarity inter-subject and intra-subjects using the DOT product.

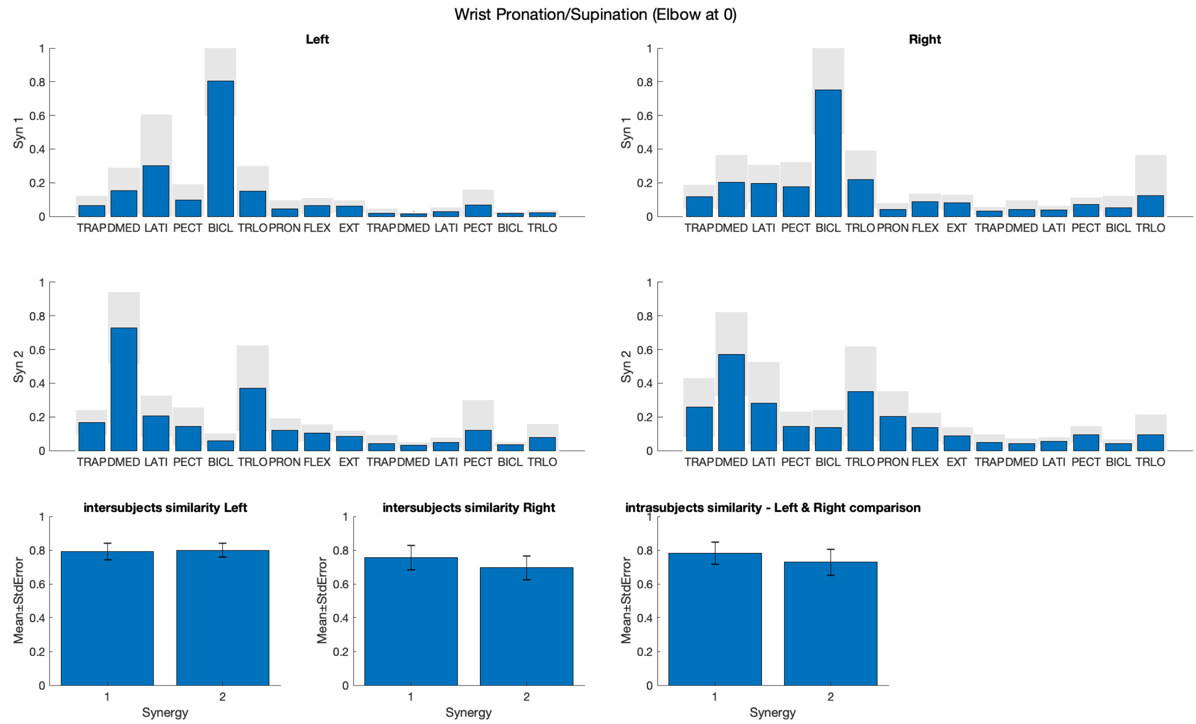


Figure 5.26: Muscle synergies of left and right arm in Wrist Pronation/Supination (Elbow at 0°) task; similarity inter-subject and intra-subjects using the DOT product.

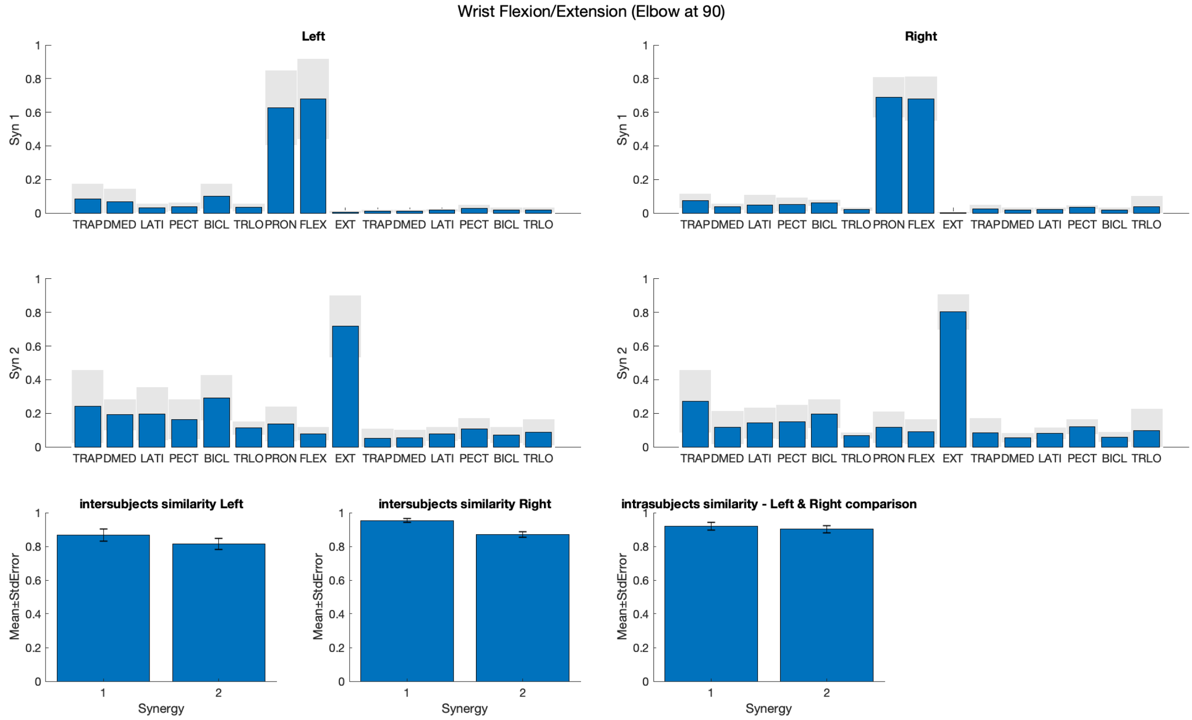


Figure 5.27: Muscle synergies of left and right arm in Wrist Flexion/Extension (Elbow at 90°) task; similarity inter-subject and intra-subjects using the DOT product.

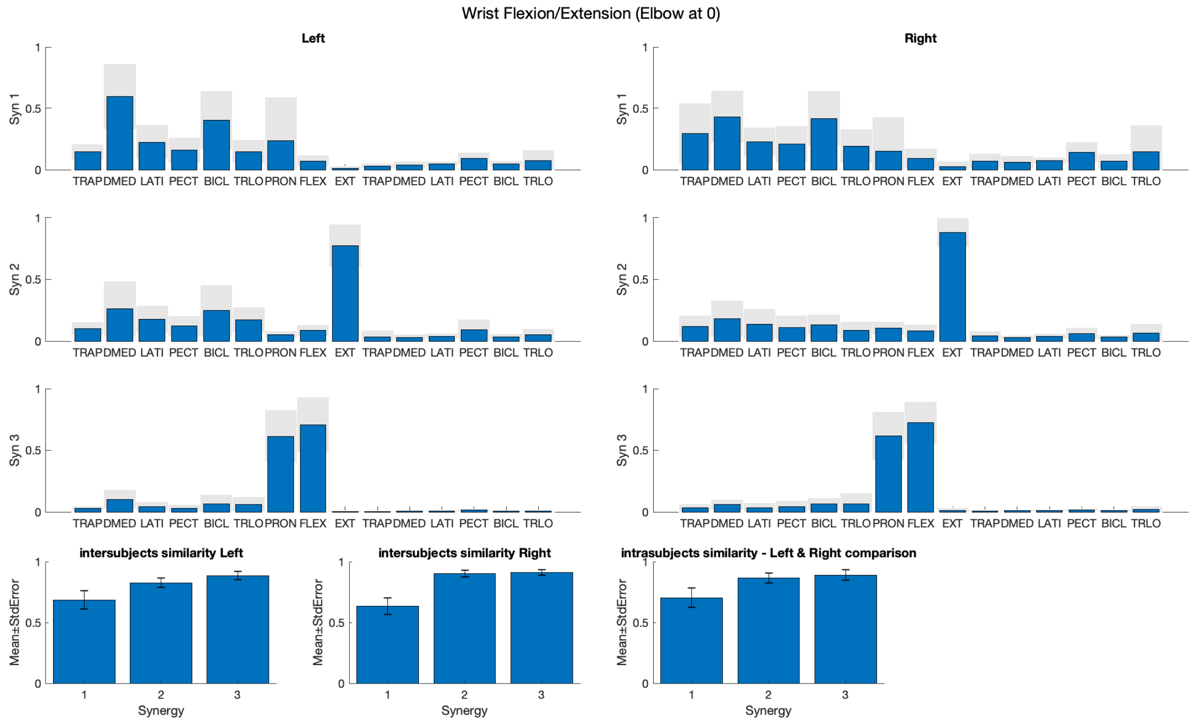


Figure 5.28: Muscle synergies of left and right arm in Wrist Flexion/Extension (Elbow at 0°) task; similarity inter-subject and intra-subjects using the DOT product.

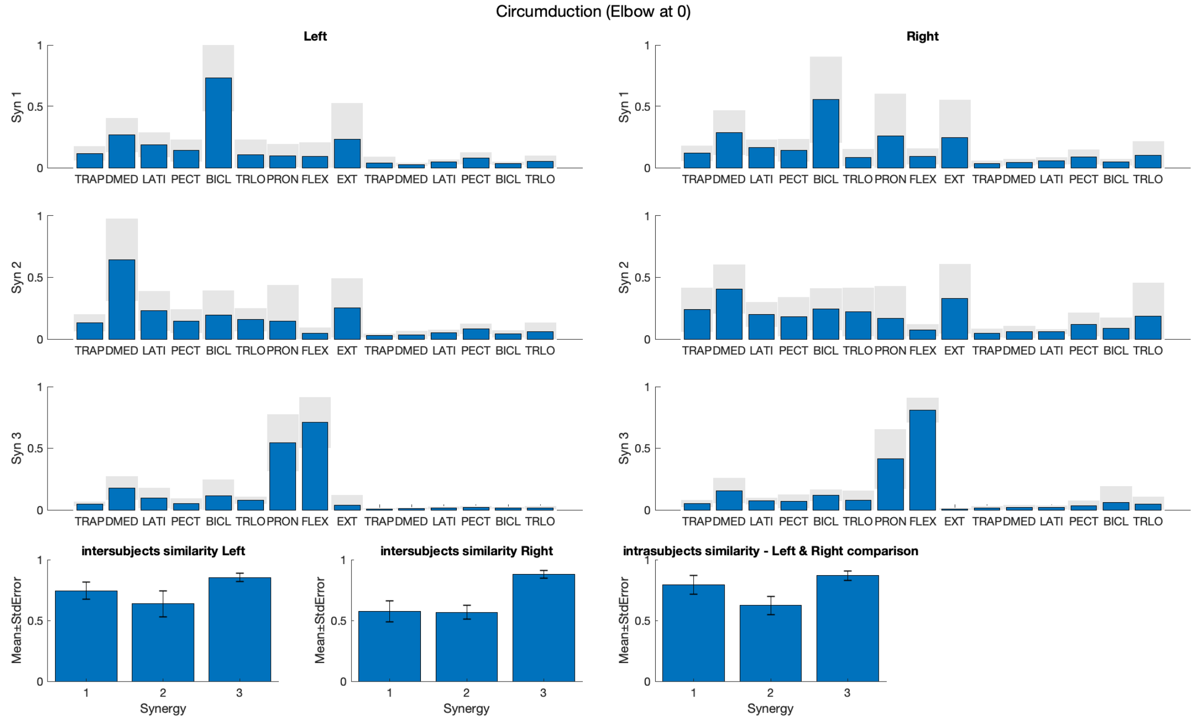


Figure 5.29: Muscle synergies of left and right arm in Circumduction (Elbow at 0°) task; similarity inter-subject and intra-subjects using the DOT product.

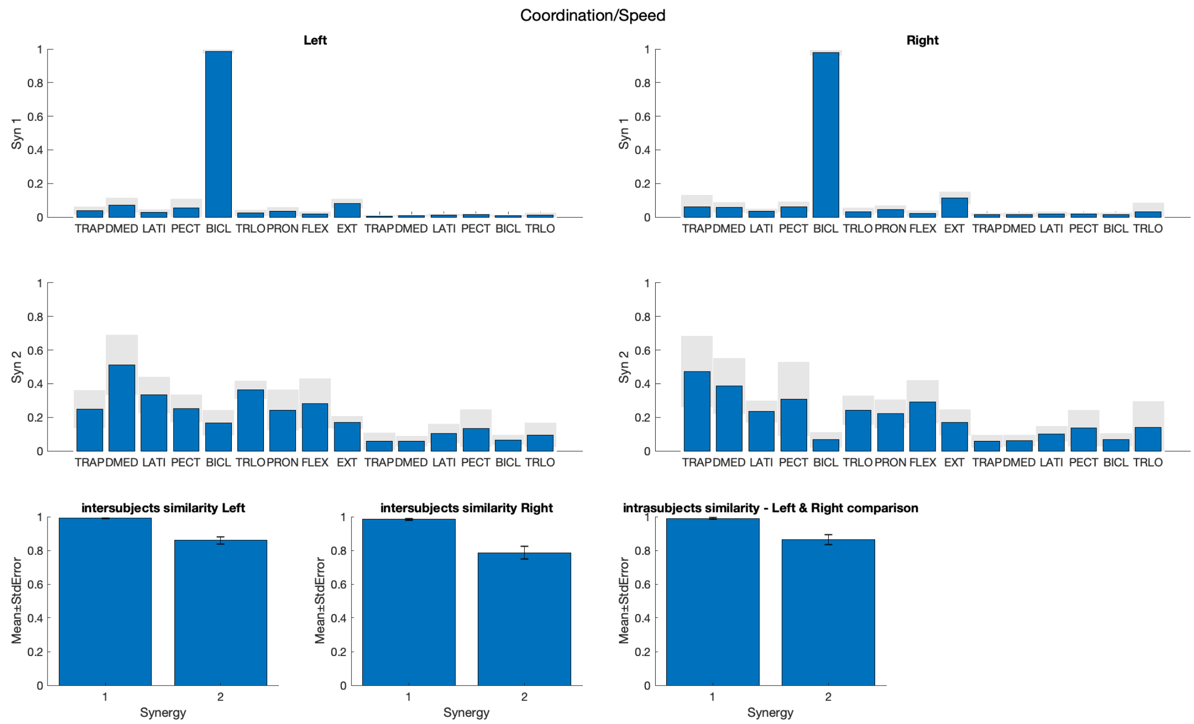


Figure 5.30: Muscle synergies of left and right arm in Coordination/Speed task; similarity inter-subject and intra-subjects using the DOT product.

Chapter 6

Conclusion

This thesis had the aim of searching a set of parameters for qualitative and quantitative analysis of upper limb motor function for stroke subjects, using inertial measurement unit and the elettromyography. Since the clinical scale was affected to subjective evaluation, time consuming, and less accurate, wearable technologies and mathematical techniques permitted to create a new tool able to assess the motor performance of stroke subjects in objective way.

In the past, other studies implemented and provided automative assessment not only in the field of stroke, but also in other pathologies such as Multiple Sclerosis or Alzheimer. The feature extraction from movements is a common steps used in the previous studies, and other used machine learning algorithms to test classifier, and to give in output the scores. Some previous works used a lot of IMU sensors to reach the purpose, but other supported that also with one inertial measurement unit on the wrist can retrieved parameters to assess the movement. In the market several companies produced IMU sensors, and in this study Xsens experimental setup was used. Although this sampling system is efficient and accurate, probably for stroke patients is not the best one. Indeed, the placement of all sensors on the subject's body is not so easy, and if a subject is very large, there is no possibility to fix the system on the subject. Furthermore, the unit placed on hand and wrist, while performing a flexion of wrist, collided each other not allowing the complete flexion of wrist. Maybe, in the future, IMU sensors smaller can resolve the problem, and they are also useful when the sampling system is used in combination with the EMG system.

The segmentation of the speed profile was the hardest part of the work, since it was difficult to compute. The speed profile was not always clear and with the right number of peaks. Although an algorithm was coded to reach this purpose, sometime the change of the parameters of the algorithm was time consuming.

The experiment was conducted on ten healthy subjects, performing twelve motor tasks of FMA-UE. The metrics obtained on kinematic data permitted to retrieve qualitative parameters, represented in the end-point space, and quantitative parameters, represented in the joints space. The healthy population was chosen with the same age, although a higher number of left-handed subjects would be the better choice in order to not have a population with the same dominance. In the future a population with higher age, or a population with different age can provide complementary results to these obtained in this study.

About the analysis of EMG, this can be considered as the mainly part of the work. The muscle synergies extracted from the tasks provided which muscles are involved during the execution of the movement. Comparing this synergies with those obtained from stroke patients, if a stroke subject has synergy with muscle intensity lower, the rehabilitation can be focus on that specific muscles in order to re-establish the motor function of the muscle. For EMG data analysis, maybe the extraction of other parameters more than the RMS, can provide other information about the muscle involed in the motor performace.

Although some limitations of this work, a set of parameters presented in this study can automate and assess the upper limb motor function of stroke patient, giving a valid and objective tool to clinicians.

Appendix A

Even if the segmentation of the signals was not the principal aim of the thesis, it had an important role since each value metrics obtained was strongly correlated to time instant of starting and ending of the movement. The shape of joint angle was useful to correct and check the segmentation. Indeed, since the detection of peaks of velocity speed profile was difficult to compute, sometimes the algorithm detected wrong peaks of the velocity, bringing to consider wrong movements or to switch the going movement with the end movement. The signal associated to the shoulder angle of the left and right was useful to check the tasks Hand to lumbar spine, Shoulder Flexion 0°-90°, Shoulder Flexion 90°-180°, and Shoulder Adduction 0°-90°. The signal associated to the elbow angle was useful to check the tasks Flexor synergy, Extensor synergy, Circumduction, and Coordination/Speed. The signal associate to the wrist angle was useful to check the tasks Wrist Pronation (Elbow at 90°), Wrist Pronation (Elbow at 0°), Wrist Flexion (Elbow at 90°), and Wrist Flexion (Elbow at 0°). The results of the left arm are reported in Fig A.1. For example, a wrong segmentation of velocity speed profile of Flexor synergy of subject 9 while he performed the movement with the left arm, brought to consider wrong time instant of going and ending movement as can be seen in Fig A.2(a); after the correction of the segmentation the shape of the shoulder angle underlined that the segmentation was successful, as can be seen in Fig A.2(b).

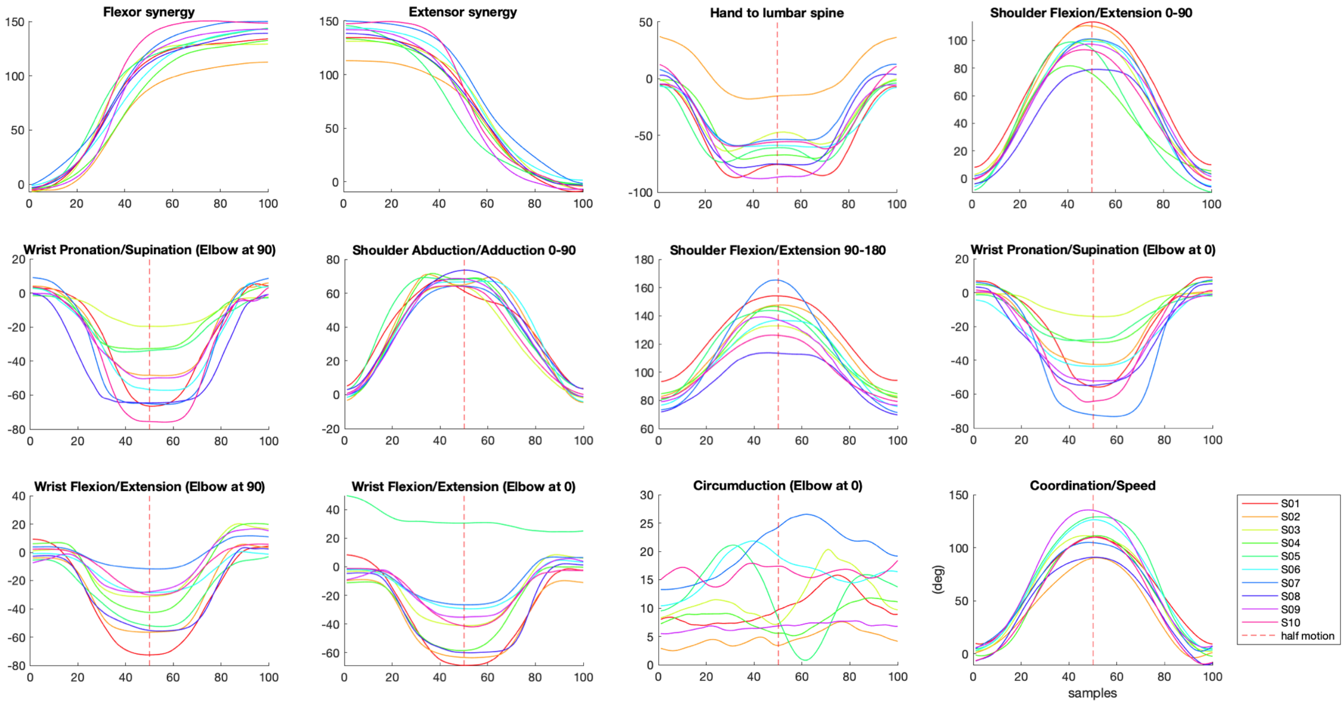
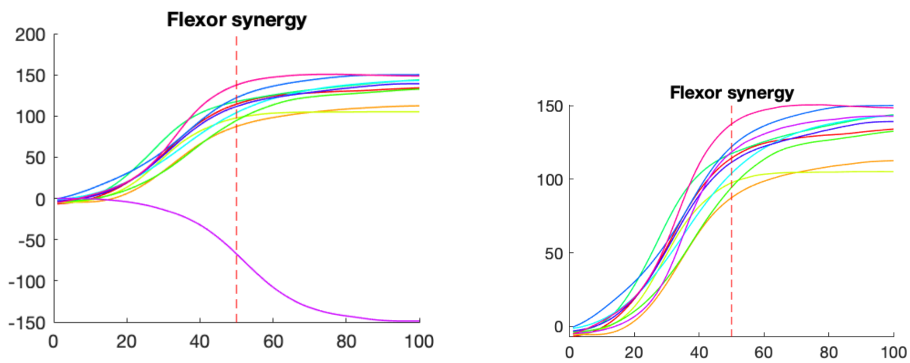


Figure A.1: Joint angle of shoulder, elbow or wrist depends on the task. The averaging the of five repetitions of the movement is showed, all subjects are compared.



(a) (b)

Figure A.2: (a) Shoulder angle in Flexor synergy task with the left arm after wrong segmentation of velocity speed profile.; (b) Shoulder angle in Flexor synergy with the left arm after with a correct segmentation of velocity speed profile.

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