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A new approach for quantitative assessment of upper-extremity impairment in post-stroke patients using wearable sensors: a pilot study

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Abstract

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by Francesca SALIS

Stroke is the second leading cause of death in Europe and the leading cause of long therm disability. With the decrease in deaths rate, the number of stroke survivors is growing up and a good post-stroke rehabilitation plan is fundamental for regaining autonomy.
Before starting rehabilitation, it is necessary to assess motor function impairment and this is done using clinical scales. In particular Upper-Extremity Fugl-Meyer Assessment is the most used for stroke patients in case of upper limb motor deficits. However, this scale is clinician-dependent, the evaluation is qualitative, gives only partial information and has only poor sensitivity to mild impairment.
For those reasons, in this thesis a new approach for quantitative assessment of upper-extremity impairment in post stroke-patients is proposed. XSens Awinda and Myo armband systems were used for testing a total of 11 tasks from the Upper Extremity Fugl-Meyer Assessment scale. Two experiments were performed, the first one involving 9 healthy subjects and the second on one stroke patient.
A complete analysis was performed on kinematic data (XSens used on all the 10 subjects) and several parameters were extracted: some of them were deriving from a single segment, while Correlation Coefficient estimation and PCA were done using data from several joints.
An exploratory analysis was executed on EMG data, since recording with Myo armband was performed on only 3 healthy subjects. Also in this case, several metrics were chosen, including RMS value, Correlation Coefficient and PCA.
Results obtained suggest that the selected parameters can lead to a more complete description of impairment, since they are able to capture differences between stroke and healthy subjects. Moreover the evaluation obtained is quantitative, clinician-independent and more sensitive to mild impairment. It is a method which allows to consider the contribute of the entire upper body section, in order to identify possible compensatory strategies or abnormal synergies.
There are some limitations regarding the Myo armband, which only records data from forearm segment, the offline analysis and the fact that, for now, the system was tested on a single patient.
However, all those limits can be easily overcome in line with the future perspectives.

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List of Abbreviations

ANN	**A**rtificial **N**eural **N**etwork
ARAT	**A**ction **R**esearch **A**rm **T**est
EMG	**E**lectro **M**yo **G**raphic
FAS	**F**unctional **A**bility **S**cale
FMA	**F**ugl **M**eyer **A**ssessment
HDL	**H**igh **D**ensity **L**ipoproteins
IMU	**I**nertial **M**easurement **U**nit
LDL	**L**ow **D**ensity **L**ipoproteins
MS	**M**ultiple **S**clerosis
PCA	**P**rincipal **C**omponent **A**nalysis
PCs	**P**rincipal **C**omponents
RMS	**R**oot **M**ean **S**quare
SVM	**S**upport **V**ector **M**achine
SVR	**S**upport **V**ector **R**egression
UE-FMA	**U**pper **E**xtremity **F**ugl **M**eyer **A**ssessment
UE	**U**pper **E**xtremity
VAF	**V**ariance **A**ccounted **F**or
WMFT	**W**olf **M**otor **F**unction **T**est

Chapter 1

Introduction

In this Chapter, stroke disease is introduced with its definition, risk factors and consequences. In the second paragraph the dimension of the problem is defined reporting some statistical evidences. The third paragraph is about stroke treatment, focusing on post-stroke motor rehabilitation. The fourth paragraph deals with upper-extremity impairment, i.e. the nature, functional consequences of this kind of impairment and its assessment, with an overview on clinical scales. Then, the aim of the thesis is presented in the last paragraph.

1.1 Introduction to Stroke

In order to contextualize the problem, it is important to understand what is stroke, the risk factors which lead to that disease and the main consequences according to the National Institute of Neurological Disorders and Stroke [1].

1.1.1 What is Stroke

Stroke (also called "cerebral attack") happens when, due to the obstruction of a blood vessel or to its breakage, cerebral cells stop receiving oxygen and nutrients for a prolonged period of time such as to cause their damage or death. When brain cells stay for a long time without their oxygen and nutrients supply because of an inadequate blood flow, they are damaged and is called Ischemia; when this condition is prolonged, cells die and are replaced by a cavity filled with fluid, the infarct. Death cells cannot be saved, while for ischemic cells it is possible to obtain a recovery only with an early treatment [1]. There are two forms of stroke, distinguished by the trigger.

Ischemic Stroke

Ischemic stroke [1] occurs when a blood vessel in charge of carrying blood to the brain is obstructed. This event leads to a lack of perfusion that results in infarction if prolonged. Vascular occlusion may basically depend on two phenomena:

- the abnormal formation of blood clots which hinder the correct flow, in particular the cases are the following:
  - A blood clot is formed on the wall of a vessel which is far from the brain, but at a certain point it comes off and is transported by the bloodstream until it reaches a cerebral artery, causing the occlusion. In this case the clot is called embolus and the stroke is an embolic stroke.

  - A blood clot is formed in a cerebral artery and its dimensions are such that the vessel is closed. In this case the formation of a clot is called thrombosis and the stroke is thrombotic.

- the narrowing of the vessel itself, which can happen as a result of two events:
  - Stenosis is a narrowing of the vessel depending on the variation in mechanical properties and elasticity of the vessel wall due to repetitive stresses. Walls become weak and tend to collapse inward. If an excessive shrinking happens, the blood cannot flow correctly.
  - Vessel narrowing can also be caused by the formation of plaque or blood clots that alter the regular membrane morphology and so the bloodstream.

Hemorrhagic Stroke

Hemorrhagic stroke [1] occurs when a blood vessel near the brain breaks so that blood comes out in or around the brain. Under normal conditions blood does not come into direct contact with cerebral cells. The exchange of oxygen and nutrients is possible thanks to a high selectivity membrane, called blood-brain barrier. When a cerebral artery breaks, blood comes out from the vessel and comes in contact with brain cells leading to an alteration of chemical balance.
The breakage of a blood vessel can happen in two ways:

- The presence of an aneurysm, i.e. a localized bulge in the vessel, which constitutes a pocket where blood is stagnating. Here elasticity is altered, walls are weaker and thinner, so this part of the vessel is more sensitive to mechanical stresses. Aneurysm is asymptomatic till its breakage.
- The presence of a plaque that in the same way reduces the elasticity of the wall, so it makes higher the probability for the blood vessel to break.

1.1.2 Risk Factors

There are different risk factors [1] which can be classified as non-modifiable or modifiable depending on their origin. Basically risk factors associated to aspects like genetics, age, gender, race/ethnicity or family history are considered as non-modifiable factors, since they do not depend on a personal choice and some of them can only be monitored. On the other side, risk factor associated to a personal choice, for example regarding lifestyle, are modifiable. Most important risk factors are discussed in the following:

- Age: stroke affects people of every age for different causes, but stroke risk increases proportionally with increasing age. There are risk factors which have more importance in young adults, while other factors become decisive in older adults.
- Gender: men are most affected with respect to women, but less women are able to survive after a stroke. This can be due to the fact that life expectancy is higher for women, so they are affected by stroke in older age compared to men and their probability of survival is lower.
- Ethnicity/race: depending on the race there is a different risk rate. In fact, Afro-Americans result to be the population with the higher incidence of stroke, which is probably linked to genetic and environmental factors.

- Hypertension: this is the most important risk factor. An elevated blood pressure can cause stroke because turbulent flows promote the formation of blood clots, plagues, and they also alter membrane properties. Hypertension can be hereditary or it can depend on an unhealthy lifestyle. In case of young adults, men are more affected than women, while for old adults the trend is the opposite.

- Heart diseases: are the second mayor cause of stroke. In particular atrial fibrillation consists in left atrium having a beat up to four times faster than the rest of the heart. This disease leads to an augmented stroke risk since the bloodstream is disturbed. Influence of cardiac diseases increases with increasing age. Other heart diseases depend on malformations.

- Cholesterol: level of cholesterol in blood affects probability of having a stroke. There are two types of cholesterol in human body, the "good" one (HDL) and the "bad" one (LDL). High levels of LDL increase the risk because increases the probability of plaques formation. On the other side, low levels of HDL also increase probability of having stroke because this kind of cholesterol does not accumulate in arteries but is given back to the liver and is used for producing hormones and vitamin D.

- Diabetes: people with diabetes are more exposed to stroke risk because this disease contributes to other risk factors, for example the hypertension.

- Smoking: is the principal modifiable risk factor since it duplicates stroke risk. It is the direct stroke responsible in young adults more than in old adults. In particular smoking contributes to pathologies like atherosclerosis and plaques formation because it increases the fibrinogen level in blood. Moreover, in case of stroke, damages are more severe in smokers because vessels have worst elastic properties, weaker endothelium and they break easily.

- Alcohol: the excess of alcohol consumption is another risk factor, because leads to an increase in blood pressure. Despite this, some studies show that the moderate consumption of small amounts of alcohol protects from stroke risk, since it has an anticoagulant effect.

- Illicit drugs: use of drugs like cocaine increases the stroke probability because it affects other risk factors, such as cardiovascular diseases and hypertension, increasing the vasoconstriction. Other drugs like marijuana have the opposite effect of decreasing blood pressure. Others like heroin and anabolic steroids are vasoconstrictors.

- Neck and head lesions: sudden injuries of neck and head can cause arteries breakage and lead to hemorrhagic stroke. This is a frequent cause in young adults.

- Bacterial and viral infections: infections trigger a response of immune system that increases blood defences. This phenomenon leads to higher coagulation rates and so stroke risk is augmented.

- Genetic factors: those risk factors are linked to environmental factors, a sedentary lifestyle and unhealthy diet.

All the above listed risk factors were described according to [1].

1.1.3 Consequences of Stroke

Depending on the area of the brain affected by stroke, the consequences of this disease can be different [1]:

- Cognitive deficits derive from disorders of cognitive functions, which are attention, memory, perception, reasoning.
- Language deficits consist in having problems in understanding or forming speech, even in reading and writing (aphasia).
- Emotional deficits result in difficulty in expressing or controlling emotions. Many stroke patients suffer from post-stroke depression.
- Pain or numbness sensations.
- Motor deficits can consist in the complete paralysis of one side (hemiplegia) or one part of the body, depending on the extension of motor cortex area affected by stroke. Another type of motor deficit, less debilitating than paralysis, is one-sided weakness (hemiparesis).

In this work the attention will be focused on the motor deficits.

1.2 Dimension of the Problem

According to the European Heart Network [2] the key statistics about stroke incidence and mortality in Europe are summarized in the following points:

- Stroke is the leading cause of long-therm disability in Europe.
- Stroke is the second leading cause of death in Europe. Each year there are 405,000 deaths in men (9%) and 583,000 (13%) deaths in women.
- Also in European Union, stroke is the second cause of death. Each year there are 176,000 deaths in men (7%) and 250,000 (10%) deaths in women.
- In Europe, Stroke is the second single cause of mortality in women (137,000 deaths) and the third in men (183,000 deaths) under 75 years.
- Stroke is, with breast cancer, the most common cause of mortality in women under 65 years (51,000 deaths) and the third in men (90,000).
- Age-standardised death rates for stroke are higher in males than in females for all European countries. Death rates are higher in Eastern and Central regions than in Northern, Southern and Western regions.
- Declines in age-standardised mortality rates for stroke are occurring since the 1980s, mainly in Northern,Southern and Western European countries. More recent decreases have been registered in Central and Eastern regions.

1.3 Stroke Treatment

Therapies available for stroke include medications, surgery or rehabilitation [1]. Stroke treatment can be divided in three stages:

- Prevention of new or recurrent stroke consists in getting under control risk factors, such as cholesterol, hypertension, diabetes, heart and vascular diseases. Since one of the causes of ischemic stroke is the occlusion of a cerebral artery due to blood clots, drug therapy is the most common type of treatment. Antithrombotics and thrombolytics are used for reducing blood-clots formation. Also surgery can be used for preventing stroke.

- Treatment immediately after a stroke can be done using strong drug therapies in order to dissolve the blood clot and stop the stroke. In the same way, surgery can be used for repairing vascular damages in case of hemorrhagic stroke or for treating acute stroke.

- Post- stroke treatment consists in rehabilitation for recovering deficits caused by the disease. Depending on patient's deficits, the therapy plan is personalized according to his need. Occupational therapy (OT) focuses the attention on the relearning of everyday activities, important for regaining the independence or semi-independence. Speech therapy is fundamental in case of language deficits, while Psychological therapy is necessary for supporting the patient and the family in dealing with post-stroke condition. However, the basis of rehabilitation plan for the main part of post-stroke patients is physical therapy (PT), which aims to regain the ability of performing simple motor activities in case of motor deficits.

Physical rehabilitation in post-stroke phase is a very important topic, since the decrease in stroke deaths leads to a greather number of stroke survivors that need an effective rehabilitation plan.

1.4 Upper Extremity Interventions

The status of a post-stroke patient is defined by the kind of impairment which affects the subject itself. Defining and understanding this condition is fundamental for successive evaluations about the treatment and rehabilitation process [3].

1.4.1 Nature of the Impairment

Stroke can lead to two types of motor impairment:

- Body functions impairment, i.e. the loss in functional abilities related to muscular tone, involuntary movements, muscles power and joint mobility;

- Body structures impairment, i.e. the deviations in structure related to movement or in some nervous system structures.

Post stroke upper limb impairments result in functional limitations in the use of the affected arm itself. However, patients affected by stroke show a non-static impairment and multiple impairments can be present simultaneously. For this reason, it is fundamental to well understand the impairment degree of a patient to plan the correct treatment [3].

1.4.2 Functional Consequences of the Impairment

According to Raghavan et al. [3], functional consequences of impairment can be the following:

- Learned non-use. Due to paralysis or sensory loss, many patients stop using the affected arm right after stroke. The problem is that it can become a habit even if the subject is able to move its arm, leading to obvious limitations in functional activities. Since it is a learned behaviour, it is called learned non-use.
- Learned bad-use consists in the adoption of compensatory strategies which substitute the normal movement. This can be due to pain, sensory loss or weakness, so that the patient starts computing certain movements through an abnormal strategy. The problem in that case is the loss in accuracy and the increase of failure probability, even if the patient is initially able to complete the task.
- Forgetting is very common in post-stroke patients when breaks in rehabilitation occur. In fact, they tend to forget upper extremity exercises after intervals of no training and so, new skills learning in stroke subjects is more difficult to achieve.

1.4.3 Assessment of the Impairment

Assessment of upper extremity functions is necessary for clinical decision making and it is also an instrument to monitor progresses made by the patient [4]. In accordance with Lang et al. [4], measures used by clinicians can be divided in two groups:

- Performance measures, where the clinician evaluates several tasks computed by the patient giving a score.
- Self-reported measures, i.e. the functional ability of the patients is evaluated by the clinician with a number of questions answered by the patient or by proxy.

The attention is focused on performance measures, that are executed using the clinical scales as tool for the evaluation. There are several clinical scales used for assessing post-stroke condition:

- Wolf Motor Function Test (WMFT) consists of 15 timed items and 2 strenght items. The 15 items are evaluated according to the Functional Ability Scale (FAS), i.e. a score between 0 and 5 is given to each exercise for a total score of maximum 75 [5].
- Action Research Arm Test (ARAT) is a clinical scale used for the assessment of impairment after neural injuries, so it is not specific for stroke patients. It assesses the ability of grasping objects of different weight and size. Each movement is evaluated with a score ranging from 0 to 3 [6].
- Upper-Extremity Fugl-Meyer Assessment (UE-FMA) scale is the most used clinical scale for measuring motor recovery post-stroke [7]. It is based on the method of sequential recovery of motor function described by Brunnstrom, who states that recovery proceeds in proximal-to-distal direction and going from synergistic to isolated movements [8]. The UE-FMA consists of 33 exercises divided in three main sections: motor function, sensation qualities, passive range of motion and joint pain. A score between 0 and 2 is assigned to each exercise. Zero is used when the task is not performed at all, 1 corresponds to a partially executed task and 2 indicates the complete execution of exercise. The

total score for upper extremity goes from a minimum of 0 (hemiplegia) to a maximum of 66 (normal motor performance) [9].

Since it is the most used in case of stroke patients, attention is focused on Fugl-Meyer Assessment scale.

1.4.4 UE-FMA limitations

Even if the FMA is stroke-specific, there are several limitations linked to the evaluation obtained:

- Clinician-dependency. The evaluation depends on the observer who gives the score and so it has an high subjective component [10].
- Qualitative evaluation, because it is based on the observation of the movement and not on experimental measures.
- Partial description of the patient condition, since it is reduced to a single number. Moreover, the FMA is an impairment index, so how it is related to disability is not determined completely [11].
- Poor sensitivity to mild impairment, linked to the small range of the scale [12].

For the above listed reasons, the use of wearable sensors can provide more quantitative information to be used for the evaluation of functional ability.

1.5 Aim of the thesis

Starting from the limitations of Fugl-Meyer Assessment, the aim of this thesis was to find a complete set of parameters for the quantitative assessment of impairment in post-stroke patients using data obtained with wearable sensors during the performance of FMA items. This new approach can lead to the following advantages:

- The evaluation obtained is objective, since it depends on parameters obtained from the signals recorded.
- The assessment made is quantitative, since it is based on signal analysis.
- The parameters used give a more complete description of the impairment with respect to that obtained with scoring.
- The sensitivity to mild impairment is higher than that of clinical scales.

The work started with the research in literature, whose results are illustrated in Chapter 2. Materials and methods are illustrated in Chapter 3. Results are presented and discussed in Chapter 4. Chapter 5 includes conclusions and future perspectives.

Chapter 2

State of the Art

In this chapter the more important studies regarding the evaluation of upper limbs impairment are illustrated. Those are divided in three sections: automation of Fugl-Meyer Assessment scale, automation of other clinical scales (including WMFT,FAS and ARAT) and other works. In the first two sections are summarized the studies where the assessment of impairment in post-stroke patients is addressed as a classification problem. Several types of wearable sensors are used for extracting features and performing classification in order to obtain the score of the clinical scale as an output. The studies described in the third section are more focused on the quantitative assessment made by a set of paramenters, also in this case obtained from data extracted using wearable sensors.

2.1 Automation of Fugl-Meyer Assessment scale

Some of the principal works regarding the automatic evaluation of Fugl- Meyer scores for upper extremity impairment are presented in the following.

In 2006 Hester et al. [13] proposed the use of wearable sensors for obtaining clinical scores in post-stroke patients. In this work twelve subjects participated and their condition was assessed by a clinician before starting the experiment. Accelerometers were positioned on the affected arm and the trunk. Vitaport3 ambulatory recorder was used for recording signals during the performance of several tasks selected from clinical scales including FMA and WMFT. Each task was repeated between 10 and 20 times. Data were filtered and then segmented through the use of markers. Then a series of features was extracted from each epoch, including mean value, root mean square value, RMS of jerk, approximate entropy. Features were imported in WEKA and linear regression models were built for understanding which features were the most useful for predicting the clinical scores. Features were selected by the M5 method, obtaining a set of features for each clinical score. Then linear regression models were rebuilt in Matlab using leave-one-out method. Results showed that the models were more efficient in predicting the shoulder and elbow portion of Fugl-Meyer scale,obtaining relative errors around 10%, while they were less efficient in predicting scores of other clinical scales [13].

Based on previous study, in which wearable sensors data were used for estimating FAS scores from items of WMFT [13, 14],in 2011 Del Din et al. [15] verified if the same dataset could be used for estimating Fugl-Meyer scores. Data were collected in the previous work using wearable sensors during the performance of a series of tasks from WMFT. A total of 24 subjects participated to the study: they were evaluated by a clinician for the 15 tasks of WMFT but sensor data were collected for only

8 tasks using six accelerometers positioned on the trunk and the affected arm. Vitaport3 system was used for data recording. Each task was repeated between 5 and 20 times. Segmentation was performed to isolate the repetitions and then several features were extracted. Feature selection was done in WEKA environment using a ReliefF algorithm. Last step was the determination of FMA scores using Random Forest method. Results showed that FMA scores can be determined using data obtained from the performance of WMFT items [15].

In 2014 Olesh et al. [16] proposed the use of Kinect Sensor for obtaining kinematic data and quantifying upper extremity impairment in post-stroke patients with automated clinical scoring. A total of 9 patients participated to the experiment, consisting in the performance of 10 different tasks from FMA and ARAT. Each exercise was repeated several times while recording with Impulse (standard system), Kinect Sensor (low-cost system) and a video camera for human raters. Matlab environment was used for data processing and the following joint angles were calculated: Shoulder flexion/extension, Shoulder abduction/adduction, Elbow flexion/extension, Wrist flexion/extension (Figure 2.1).
The minimum number of repetitions giving accurate motion was chosen. Principal Component Analysis was performed using joint angle data from unaffected arm, in particular averaging repetitions of the same task. The number of principal components sufficient for explaining 95% of variance were selected and utilized for reconstructing joint angles profiles for the affected arm. The result was compared with the original joint angle profiles through the coefficient of determination. This coefficient is an index of impairment because it shows how well PCs from non-paretic arm represent movements of affected arm. The dimensionality reduction also reduces the sensitivity to noise of the system.
Movements were first rated by 30 students of physical therapy using Fugl-Meyer scale. A correlation coefficient was calculated for verifying reliability of the scores.
Linear regression model was used for comparing the low-cost system with the standard one and with the qualitative scores.
Comparisons showed that the use of a low-cost system such as Kinect is a valid method for automatically determine impairment scores reaching a certain accuracy [16].

In their work of 2014, Wang et al. [17] proposed a model based on Support Vector Regression (SVR) for automatically estimating FMA scores for the selected 4 tasks. A total of 24 stroke patients were evaluated by a clinician, then data were recorded on them during the execution of the tasks. The WBSN (Wireless Body Sensor Network) system used for the experiment consisted of two triaxial accelerometer nodes and one receiving node, one system was attached to the upper arm and one to the forearm. Every subject repeated each task five times and all recordings were put together in a single dataset. After preprocessing, several features were extracted including statistical and physical features. Then feature selection was applied using a ReliefF-SVR system. The ReliefF algorithm was implemented on WEKA for ranking features according to importance and then SVR was used with the first N features. Several SVR models with different number of features were built and compared between each other to find the optimal number of features, that resulted to be 14. The single-task model with 14 features was obtained applying two different kernels (RBF and polynomial) for evaluating the differences. The last step was the construction of a comprehensive model including information about all the tasks.

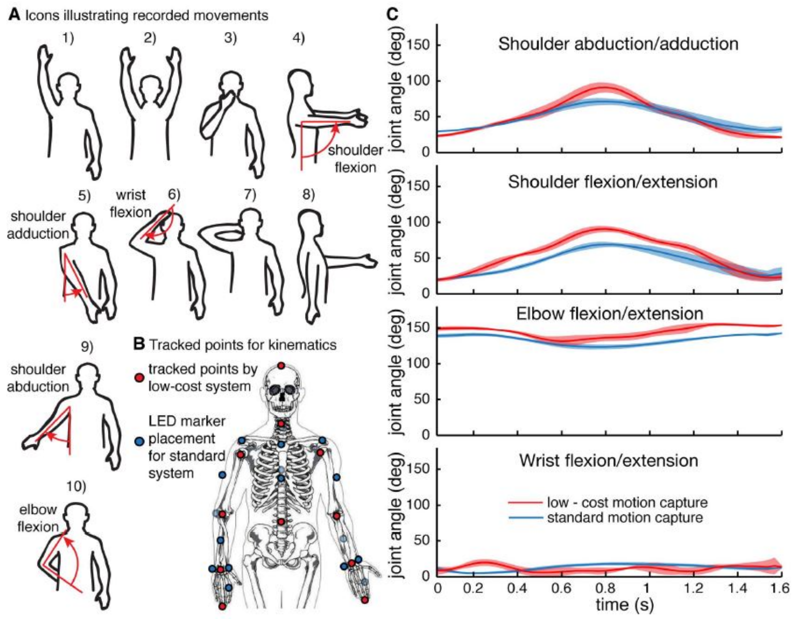

FIGURE 2.1: Olesh et al. A-Movements performed B-Markers positioning C-Joint angles. Adapted from [16]).

This model was compared with single-task models using leave-one-out cross validation method. Here the data of 23 patients were used as training set and those of the remaining subject as test set. Comprehensive model resulted to be better than the others [17].

Otten et al. in 2015 submitted a method for automatically estimating Fugl-Meyer score for 24 of the 33 upper extremity exercises of that scale [18]. The system used included three sensors:

- Kinect for motion capture
- Shimmer inertial measurement unit and/or Glove sensors (flexion sensors and IMU sensors) for having information about hand/fingers movement, since Kinect is not able to give them
- Pressure sensor for measuring grip strength

In fact, using only the Kinect, it could not be possible to discriminate movements such as pronation/supination, circumduction and dorsiflexion of the wrist. Each sensor was driven with a separate program, in order to automatically start or stop the recording and obtain the data. Data were acquired and then pre-processed. Then feature extraction was performed with a different routine for each task, because they have different requirements, even if some movements have features in common. Each device used in the system gives some features. The Kinect gives joint angles and limb orientation; IMU give information about pronation/supination; the glove gives fingers flexion/extension depending on the movement; pressure sensor gives the maximum grip strength. The features extracted were the imput of the classification algorithm. In this case, both SVM and BNN algorithms were implemented for chosing the best one. The system was first tested on eigth healty subjects, who performed each movement three times, one for each score of the FMA (0 movement not performed, 1 partially performed, 2 completely performed) in order to have all possible cases. Five training examples for each test were used, for a total of 15 training examples per test. This procedure was followed for every subject. Then the system trained with healthy subjects dataset was evaluated on a stroke subject and the results were compared with the scores given by a clinician. The BNN algorithm resulted to have higher accuracy than SVM but the difference was not statistically significant. The next experiment with two stroke patients was executed only using the SVM classifier and in this case the accuracy was very low. This can be due to the fact that the system has been tested on healthy subjects [18].

Yu et al. [19] proposed the use of wearable sensors for automatically estimating FMA scores in non-clinical settings. The system included two accelerometer sensors (one on the forearm and one on the upper arm) and 7 flexion sensors wrapped into a glove (Figure 2.2). The experiment consisted of:

- A clinical phase, in which 24 patients were evaluated using the system and also by two clinicians.
- A home setting phase, where only 5 of the 24 patients participated.

Data were recorded during the performance of 7 tasks that, according to the author opinion [19], represent the 33 items of UE-FMA: shoulder extension, shouler antexion, forearm pronation/supination, wrist flexion/extension, lumbar touch, lateral pinch, finger touch. A software made by the same group was used for sampling and management procedures. After data recording, the following features were extracted: amplitude, mean, RMS value, ApEn, Jerk. In total, 7 ELM regression models per task were implemented, resulting in a high error between clinician and system estimation with no feature selection performed. For that reason, feature selection was made using RRelief algorithm, which led to a reduction of error, since FMA score estimated by the system was very similar to that given by clinician [19].

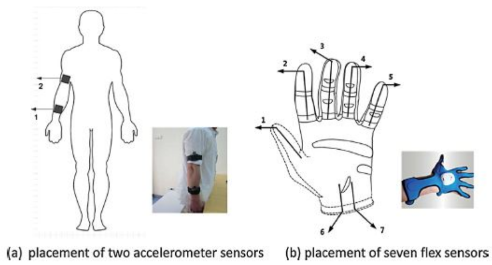

FIGURE 2.2: Accelerometers and Glove sensors used by Yu et al. Adapted from [19]).

Lee et al. decided to use Kinect v2 and force sensing resistors (FSR) for the automation of FMA [20]. The system was validated on a male healthy subject, who executed three exercises from Fugl-Meyer test: forearm pronation/supination, hand grasp, grasp with force. The experiment consisted of two parts: in the first one the subject had to compute each movement twice in the best way; in the second phase he had to compute each movement twice miming the condition of a stroke patient. Classification was based on joint-level motions. In fact, many FMA items can be evaluated relating to the value of the angle that specific joints assume while performing the movement, which can be obtained by the sensors. Lee et al. decided to translate this information in linguistic-like variables, thus leading to a fuzzy-logic classifier. The algorithm was based on a scoring table containing combinations of joint motion. The system was able to automatically estimate FM scores [20]. The same system was tested on 10 stroke patients in the following work in 2018 [21]. A total of 26 exercises from UE-FMA was executed. The level of accuracy obtained without considering subjects who did not follow the instructions intentionally was 85% [21].

The aim of the study made by Kim et al. in 2016 was to predict FMA scores using Kinect system and evaluating the accuracy of the estimate through a comparison with the scores given by a clinician [22]. Fourty-one hemiplegic patients participated to the experiment. Data were recorded during the performance of 13 tasks from UE-FMA. Both affected and unaffected arm were evaluated. Feature extraction was performed on the obtained data, in particular joint angles, distance between two joints, normalized jerk and the score given by the clinician were considered. PCA was used for dimensionality reduction and a different number of principal components was chosen for each task. ANN algorithm was applied for predicting the scores, using the features as input and performing 8/10-fold cross validation. The obtained scores were compared with the scores given by the clinician for each task using Pearson's correlation coefficients. The same comparison was done considering the total score. Another evaluation was done on jerky scores (normalized jerk). Results showed an accuracy above 70% for nine tasks and between 60% and 70% for the remaining four. Moreover jerky scores allowed to make a quantitative evaluation on smoothness [22].

In the work of Julianjatsono et al., score for 6 items of FMA was automatically obtained using data from Kinect Sensor and Glove Sensor [23]. A total of 7 healthy subjects participated to the study. The experiment included the execution of six exercises from FMA at least three times for each score (simulating the three possible conditions). Different raw data were considered depending on the type of movement and partitioned. Then the following features were extracted: mean, variance, minimum value, maximum value, normalized jerk according to [22]. Five regression algorithms for predicting scores were tested using 10-fold cross validation. Performance was evaluated through Pearson's correlation between the score and the kinematic features. All systems were able to return the scores with high accuracy but the best one resulted to be the Neural Network [23].

2.2 Automation of other clinical scales

In this paragraph, some studies regarding the automation of other clinical scales used for evaluating upper extremity impairment are described.

In their work of 2006, Knorr et al. [24] proposed the use of accelerometer sensors for recording signals from the affected side of the body during the performance of a subset of tasks from Wolf Motor Function Test. Eight post-stroke patients with upper limb hemiparesis participated to the study and accelerometers were positioned on hand, forearm and upper arm. Accelerometer signals were recorded using Vitaport ambulatory digital recorder. After filtering and segmentation processes, feature extraction was performed. In particular, two linear parameters and one non-linear parameter were considered:

- RMS value of accelerometer data

- RMS value of the derivative of accelerometer data (jerk)
- Approximate entropy (ApEn) of accelerometer data

Several linear regression models were built for each task, three of them were used for proving the efficiency of selected features in predicting the Fugl-Meyer scores differences among patients; the other three were used for the FAS scores. For each model, six independent variables were used. The high accuracy of the analysis performed using linear regression models showed that the features extracted from accelerometer data contained the information about post-stroke condition of that specific patient. Moreover, features obtained from distal segments showed a better correlation with clinical scores than those from proximal segments [24].

Roy et al. in 2009 [25] proposed the use of sEMG and ACC sensors to monitor 11 activities of daily living (ADL). In this case there was not the determination of an automatic score but only the recognition of those specific activities in stroke patients. Ten post-stroke patients participated to this experiment after being evaluated through FMA. The system used for recording included 8 sEMG electrodes plus one reference electrode and eight miniature uniaxial accelerometers. Pairs of sEMG and ACC sensors were placed near one another over eight different anatomical sites. Data were acquired during the performace of the 11 tasks. In particular, tasks consisting in repetitive actions were executed continuously for 1 min, while the other tasks were repeated 15 times. The next step was feature extraction from sEMG and ACC signals after preprocessing. An artificial neural network was implemented for associating the features with the identification tasks and the best configuration was choosen after testing four different topologies. The ANFIS (Artificial Neuro-Fuzzy Inference System) was built for evaluating the output of the chosen neural network in order to distinguish identification tasks from non-identification tasks. The output of ANFIS was included between 0 and 1 (0 identification task, 1 non-identification task) and a threshold equal to 0.65 was imposed to discriminate the two types of task. Classification performance was evaluated calculating sensitivity, specificity and misclassification. Optimization of classifier was performed comparing the ones obtained using both sEMG and ACC, only sEMG, only ACC. The only system with low sensitivity resulted to be the one using only sEMG data, suggesting that those information may not be sufficient for discriminating the tasks considered [25].

Patel et al. in 2010 [14] focused their attention on the automatic estimation of Functional Ability Scale scores using data collected with accelerometer signals during the performance of a subset of tasks from that clinical scale. Twenty-four subjects participated to the study and were evaluated by a clinician for 15 tasks, while data recording was performed only for 8 of them. Each task was repeated between 5 and 20 times. Accelerometers were positioned on upper arm, forearm, hand and trunk (Figure **??**). Recording was performed using Vitaport3 ambulatory recorder. Data were segmented using digital marks and then features extraction was performed for a total of 8 features. Each repetition was considered as a single observation and features relative to repetitions of the same task were put together in a unique dataset, obtaining in this way one dataset for each task. The next step was feature selection performed using WEKA implementation of ReliefF algorithm for ranking the features in decreasing order of importance in order to select only the first 20 features. The FAS scores were estimated using Random Forest in WEKA environment. A linear equation was implemented for calculating the total FAS score. According to the results, dominant features were the mean value of low-pass filtered data and the correlation coefficient of pairs of accelerometer time series. Moreover, features deriving from distal segments were extracted more often than those deriving from proximal ones [14].

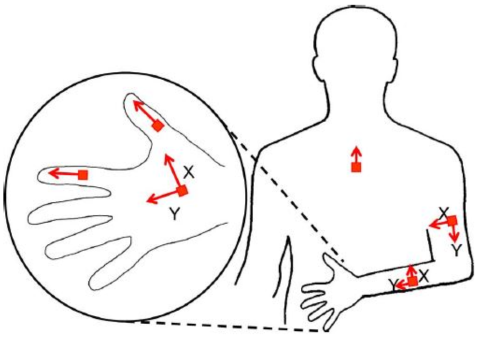

FIGURE 2.3: Placement of accelerometer sensors - Patel et al. 2010. Adapted from [14]).

In their study of 2010, Parnandi et al. [26] used one on-body IMU for estimating automatically Functional Ability scores of WMFT. The most relevant aspect is that the authors decided to use a gyroscope with the accelerometer in order to determine the scores, since the use of this kind of sensor had not been deeply investigated for post-stroke applications. For that reason an IMU sensor was chosen and positioned on the wrist of the subject. The sensor contained an accelerومenter, three gyroscopes and one magnetometer. The Gumstix-Wifitix was used as wearable central controller and Player as software for system control. Only one post-stroke patient participated to the experiment and WMFT tasks were performed with the assistance of an expert clinician. Data were then processed and used for extracting statistical features to determine the scores through a naive Bayes classifier. The list of extracted features is shown below (Figure 2.4). Both unaffected and affected arm were evaluated: in particular, for obtaining scores of affected arm, the features were normalized by dividing them with the corresponding features of unaffected arm and then used for classification. In this work also spectral analysis was performed and results show that PSD can be a function of motor capabilities, since different functional abilities are associated to different frequency bands [26].

	Features for classification
FAS	Kurtosis, Skewness, Mean, Variance Approximate Entropy, RMS of jerk, Power in $1.5-3$ Hz band, Power in $5-8$ Hz band, Time taken to perform the task

FIGURE 2.4: Extracted features - Parnandi et al. 2010. Adapted from [26]).

In 2012 Huang et al. [27] proposed the utilization of MSULS (Micro-Sensor-based Upper Limb rehabilitation System) for automatically measuring the Active Range of Motion scale. Motion capture units were attached to upper arm, hand, trunk and lower arm. Output data (acceleration, velocity and magnetism) were transmitted

to PC by Bluetooth for real time processing. 3D orientation for each segment was determined by the collected data and the full upper limb motion was derived based on a model considering the trunk as the root and the other segments as extensions. MSULS was able to extract AROM scale scores from data collected during the execution of 10 exercises from AROM scale itself. For each task the range of motion was evaluated and a certain task was valid only if stability conditions (depending on trunk orientation) during the performance were verified. The level of impairment was assessed through an index called LMF (loss of motor function): the larger the LMF value, the higher the impairment level. The following step was feature extraction from upper arm, forearm and hand, except for joint angles and balance. Feature selection was performed using L1-norm minimization learning algorithm; then validity and accuracy of those features was evaluated by a comparison with motor functionality measures achieved from FMA scale.
Twenty-two patients participated to the experiment. They were first evaluated by a clinician using FMA scale. Then feature extraction was performed. MFI were compared with FM scores in order to determine the correlation level between features values and motor impairment. Results showed an high correlation and also AROMs computed agree with the references. Other observations regarding the coordination index agreed with the results obtained by Cirstea and Levin [28], demonstrating that coordination indicates shoulder-wrist synergy, while NPL (Normalized Path Length) and PDE (Position Directional Vector) are linked to the movement control ability of the patient [27].

In the paper of Cruz et al. of 2014, a new portable system for automatically evaluating impairment was proposed [29]. It was realized using MARG (magnetic, angular rate and gravity) sensors, data were memorized in a SD card and sent via Bluetooth. The system included three blocks: an algorithm for obtaining the orientation of the body frame with respect to that of the earth frame combining information obtained by MARG sensors; human kinematic model; a part for the clinical evaluation. The device was designed for evaluating both the affected and unaffected sides. Each segment was associated to a 3D vector in the kinematic model with a specific length. The first assessment was done on the performance of 15 tasks of WMFT. Both paretic and non-paretic limb were evaluated. Each motor task from 0 to 5 was evaluated using an automatic decision tree with a series of five features described in the article, including jerk. Five patients participated to the experiment consisting in the performance of 5 tasks. The automatic estimation of the quantitative score was made by the system in real time. The results showed an high rate of agreement with the clinician [29].

The work of Zhang et al. in 2016 was based on the realization of a classification system for stroke patients rehabilitation, in order to recognize the exercises executed by the subject [30]. For that purpose, a single IMU sensor from XSens MTi-300 was positioned on the forearm, near to the wrist (Figure 2.5). Data were recorded on 14 stroke subjects during the performance of six upper limb rehabilitation exercises. For each patient, row data of acceleration, velocity and orientation were obtained along the three axis. Then the following features were extracted from those data for a total of 63 features:

- Mean
- Standard Deviation

- Duration
- Energy
- Dominant Frequency Power
- Dominant Frenquency
- Mean Power

PCA was implemented for dimensionality reduction before performing the classification. Data were normalized before classification process. A Fuzzy Kernel Motion Classifier (FKMC) was made and trained using a matrix were rows represent the feature vector. All the data collected from patients were included in the dataset even if movements were only partially performed. The system was evaluated with 10-fold cross validation method.Two datasets were used, one with data from 6 patients with higher Brunnstorm stages and the other one with data of all the 14 patients, in order to prove the dependence of system accuracy from quality of movement performance. Other classifiers were tested in the same conditions for making a comparison with the FKMC, which resulted to be the best algorithm [30].

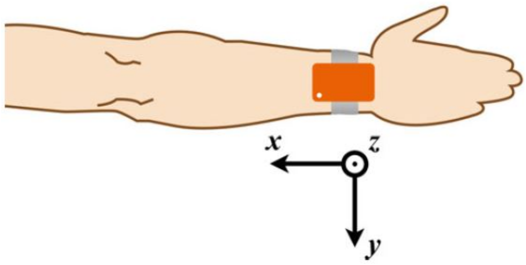

FIGURE 2.5: Xsens Sensor positioning - Zhang et al. 2016. Adapted from [30]).

2.3 Other works

The works presented in this paragraph are more related to the quantitative assessment using a series of features for making the evaluation more objective.

Carpinella et al. proposed the use of a single IMU (MTx, XSens) for a quantitative evaluation of upper limb impairment in subjects affected by Multiple Sclerosis [12]. Data were recorded during the execution of ARAT. A total of 21 MS patients and 12 healthy subjects participated to the study. Only the most affected arm was evaluated in MS patients. The performance of each task was scored with a 4 points scale by a clinician. The IMU was positioned near the wrist. Data analysis was performed starting with segmentation and then extracting the following parameters for each task for every submovement:

- Duration of the movement
- Jerk, calculated as the logarithm of the mean amplitude of first derivative of acceleration, normalized with respect to the duration and the mean absolute acceleration

- Z-score related to duration and jerk.

Those parameters were described by median/range values and analyzed by non-parametric statistical tests including Kruskal Wallis. Moreover, a cluster analysis was applied for identifying subgroups of MS patients with different levels of impairment starting from the scores given to evaluate the subjects in the preliminar analysis. The method was able to discriminate motor performances of MS patients from those of healthy subjects [12].

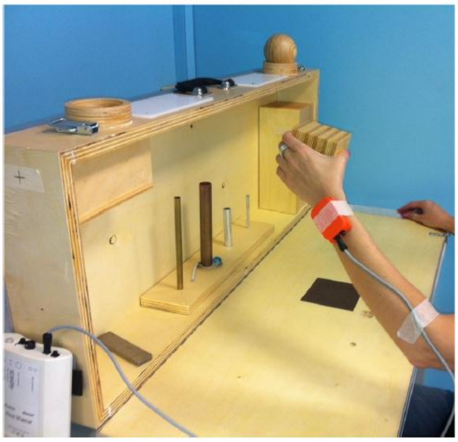

FIGURE 2.6: Xsens Sensor positioning in the experiment of Carpinella et al. 2014. Adapted from [12]).

In the work of Zhang et al. the aim of the study was the quantitative evaluation of impairment in stroke patients [31]. One wearable inertial measurement unit sensor, called MotionNode, was attached to the forearm of the subjects and used for signal recording. One healthy subject and 2 stroke patients participated to the study. Data were recorded during the performance of 5 tasks from FMA with the help of a physical therapist: flexor synergy, hand to lumbar spine, shoulder flexion, pronation and supination. Each task was executed with both arms. Raw data were divided into windows of the same length, much smaller than the duration of the item. Then a series of features was extracted in order to have a feature vector for each window:

- Mean Value of Movement Intensity (MI)
- Movement Intensity Variation (VI)
- Smoothness of Movement Intensity (SI)
- Averaged Acceleration Energy (AAE)
- Averaged Rotation Energy (ARE)
- Time for completing the task (TIME)

All the above listed features are described in detail in the article. Moreover an algorithm based on dynamic time warping (DTW) was developed for comparing trajectories and estimating the differences in subjects behaviour in an objective way. The method resulted to be efficient for the assessment of impairment [31].

2.4 Conclusions

To our best knowledge, almost all the works in literature focused their attention on the automation of the clinical scales, going from FMA to other clinical scales such as WMFT, FAS, ARAT. Data obtained from wearable sensors or optical-based sensing technology were used for extracting features to be used as input for a classification system. The built classifier gave the scores as output.
The automation of a clinical scale can lead to a faster evaluation and the scores obtained are based on the extracted features instead of on clinician evaluation. However, the score remains a qualitative evaluation and it does not describe patient impairment in a comprehensive way. It is also low sensitive to mild impairment [12].
Only two works were found regarding the quantitative assessment using a set of paramenters. The first one proposed the use of three parameters but for Multiple Sclerosis patients and using ARAT test [12]. The second one proposed some parameters for evaluating post-stroke patients using FMA [31], but only five items were tested and only 3 subjects (1 healthy and 2 patients) participated to the study. Moreover only one IMU sensor was used for obtaining data in both studies.

The work illustrated in the following chapters proposes the use of a more complete sensor system in order to acquire the information from the whole upper body during the execution of 11 items from UE-FMA.

Chapter 3

Materials and Methods

In this chapter, materials and methods are described. In the first paragraph, selected items from FMA are listed end briefly described. The second paragraph illustrates the sensors systems used: XSens and Myo armband. In the third paragraph, experiments are described from the point of view of participants and experimental protocol. The paragraph number 4 is about Kinematic data analysis: preprocessing, qualitative evaluation of movement repeatability, paramenters extracted from simple and complex movements and statistical analysis are illustrated. The last chapter describes the exploratory EMG analysis on data collected from three subjects with Myo armband.

3.1 Selection of Upper Extremity FMA items

The first step was the selection of UE-FMA items to be tested in the experiments. A total of 11 items were chosen in order to have a group of tasks able to cover the main aspects of Fugl-Meyer scale. In fact, the selected tasks allow to evaluate the impairment of almost all the segments of upper limbs.
The items are listed in the following:

1. Flexor Synergy: Hand from contralateral knee to ipsilateral ear.
2. Hand to lumbar spine. The subject has to touch his lumbar spine with the back of his hand.
3. Shoulder flexion from 0° to 90°.
4. Forearm pronation-supination with elbow at 90°.
5. Shoulder abduction from 0° to 90°.
6. Shoulder flexion from 90° to 180°.
7. Forearm pronation-supination with elbow at 0°.
8. Wrist dorsiflexion with elbow at 90°.
9. Wrist dorsiflexion with elbow at 0°.
10. Wrist circumduction in clockwise direction with elbow at 90°.
11. Tip of the index finger from knee to nose as fast as possible.

Those tasks are all included in the section of motor function evaluation [32]. The tasks from 1 to 7 are included in the shoulder/elbow/forearm section. Tasks from

8 to 10 are included in the wrist section. Task 11 is for the evaluation of coordination/speed. In Task 1 each submovement is evaluated with a score from 0 to 2, so that a maximum score of 12 is associated to this exercise. For the task 11, tremor, dysmetria and time are evaluated for a maximum of 6 points in total [32].
Considering the set of selected tasks, the total score is given by the sum of the scores associated to each task and goes from a minimum of 0 to a maximum of 36 points.
The only tasks that were not considered for the experiments are those included in the hand section and those for assessing stability and reflexes [32].
From now on, reference is made to a certain task using the corresponding number in the above list.

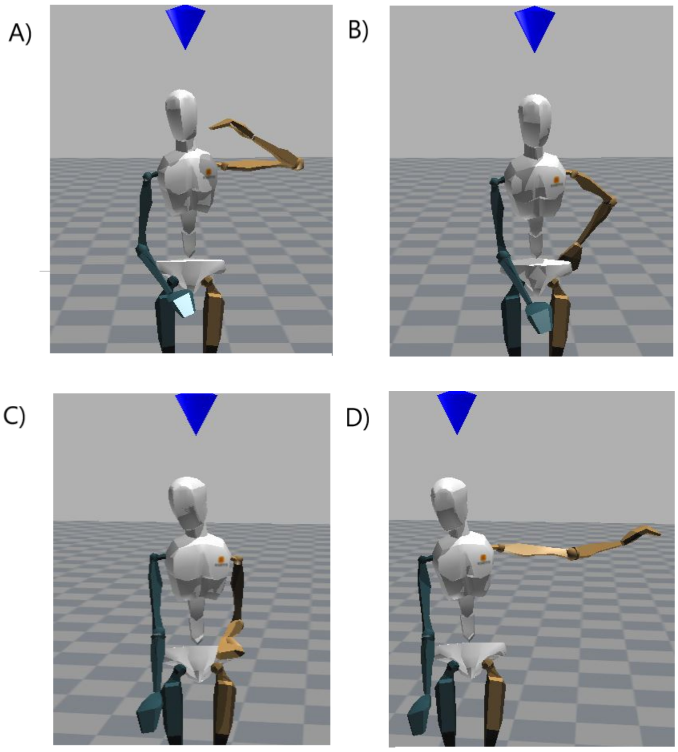

FIGURE 3.1: Some tasks selected from UE-FMA. A) Flexor synergy. B) Hand to lumbar spine. C) Pronation/Supination with elbow at 90°. D) Shoulder abduction 0°-90°.

3.2 Sensors system

The systems used for the experiments are XSens MTw Awinda (Xsens, The Netherlands) for kinematics and Myo armband (Thalmic Labs Inc., Waterloo,Ontario) for EMG recording. Those are described in the following paragraphs.

3.2.1 XSens MTw Awinda

MTw Awinda is a human motion tracker system, developed by XSens, based on a completely wireless solution. It includes a total of 17 motion trackers for measuring the full body motion, which are attached in specific positions. Each MTw is a wireless inertial and magnetic measurement unit (IMMU) containing 3D accelerometers,

3D gyroscopes, 3D magnetomenters and a barometer. Data are internally sampled at high frequency (1.8 kHz), then digitally filtered and down-sampled at 600Hz. The sensor calculates rotation and velocity increments through an SDI algorithm and transmits them wirelessly to the Awinda Station.
The system gives as output data several kinematic variables, all expressed in a local reference frame. The frequency of the output data depends on the number of sensors used. In fact, this system allows to record data in three configurations: full body, upper body and lower body. In that case, the upper body configuration was chosen, which provides for the use of 11 sensors: shoulder, upper arm, forearm, hand (both left and right sides), head, thorax and pelvis.
The sample frequency for upper body configuration is 60Hz. The SDI algorithm allows to maintain the maximum accuracy even at low frequencies, only decreasing the time resolution. Another important component is the Kalman filter, which uses the outputs of SDI algorithm and magnetometer data for estimating the 3D orientation of the sensor with no drift and high accuracy.
The Awinda Station is connected to the PC via usb cable and receives the output data wirelessly. Using the MVN Software, MTw data are combined with biomechanical models in order to obtain orientation and trajectory measures for each body segment [33, 34, 35].
Using upper body configuration kinematic data can be recorded from all upper body segments. In this way it is possible to evaluate not only the movement of the arm used for executing the tasks but also the behaviour of the controlateral side of the body, head and thorax. This allows to identify possible compensation strategies or pathological synergies.

FIGURE 3.2: XSens sensors - upper body positioning. Adapted from [36]).

3.2.2 Myo armband

Myo armband is a wearable device which can be used for Human Computer Interaction (HCI). It includes 8 EMG sensors (Medical Grade Stainless Steel EMG sensors) and one inertial measurement unit (IMU) consisting of 3D accelerometer, 3D gyroscope and 3D magnetometer (Figure 3.3). The device is connected to the PC via Bluetooth. The LED shows the state of the device itself: blue if the device is connected, orange if battery level is low, green if the device is on charge. There are five gestures the Myo is able to recognize: fist, double tap, finger spread, wave left and wave right. The sample frequency of EMG data is 200Hz, while the sample frequency of IMU data is 60Hz [37, 38].

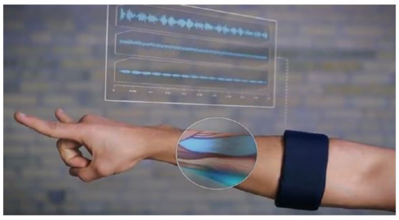

FIGURE 3.3: Myo armband structure. Adapted from [38]).

3.3 Experiments

Two experiments were executed for testing the system. A total of 10 subjects participated to the study, 9 healthy subjects and one stroke patient. The characteristics of participants and experimental protocol are illustrated in the following.

3.3.1 Participants

A total of 9 healthy subjects (7 females, 2 males) were recruited from may 2018 to july 2018 for participating to the first experiment. The mean age was 26 ± 2.3 years and 2 of the 9 subjects were left-handed. All participants were informed about the experimental procedure before starting. Recordings were made in two different sessions: the first one involved 6 subjects and was conducted at Campus Biotech, the second one involved the other 3 subjects at Crr SUVA in Sion. During the first recording session only XSens Sensors were used, while during the second one recordings were made using both XSens and Myo armband. All the 11 tasks selected were executed and each one was repeated 5 times in order to evaluate also the intra-subject repeatability.

The second experiment was done on a stroke patient (female, 43 years) from the Crr SUVA in Sion. The subject was right handed and the tasks were executed with the help of a physical therapist with both the more affected (right) and less affected (left) arm. Moreover, the patient was evaluated by the therapist using UE-FMA and obtained a score equal to 26/36.

3.3.2 Protocol

The experimental protocol consisted of the following fundamental steps:

1. Sensors positioning: XSens sensors were positioned on the subject according to the upper body configuration described in the manual [33], while Myo armband was placed on the upper limb with which the tasks were executed, precisely on the forearm, below the elbow joint.

2. Specifying Body Dimensions in Xsens Software: MVN Studio needs body dimensions to be specified in order to proceed with the recording session [33]. For that reason, body height and foot size of each subject were measured and given as input. The lengths of the other segments are automatically calculated according to the specified parameters, based on an anthropometric model [33].

3. Calibration of the two systems:

- XSens calibration consisted in the subject holding two poses, N-pose and T-pose (Figure 3.4), each one for few seconds, facing the positive direction of x-axis of the global coordinate frame [33].

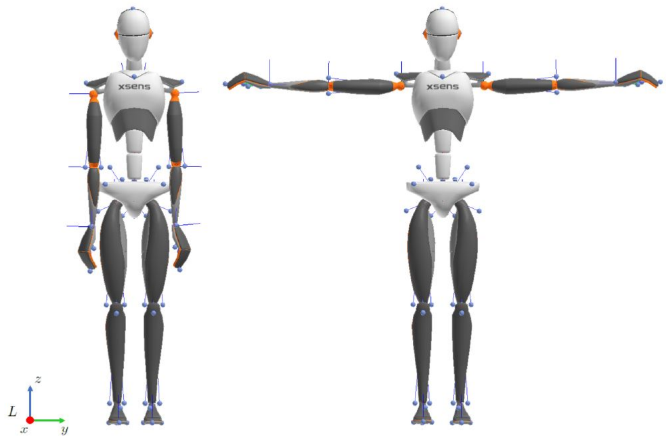

FIGURE 3.4: XSens avatar N-pose (left) and T-pose (right). Adapted from [34]).

- Myo armband calibration was performed through a sync gesture, i.e. the flexion of the wrist away from the body. When the system recognizes the gesture it starts vibrating and it is necessary to hold the position till it stops. In that way, the armbrace gains the information about which is the arm wearing the device and the correct orientation [37].

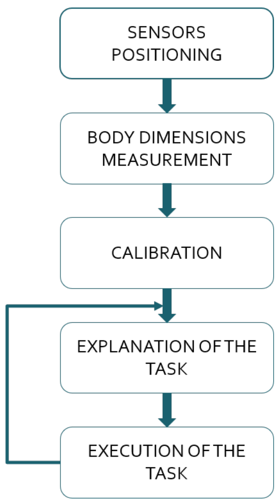

FIGURE 3.5: Flow chart of experimental protocol.

4. Execution of the selected items: the subject sat on chair, facing the positive direction of x-axis. Before the execution, a brief explanation about the task was given. The stroke patient was helped by a clinician. Every task was performed five times in succession with the same limb. Each recording consisted of one exercise (i.e. the five consecutive repetitions) with few seconds of pause before and after. The experiment consisted of two trials. About the healthy subjects,

they first performed the 11 tasks with the right arm and then executed the same exercises with the left arm. The stroke subject was evaluated first on her less affected arm and then she repeated the same exercises with the more affected arm.

3.4 Kinematic Data Analysis

Recordings from XSens sensors are in mvn format. Kinematic data were exported from XSens environment obtaining the mvnx file to be processed in Matlab. XSens also provided the Matlab code for converting the mvnx file. The output is a Matlab structure containing the raw data of several kinematic variables for each body segment along the three axis:

- Position (m)
- Linear Velocity (m/s)
- Linear Acceleration (m/s^2)
- Angular Velocity (rad/s)
- Angular Acceleration (rad/s^2)
- Euler angle (deg)

All the above listed variables are expressed in the global coordinate system, the Euler angle is calculated referring to the ISB (International Society of Biomechanics) based coordinate system.
Data were first preprocessed and then, before proceeding with the analysis, the 11 items were divided in simple and complex movements depending on the characteristics of each exercise. Are defined simple movements or single joint movements those occurring in a plane and around a single axis. Conversely, are defined complex movements or two joints movements those occurring in more than one plane and around more axis [39].
In that case, exercises from 3 to 9 are defined as simple movements, while exercises 1,2,10 and 11 are defined as complex movements.

3.4.1 Preprocessing

Data preprocessing consisted of two fundamental steps:

- Filtering
- Segmentation

Filtering

Raw data were digitally filtered using a Savitzky-Golay filter with order 4 and frame length 31 for smoothing the signal, i.e. for increasing the SNR maintaing the morphology of the signal itself (Figure 3.6).

Category	Tasks
Simple movements	Shoulder flexion 0°-90° Forearm pronation/supination - elbow 90° Shoulder abduction 0°-90° Shoulder flexion 90°-180° Forearm pronation/supination - elbow 0° Wrist dorsiflexion - elbow 90° Wrist dorsiflexion - elbow 0°
Complex movements	Flexor synergy: hand from controlateral knee to ipsilateral ear Hand to lumbar spine Wrist circumduction in clockwise sense - elbow 90° Coordination speed: index finger tip from knee to nose

TABLE 3.1: Table of simple and complex movements

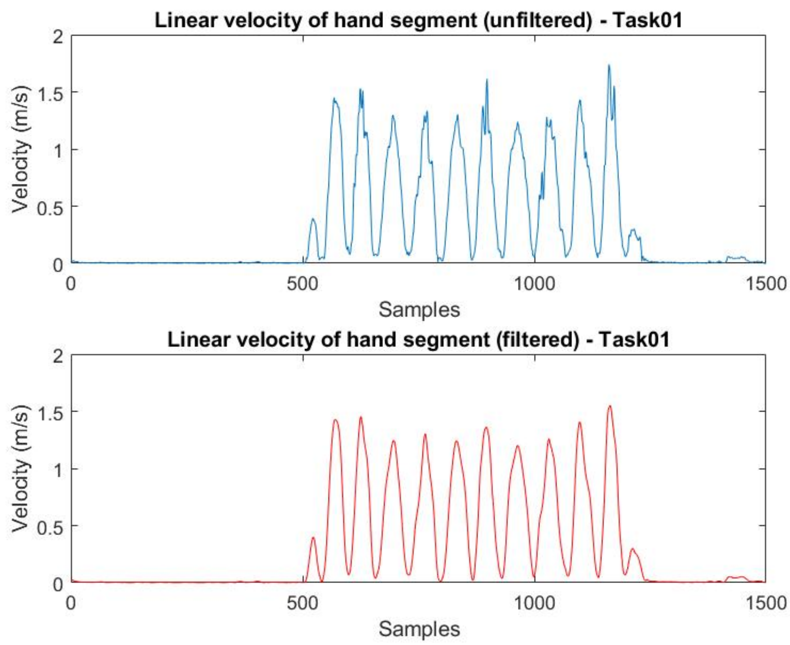

FIGURE 3.6: Example of filtered and unfiltered signal - Linear Velocity of hand segment in task 1.

Segmentation

Segmentation was performed on the filtered signal previously obtained for isolating the single movements, since each recording included the five successive repetitions of a certain task. Angular velocity of hand segment was considered for tasks 4) Pronation/Supination - elbow 90° 7) Pronation/Supination - elbow 0° 8) Wrist dorsiflexion - elbow 90° 9)Wrist dorsiflexion - elbow 0° and 10) Circumduction. In fact those exercises were based on a rotatory movement. Linear velocity of hand segment was considered for the remaining tasks.

The first step was the identification of signal peaks associated to back and forth movements using the Matlab function *findpeaks*. Indeed, each task included a forth movement and a back movement for each repetition, for a total of 10 peaks per item (Figure 3.7). Only task 10 was considered as a single movement, so that one peak corresponded to the complete circumduction. A different minimum peak height and peak distance was specified for each patient for every task.
Peaks relative to other movements were removed after peaks identification.
Based on the identified peaks, start and stop instants for each back and forth movement were detected (Figure 3.8). The implemented algorithm was based on one common criterion and other different control criteria depending on the position of the peak. The common criterion consisted of introducing a threshold equal to the 10% of the peak height. The signal portion on the left of the peak was considered to find the start instant, the one on the right for finding the stop instant. All the points with value equal or less than the threshold were considered as potetial candidates and saved in a row vector. In case of start instant search, the last element of the vector was chosen; in case of stop instant search the optimal candidate was the first element.

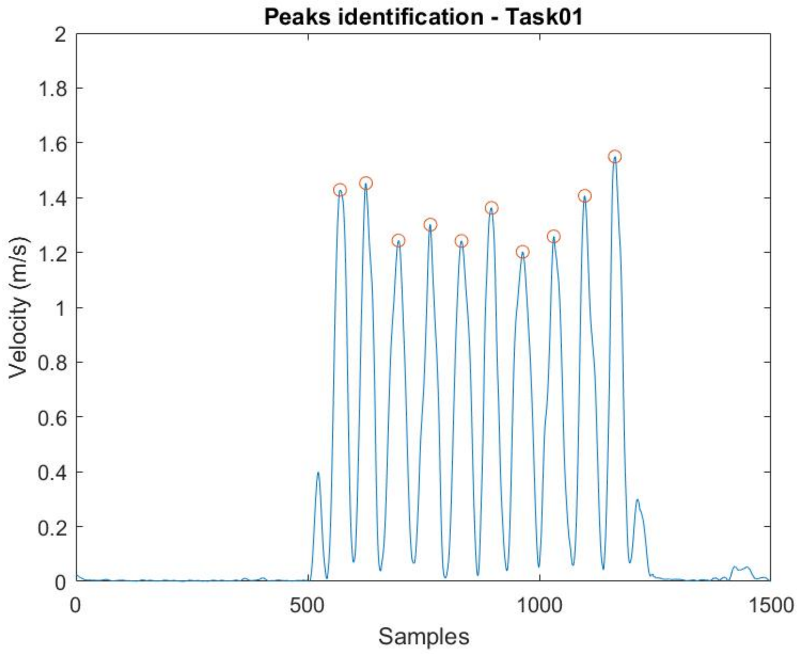

FIGURE 3.7: Example of peaks identification - Linear Velocity of hand segment in task 1.

The other control criteria were necessary if the common one was not sufficient for finding the start or stop instant. Those are described in the following:

- If the peak considered was the first one, the first sample of the signal was considered as start instant if no other values were found. Relating to the stop instant, an additional criterion based on local minimum search was applied.
- If the peak considered was an interim one, the search for local minimum was applied for both start and stop instant detection.

- If the peak considered was the last one, the last sample of the signal was considered as stop instant if no other values were found. For the start instant, the criterion of local minimum search was used.

The so obtained instants of start and stop were then used for separating the back and forth movements of each repetition or the complete repetitions depending on the analysis to be done.

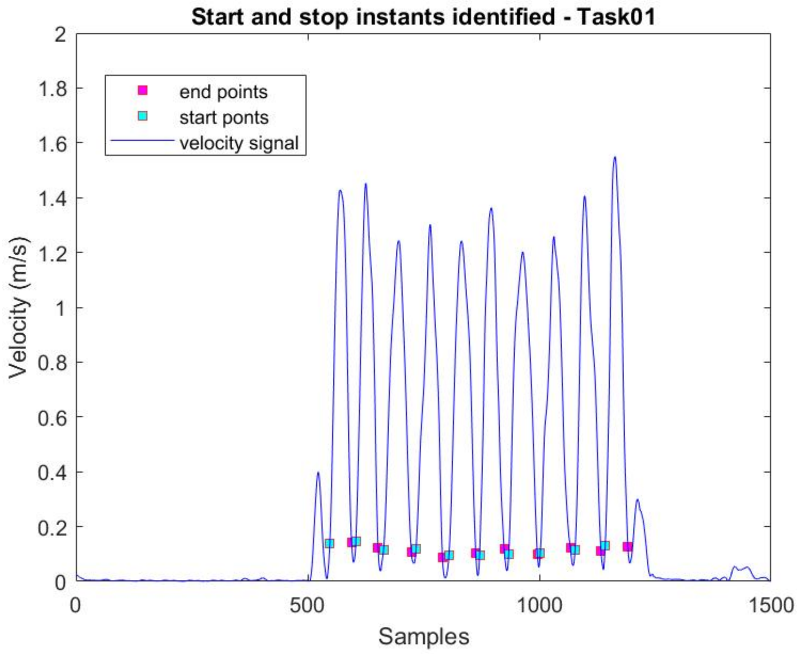

FIGURE 3.8: Example of start and stop instants identification - Linear Velocity of hand segment in task 1.

3.4.2 Qualitative evaluation of movements repeatability

Before proceeding with the quantitative analysis, the repeatability of each task was evaluated in a qualitative way observing the envelops of joint angles and trajectories. The same procedure was followed for both the healthy subjects and the stroke patient.
For example, the values of angles for shoulder, elbow and wrist for task 03 (Shoulder flexion 0°-90°) are shown in figure for both healthy subjects and stroke patient. The envelopes of healthy subjects are relative to the right arm, while for stroke patient the envelopes of both more affected and less affected arm are illustrated. It is possible to notice that the envelopes of healthy subjects are all similar to each other, indicating high repeatability of movement. About the stroke patient, the difference between more affected (right) and less affected (left) arm is evident, since the stardard deviation between repetitions obtained for the right arm is higher than that obtained for the left one.

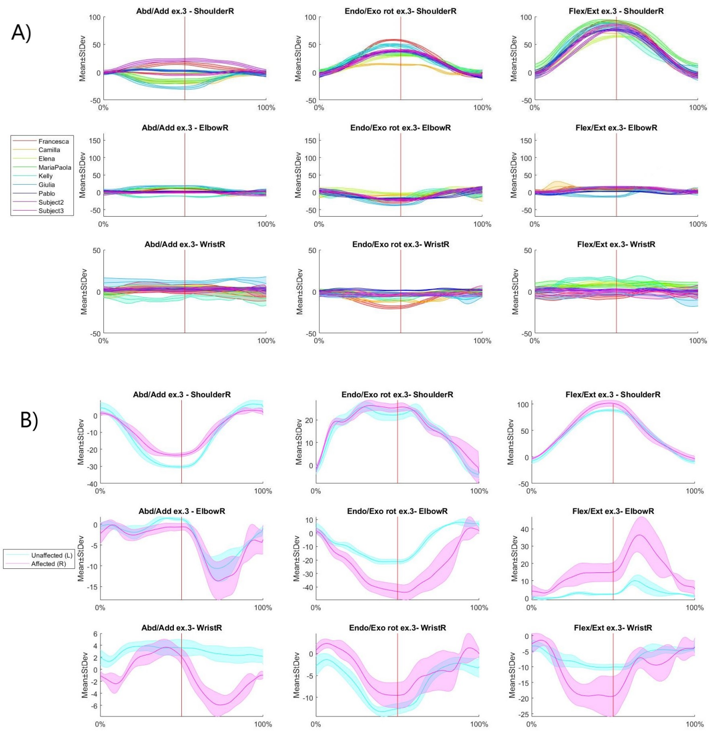

FIGURE 3.9: Example of joint angles envelope - Task 3. A) Envelopes of healthy subjects, right arm. B) Envelopes of stroke subject - More affected (pink) and less affected arm (blue).

3.4.3 Simple and Complex movements analysis

After signal preprocessing, tasks were divided in simple and complex movements according to the definition explained previously.
A different analysis was performed for the two categories. First of all, a series of features was extracted from raw data deriving from single segments:

- Average Angle of elbow joint
- Average angle of shoulder joint
- Time required for performing the task
- Average Velocity module of hand segment
- Jerk value of hand segment
- Normalized trajectory with respect to the ideal path

Time, velocity, jerk and normalized trajectory were all derived considering raw data from the more distal segment, which was the hand. Also the other two parameters of course derive from a single segment/joint, respectively elbow and shoulder.
For simple movements all the listed features were considered, while for complex movements time, average velocity and jerk value were computed. This because was not possible to identify a shoulder or elbow angle characterizing each complex movement. The same for the normalized trajectory regarding the definition of the ideal path. The very definition of complex movements leads to the exclusion of

those parameters for that kind of tasks.
Then other two metrics were considered:

- 2D Pearson Correlation coefficient between subjects for the same task
- Principal Component Analysis (PCA)

The first one was computed for both simple and complex movements, while the second one only for complex tasks. Those metrics differ from the features described above because were obtained considering the information deriving from several joints and not only from a single one. The joint angles used for correlation coefficient and PCA are listed in the table 3.3.
Considering the raw data recorded on different segments allows to have a complete information about the arm used for performing the items, since data from shoulder, elbow and wrist are considered. Moreover, considering also thorax and controlateral shoulder angles, it is possible to verify if there are abnormal synergies or compensatory movements.
Parameters extracted for simple and complex movements are summarized in table 3.2.

Category	Parameters
Simple movements	Shoulder angle Elbow angle Time Averaged velocity Jerk Normalized Trajectory Correlation Coefficient inter-subjects
Complex movements	Time Averaged velocity Jerk Correlation Coefficient inter-subjects Principal Component Analysis (PCA)

TABLE 3.2: Table containing the parameters extracted for simple and complex movements

Angle of elbow and shoulder joints

In tasks classified as simple movements a correct execution is fundamental. The accuracy of the movement depends on the position of the upper limb holded by the subject during the performance of those exercises. The specific position is defined for each item in therms of joint angles of shoulder and elbow. First, offset was removed from filtered raw data of shoulder and elbow angles in order to have an initial position corresponding to 0°. Average angle of shoulder and elbow was calculated for those tasks in which the value of one or both joints was expected to remain constant during the entire execution. In case of items which provided for different initial and final value of joint angle, the value of the angle at the end of forth movement was considered. Those tasks were 3) Shoulder flexion 0°-90°, 5) Shoulder abduction 0°-90° and 6) Shoulder flexion 90°-180°.

Tasks 4 and 8 were not considered in the elbow joint calculation since in both exercises it was necessary to maintain the elbow at 90° but this was not fundamental for the correct execution of the exercise. The joint angle evaluation was made for each repetition of every task and then the mean value between repetitions was considered for every subject.

Time required for performing the task

Time was chosen as feature to be considered in this analysis since is one of the most simple performance indicators. All simple movements are self-paced movements, i.e. the performer has a full control on the time required for executing the task. For that reason, considering a group of healthy subjects, the average time taken for a certain exercise should be almost the same for everyone, without a large variability. Time was calculated for each repetition of every task and then the mean value between repetitions was computed for every subject.

Average velocity module of hand segment

The third feature considered was average velocity during the task execution. This variable is strictly linked to the time required for the performance and so, to the concept of self-paced movement. For healthy subjects, it is expected that also the average velocity during a task is nearly the same. Moreover, the trends of time and velocity must be opposed to each other: for an exercise requiring a shorter time interval the velocity must be higher and viceversa. The only exceptions can be given by a different execution of the task in therms of travelled path or in presence of abnormal strategies. This can be the case of a stroke subject. Velocity was calculated considering the velocity raw data of hand segment along the three axis and calculating the module. Then the average value of the obtained raw vector was considered. This procedure was followed for each repetition of every task and then the mean value between repetitions was calculated.

Jerk value of hand segment

Jerk is a parameter linked to smoothness, it indicates the regularity and coordination of a movement. A smooth movement is typical of a healthy subject, it is executed without hesitation and anomalies. Basically, when a movement is defined as smooth, it can be described as a set of few submovements closely spaced in time. Conversely, an irregular movement is caracterized by a larger number of spaced submovements, which cause undulations. It is typical of children or people affected by motor deficits, since they tend to perform an activity with more hesitation [40]. From a mathematical point of view, jerk is defined as the first derivative of acceleration. However, according to the state of the art (Chapter 2), different jerk metrics have been used for characterizing smoothness. Some of them are RMS value of first derivative of acceleration[13, 15, 17, 19, 24, 26], third derivative of position [27], RMS normalized to the maximum of velocity [14], dimensionless jerk [29, 23] and integrated squared jerk [22].
In this case, jerk was calculated following the method proposed by Balasubramanian et al. [40], called Spectral Arc Length. Among the others, this metric has been chosen because, according to the authors, it is characterized by:

- Validity: it is dimensionless and so it is independent from amplitude and duration of the signal.

- Consistency: it follows a monotonic behaviour, which means that the less the number of submovements and the time intervals in between, the higher the smoothness.
- Sensitivity: it perceives the changes in movement.
- Robustness to noise.

The spectral arc length was obtained computing the frequency normalized Fourier magnitude spectrum and then calculating the negative arc length of that curve. The more negative the value obtained, the higher the jerkiness of the movement. Also this parameter was calculated for each repetition of every task and then the mean between repetitions was considered.

Normalized trajectory with respect to the ideal path

The normalized trajectory is an index of efficiency of the movement. It was defined as the ratio between the path travelled by the hand during the execution of the exercise and the ideal path, i.e. the path that the segment should follow for having a correct performance.
First of all, the ideal path was defined for each simple movement as follows:

- Tasks 3,5 and 6: arc formed by a 90° angle with radius equal to the length shoulder-wrist.
- Tasks 4 and 7: arc formed by a 180° angle with radius equal to half the width of the wrist
- Tasks 8 and 9: arc formed by a 180° angle with radius equal to the length of the hand.

Since the accurate determination of the ideal path itself for tasks 4 and 7 was difficult and it was also extremely unlikely to have an arc length of exactly 180°, this parameter was not considered for those two tasks.
The trajectory was computed starting from the filtered raw data of hand position after offset removal. For each repetition, only the forth movement was considered and the trajectory was given by the sum of all the displacements Δx travelled from the $i - th$ instant to the $(i + 1) - th$ one. The only exception was task 8 and 9, for which the path travelled from the maximum flexion to the maximum extension was considered.
The trajectory was then divided by the corresponding ideal path. A ratio near 1 indicates high similarity between the real and ideal path, i.e. high efficiency, which is the result expected from a healthy subject.

Pearson Correlation Coefficient

Pearson Correlation Coefficient is a statistical index that expresses the linear relationship between two variables [41]. It is defined as the covariance divided by the product of the standard deviations of the two variables. The result is a scalar value between -1 and 1:

- If the correlation coefficient is >0, the variables are directly correlated
- If the correlation coefficient is <0, the variables are indirectly correlated

Joint	Angles
Shoulder	Adduction/Abduction (x) Endo/Exo rotation (y) Flexion/Extension (z)
Elbow	Flexion/Extension (z)
Wrist	Adduction/Abduction (x) Endo/Exo rotation (y) Flexion/Extension (z)
Thorax	Adduction/Abduction (x) Endo/Exo rotation (y) Flexion/Extension (z)
Controlateral Shoulder	Adduction/Abduction (x) Endo/Exo rotation (y) Flexion/Extension (z)

TABLE 3.3: Table containing the joint angles used for complex movement analysis

- If the correlation coefficient is equal to 0, the variables are uncorrelated

The definition can be extended to the bidimensional case for making the comparison between matrices. For each subject, a matrix for every task was constructed having the joint angles filtered raw data of the five repetitions as columns. Offset was removed and data were resampled before constructing the matrix in order to have datasets with the same number of raws and columns. Then each subject was compared with the others calculating the correlation coefficient with Matlab function *corr2* for each task.

Principal Component Analysis (PCA)

Principal Component Analysis (PCA) is a method used for reducing the dimensionality of a dataset where there is a large number of interrelated variables, but maintaining the variation of the dataset unchanged. The new variables obtained are called Principal Components (PCs): they are uncorrelated and sorted so that the first ones are those expressing most of the variation of the entire original dataset [42].
In human motion analysis, PCA is used for extracting kinematic or muscle synergies depending on the data source. In general, principal components of lower order represent the most significant synergies,since they explain most of the variance. On the other side, principal components of higher order represent the synergies which can be neglected and considered as noise, since the explained variance is only a small percentage [43]. For this analysis, the dataset was constructed considering filtered raw data of the joint angles listed in the table 3.3. In this way the contribution of both sides was considered and not only that of the arm involved in the movement. It can be useful in particular for stroke patients which tend to complete the task with unusual strategies.

Also in this case offset was removed. For each subject and for every task there was a matrix having as columns data relative to the succession of the five repetitions.
Then PCA was performed using the Matlab function *pca*. The variance explained by each principal component for each task was considered for determining the optimal number of synergies to be considered [44]. According to the values of VAF, the first two principal components were considered since they were sufficient for explaining more than the 90% of the variance (Figure 3.10).
The coefficients of the first two PCs were then examined to identify the joints giving the higher contribution in the prevalent synergies of each task.

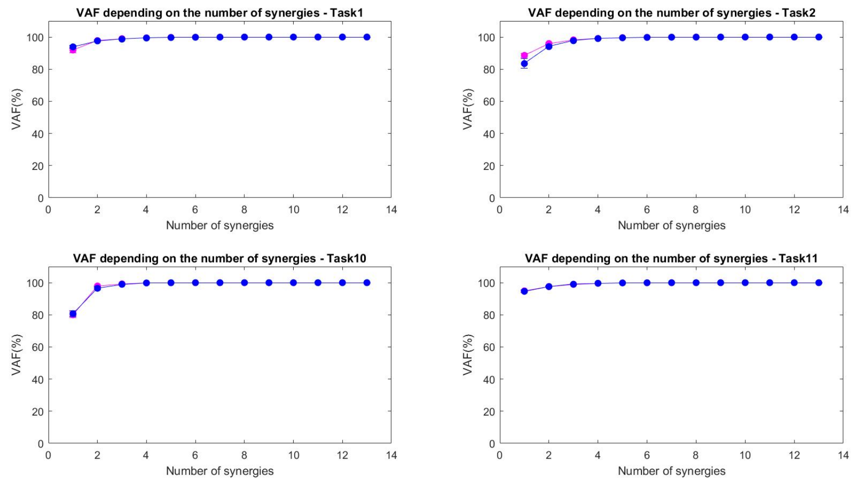

FIGURE 3.10: Variance Accounted For depending on the number of synergies (PCs) for complex movements

In the next step, three types of comparisons were done:

- Comparison between left and right arm for the same subject.
- Comparison between subjects for identical task.
- Comparison between different tasks for identical subject.

For the second one, the stroke patient was compared with the healthy subjects. Moreover, the second and third comparisons were done considering separately the performance with the right arm and the left arm.
For each case the following parameters were considered in order to quantitatively evaluate the similarity:

- Variance Accounted For (VAF). As already mentioned before, it is an index of how much data variability is explained by the considered principal components obtained from PCA. It means that this variable indicates the variance expressed by the most meaningful synergies [44].
  In this case it was used as index for comparing the same task done by the same subject with left and right arm, different tasks done by the same subject or the same task done by different subjects. The $i-th$ task was mapped in the subspace defined by the first two principal components associated to the $j-th$ task with which the comparison must be done. In this way it was possible to understand how well the PCs of the $j-th$ task were able to explain the

$i - thtask$.
The value of VAF ranges between 0 and 100: the higher it is, the higher the similarity between tasks.

- Principal Angle. It is a metric for quantifying the difference between two N-dimensional subspaces, where N is the number of principal components defining the subspace itself [45]. Since in this case the number of PCs considered for each subject was 2, we talk more precisely about planes (2-D subspaces). The principal angle corresponds to the angle formed by two planes and so its definition is an extension of the angle formed by two straight lines. It was calculated using the Matlab function **subspace**. The planes considered were associated to two different subjects with the same task or different tasks computed by the same subject. This parameter can assume a value between $0°$ and $90°$: the lower this value, the higher the similarity between two planes. The condition of overlapping planes corresponds to an angle of $0°$.

- Projected Variance. It is another parameter used for estimating the difference between two subspaces and it was proposed by Todorov et al. [46]. Considering two tasks, the dataset of the $i - th$ task is projected in its N-dimensional subspace. The trace of the projected covariance is called $T1$. Then the result is projected in the subspace defined by the PCs derived by the dataset of the $j - th$ task. In this case the trace of the projected covariance is called $T2$. If $T2 = T1$ it means that the two subspaces are identical; in the other cases $T1 > T2$, since projection reduces variance. So the principal angle index is defined as:

$$1 - T2/T1$$

The value ranges between 0 and 1. The lower it is, the higher the similarity between subspaces.

3.4.4 Statistical Tests

Statistical analysis was performed for both healthy subjects and stroke patient. The data considered were the features extracted for the five repetitions of each task for every subject. So time, velocity, jerk, normalized trajectory, shoulder angle and elbow angle were considered for the simple tasks, while time, velocity and jerk were considered for the complex tasks.
The statistical tests applied are:

- Kolmogorov-Smirnov test
- Wilcoxon test
- Kruskal Wallis test

Kolmogorov-Smirnov test

The Kolmogorov-Smirnov test is a non-parametric test used for verifying the null hypothesis according to which the distribution of data is normal. It can be used for comparing one sample with a reference distribution or two samples [47]. This test is necessary to decide whether to apply T-Test (parametric test) or Wilcoxon test (non-paramentric test) later.

In this case it was applied for verifying if data obtained from the right and left arm of the same subject for a certain task were from a normal distribution. This test was utilized separately for each feature above mentioned. Matlab function **kstest** was used.
The results of the test showed that the normality hypothesis was not verified: in fact, more than the 60% of results were statistically significant.

Wilcoxon test

Wilcoxon test is a non-parametric test used for verifying the null hypothesis of continuous distribution of data with the same median [48].
In particular, it was used for comparing data obtained from left and right arm of a certain subject for each task separately in order to know if the two samples were from the same continuous distribution. This verification was necessary to understand if the difference between data obtained from right arm and left arm was statistically significant. Matlab function **ranksum** was used.
Results of the test showed that the null hypothesis was not verified: 70% were statistically significant. It means that data from left and right arm of healthy subjects had to be considered as separated samples and not together for the comparison with stroke patient. The same for more affected and less affected arm of stroke subject.

Kruskal-Wallis test

The Kruskal-Wallis test is a non-parametric test used for verifying the membership to continuous distributions with the same median [49].
The difference with respect to Wilcoxon test is that in this case the comparison is done between populations: one included the data from right arm and the other one was formed by the left arm data. For this test only healthy subjects were considered and it was applied to each feature separately. Matlab function **kruskalwallis** was used defining two groups: right and left arm.
For the 63% of results the null hypothesis is verified.

3.5 EMG Exploratory Data Analysis

In this case, it was possible to do an exploratory analysis since only EMG data recorded from three healthy subjects were available.
Data collected with the Myo armband were imported in Matlab environment from Excel and are listed below:

- Linear acceleration
- Angular acceleration
- Euler angles
- Electromyographic signal

The first three variables are measured thanks to the IMU sensor and are relative to the forearm, according to the positioning of the Myo armband. The last variable is obtained from the 8 EMG channels.
Before proceeding with the analysis of EMG signals, it was necessary to compute the syncronization between the XSens system and the Myo armband. Then EMG was preprocessed and analyzed. Here the complete description of the process is reported.

3.5.1 Syncronization

The first step was the syncronization of the two systems, necessary for making a comparison between the kinematic and EMG data. The angular velocity of hand segment from XSens and the angular velocity from Myo armband were considered for performing the syncronization. This process included the following steps:

- Filtering
- Resampling of XSens Data
- Determining the delay
- Correction of the delay

Filtering

Raw data were digitally filtered using a Savitzky-Golay filter with the same characteristics as that one used in the preprocessing section during kinematic data analysis.

Resampling

In order to syncronize two signals, they must have the same frequency. For this reason, the data from XSens were resampled from 60 Hz to 50 Hz in order to have the same frequency of the IMU data from Myo armband.

Determining the delay

The delay was determined using the Matlab function **xcorr**. Given two signals A and B, the function is written as **xcorr(A,B)** and returns as output the delay of B with respect to A. In this case, A was the signal from Myo armband and B was the signal from XSens. The writing order was important to take into account for correcting the delay in the next phase.

Correction of the delay

The correction of the delay was first applied to the XSens data, i.e. the angular velocity and the linear velocity, necessary for the segmentation process. The following criterion was applied:

- $Delay < 0$: the XSens signal is in advance of the Myo signal. So the portion from the absolute value of the delay to the end was considered for the first one, while for the second one the complete signal was taken 3.11.
- $Delay > 0$: the XSens signal is delayed compared to the Myo signal. So the complete signal was taken for the first one, while for the second the portion from the absolute value of the delay to the end was considered.

Of course also the filtered linear velocity signal was resampled with a frequency of 50 Hz before correcting the delay. For syncronizing also the EMG signal, it was necessary to convert the delay values to the frequency of 200 Hz. Then the correction was applied using the inverse criterion with respect to that used for XSens data, since the EMG was obtained from Myo device.

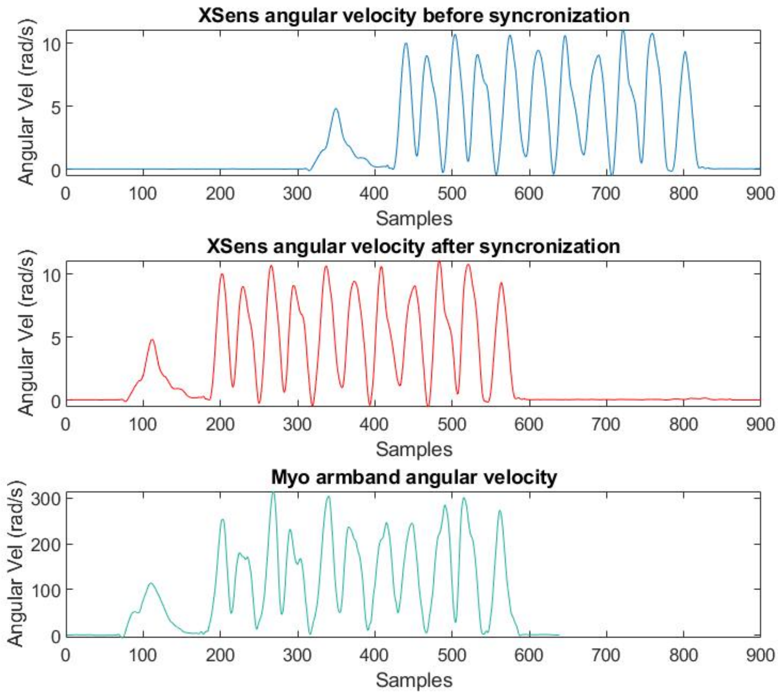

FIGURE 3.11: Example of syncronization of XSens and Myo armband angular velocities. Case of negative delay.

3.5.2 EMG Preprocessing

The syncronized EMG signal was preprocessed with a series of filters for obtaining the envelope and then segmented for separating the repetitions.

Envelope extraction

The following steps were applied for extracting the envelope:

- Detrending of the signal for removing the mean value using the Matlab function **detrend** with setting "constant".
- High-pass filtering of the obtained signal with a cut-off frequency of 20 Hz. A Butterworth filter of order 7 was used.
- Low-pass filtering of the high-pass filtered signal with a cut-off frequency of 100 Hz. A Butterworth filter of order 7 was used.
- Computation of the absolute value of the filtered signal for obtaining the rectified signal.
- Low-pass filtering of the rectified signal with a cut-off frequency of 5 Hz in order to extract the envelope.

For each subject, the envelopes relative to the same channel were normalized by the maximum value of amplitude. For every subject, one maximum for each channel among the envelopes of all the 11 tasks was calculated.

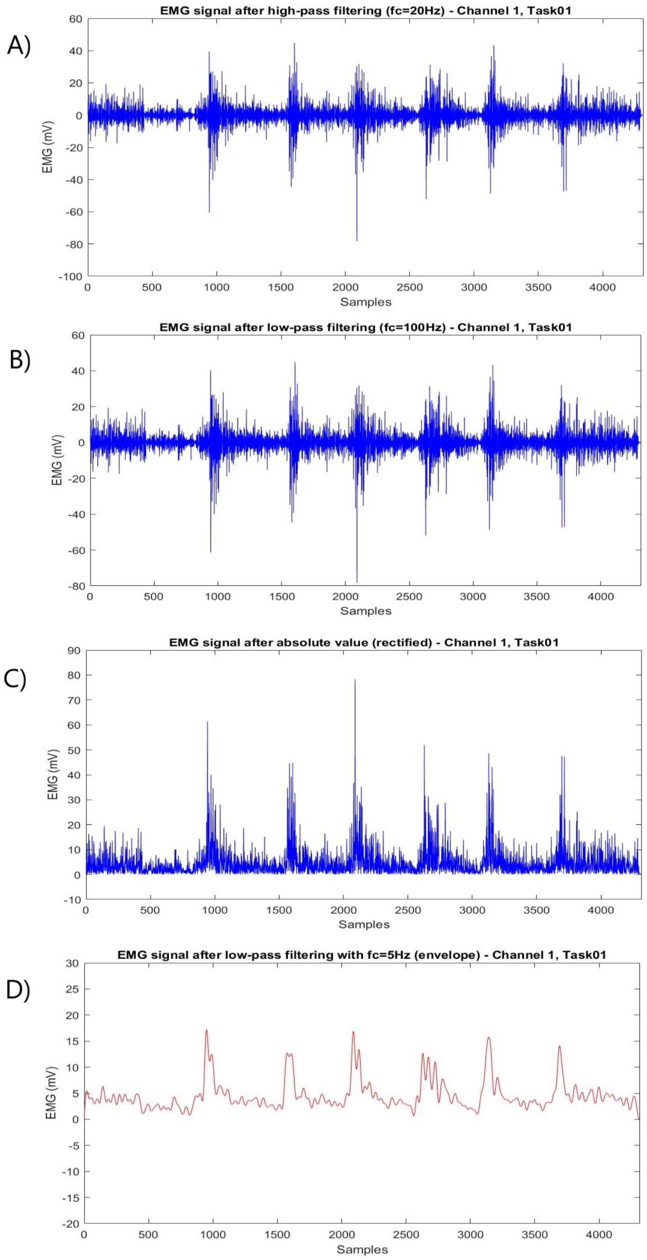

FIGURE 3.12: Example of EMG preprocessing in task 01. A) High-pass filtering B) Low-pass filtering C) Rectified signal D) Low-pass filtering for obtaining the envelope

Segmentation

After preprocessing the EMG signal was segmented. The start and stop signals were obtained from the XSens velocity signal syncronized with the Myo armband, i.e. the one with a frequency of 50 Hz. Then instants were converted to 200 Hz frequency and used for segmenting the EMG signal.

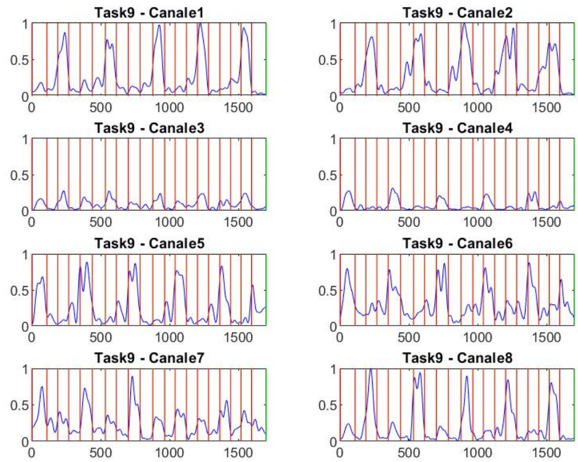

FIGURE 3.13: Example of EMG segmentation for task 09 in subject 8.

3.5.3 EMG analysis

The EMG exploratory analysis was performed using the metrics listed below:

- RMS value of each repetition of every task. It was computed for each subject separately for both left and right arm.
- 2D Pearson Correlation coefficient between different subjects for the same task. It was calculated considering matrices having the raw data from the eight channels as columns.
- Principal Component Analysis (PCA) was performed only for complex tasks. The comparison between different subjects for the same task and different tasks for the same subject were done. For each comparison the three parameters already described (Variance Accounted For, Principal Angle and Projected Variance) were extracted for assessing similarity.

3.6 Conclusions

In this chapter, materials and methods were illustrated. The system chosen allows to record data from the entire upper body section, contrary to the studies found in literature where only one sensor was used. This can lead to a more complete information and to the possibility of computing the 2D Correlation Coefficient and PCA in the way explained before, considering data from several joints. Other parameters were computed using data from only one segment.
Moreover, a huge number of tasks from FMA were tested with respect to what found in literature.
Results obtained from this new approach are presented in the following chapter.

Chapter 4

Results and Discussion

In this Chapter, results obtained from kinematic and EMG analysis are presented. Results obtained from kinematics are described showing the differences between healthy subjects and stroke patient. EMG results are obtained from an exploratory analysis from data collected on three healthy subjects.

4.1 Kinematics results

Results obtained from kinematic analysis are presented making a comparison between healthy subjects and stroke subject. All the 9 healthy subjects were able to complete the 11 tasks with both right and left arm, repeating each exercise 5 times. About the stroke patient, she executed all the tasks with the less affected arm (left arm).Exercise 6) Shoulder flexion 90°-180° was not executed and exercise 7) Pronation/Supination- elbow 0° was repeated only four times with the more affected arm (right arm).
The first results illustrated are the features, then the correlation coefficient and PCA.

4.1.1 Features

Features were calculated for each repetition of the selected task for every subject and were computed considering the information deriving from only one segment. In case of healthy subjects, mean value and standard error were computed considering, for every subject, the mean value between repetitions of the same item. The representation of stroke patient results was obtained considering the mean and standard error between repetitions of the same task. It means that the results obtained for healthy subjects derive from a comparison between the subjets themselves; those for the stroke patient derive from a comparison between repetitions made by the same subject. This because only one patient participated to the study.
Moreover, data from right and left arm were considered separately according to the results of statistical tests. The latter ones were represented in figure indicating the statistically significant outputs with a single "*" and the statistically highly significant outputs with a double "*". In particular, for healthy subjects results of Kruskal Wallis test are showed, while for stroke patient those of Wilcoxon test.
The following legend is used for presenting results of features:

- *Healthy R* (red), results for healthy subjects using right arm
- *Healthy L* (blue), results for healthy subjects using left arm
- *Stroke R* (dark yellow), results for stroke patient using right arm (more affected arm)
- *Stroke L* (light blue), results for stroke patient using left arm (less affected arm)

Time

Time was calculated for both simple and complex movements and the results are presented in figure 4.1.
Starting from results of healthy subjects, it is possible to notice that the execution time is very different among tasks, as expected.
The average time required for performing a task in the case of *Healthy R* is higher than that required in case of *Healthy L* in almost all the exercises, for both simple and complex movements. Moreover, values distribution is wider in the first case than in the second one, which means higher variability between subjects. Those two differences can be due to the fact that exercises were always executed with the right arm before and then with the left arm. However, the variability inter-subjects in both cases is low (under 1 s): this demonstrates that, since the tasks tested are self-paced movements, the time required for the execution is almost the same in all healthy subjects.
Looking at the results obtained for the stroke patient, the average time for *Stroke R* is higher than that required for *Stroke L* in all exercises and the distribution is wider. Those findings indicate that the stroke patient has less self-control in performing the tasks with the more affected arm (right) than with the less affected arm (left). The only exception is task 8) Wrist dorsiflexion - elbow 90°: the time is lower for the more affected arm but this can be due to the fact that the path travelled is reduced. This is confirmed by the score equal to 1 assigned by the therapist for this exercise.
It is also important to notice that the stroke patient is slower than the healthy subjects with both affected and less affected arm, except for tasks 8, 9) Dorsiflexion - elbow 0° and 10) Circumduction. Those tasks are all part of the wrist section and probably the time is lower for those exercises because were only partially executed. Indeed the score given by the therapist was equal to 1 for those items.

Velocity

Also the average velocity was computed for simple and complex movements (figure 4.2).
It can be noticed that different tasks are executed with different velocity.
About the healthy subjects, the average velocity for *Healthy R* is lower than that obtained for *Healthy L* for almost all the exercises. This trend is in line with that of time, since the two variables are inversely proportional. The standard error is low for all the items and this indicates high similarity between the healthy subjects, in accordance with the definition of self-paced movements.
The values of velocity related to the stroke patient are lower for *Stroke R* than for *Stroke L* in the majority of the exercises, i.e. the tasks were executed more slowly with the more affected arm, confirming the above findings.
The average velocity for stroke patient results to be lower than that obtained for the healthy subjects. Also in this case the exceptions are tasks 8, 9 and 10 because of the partial execution of those tasks. The path travelled is shorter than the expected one, so the velocity is higher.

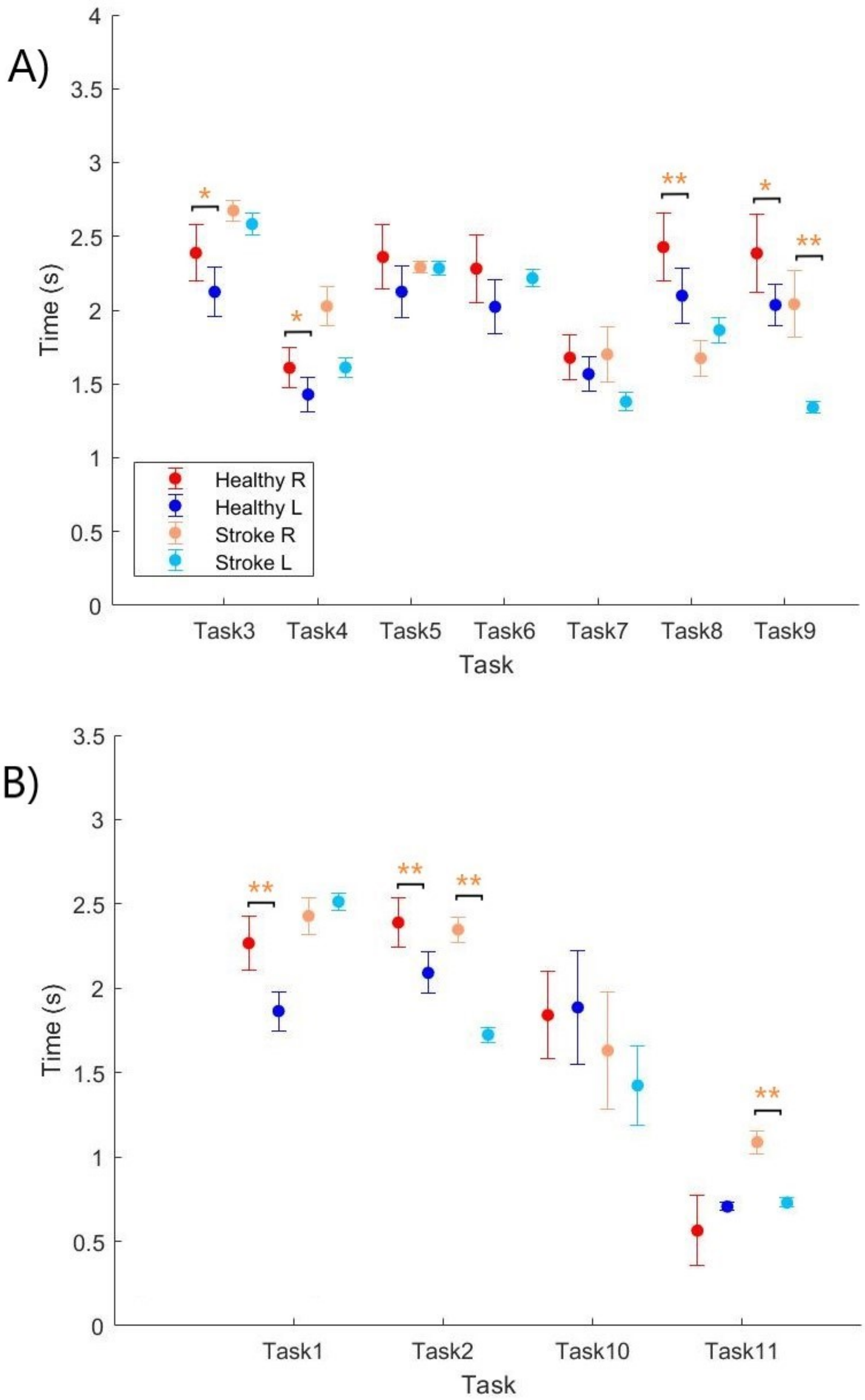

FIGURE 4.1: Mean and Standard Error representation for Time. A)Simple movements. B)Complex movements.

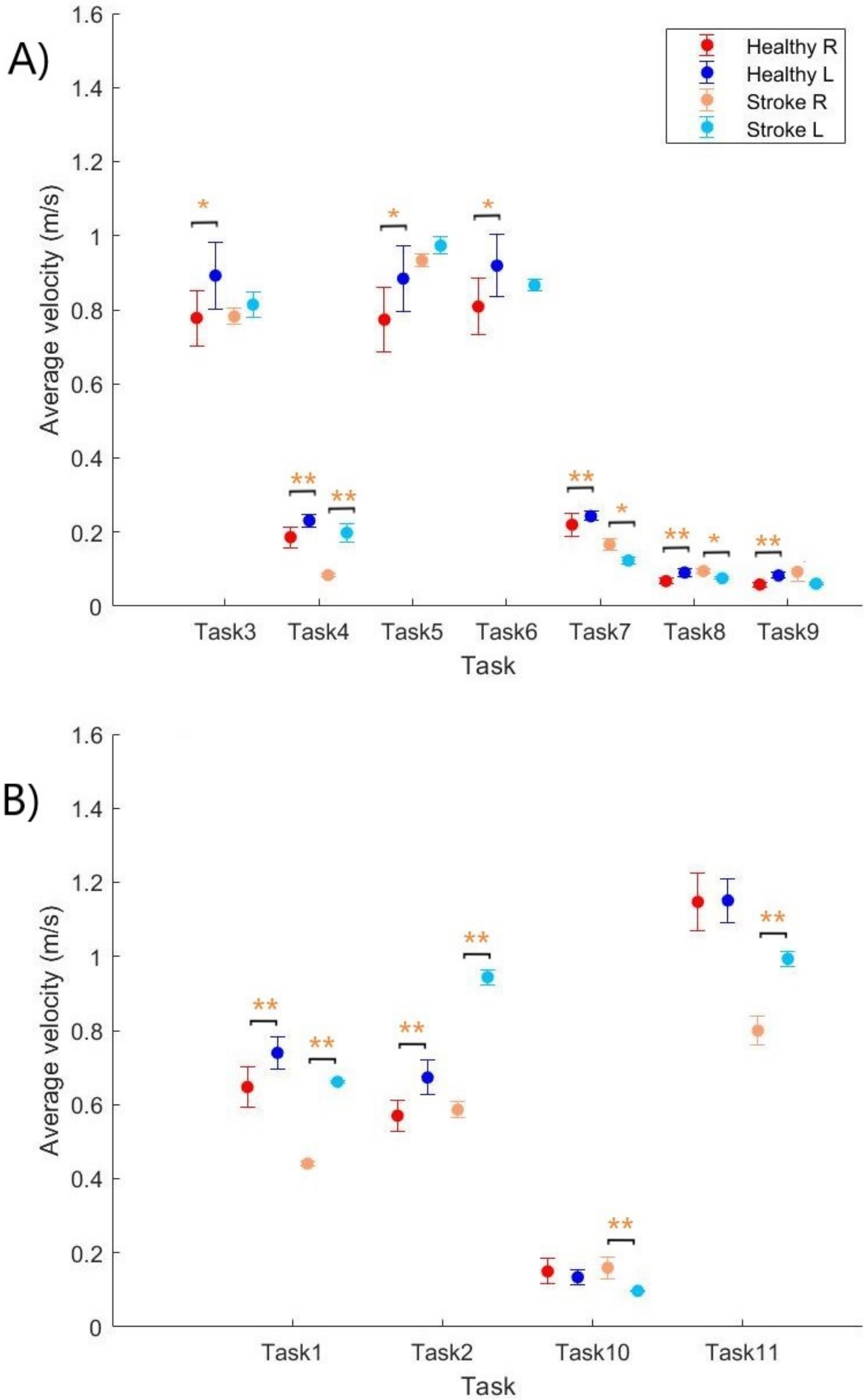

FIGURE 4.2: Mean and Standard Error representation for Averaged Velocity. A)Simple movements. B)Complex movements.

Jerk

Jerk is the third metric calculated for both simple and complex movements. The results are graphically illustrated in figure 4.3.
The value assumed by this parameter is expected to be more negative (i.e. higher in module), with increasing jerkiness. Jerkiness of movement increases with increasing number of submovements and time intervals between submovements.
Results obtained for the healthy subjects show that almost all the exercises are characterized by the same jerkiness, between -3.5 and -3. Only for tasks 8 and 9 the jerkiness is higher, around -4, but this is probably due to the fact that those tasks were executed on purpose in a more segmented way.
However, jerk trend for *Healthy R* and *Healthy L* is almost the same: the average value is similar between left and right for each task and also the standard error, which is also very low. This is a demonstration of how similar is the behaviour of healthy subjects, but also of the regularity and coordination in movements performance.
Focusing the attention on the stroke patient, the difference with respect to the healthy subjects is immediately evident. Movements result to be more jerky in the case of less affected arm and even more for the affected arm. The last one shows also an higher standard error, indicating that the repeatability in tasks executed with the right arm by the patients is lower.
Only for tasks 8 and 9 the jerk value obtained for the stroke patient is less negative than that associated to healthy subjects. This result may depend from the partial execution of those tasks and also from the fact that the execution itself was different from that of healthy participants, which was more segmented, as already mentioned before.

Normalized trajectory

Normalized trajectory was computed only for simple movements, except for exercises 4)Pronation/Supination - elbow 90° and 7)Pronation/Supination - elbow 0° (figure **??**).
The green line represents the reference value, equal to 1, which is the value of the ratio if travelled path and ideal path coincide. Looking at the healthy subjects, the values obtained are all near 1, with a low standard error and a very similar trend between right arm and left arm. This indicates that all the subjects tend to perform the exercises in a correct way which is near to the ideal path defined. The exceptions are also in that case the tasks 8 and 9, in particular for the findings from *Healthy R*. This can be linked to the fact that it is difficult for those exercises to estimate both the travelled path and the ideal path with high accuracy. Moreover, the amplitude of the movement is not always exactly 180°.
About the stroke subject, the values obtained for both affected and less affected arm are more distant from the reference value than those of healthy subjects, always taking into account the exception given by tasks 8 and 9. However, the difference with respect to the results of healthy subjects is not so huge: it is important to consider that the majority of the impairment of the stroke patient was localized in the wrist and hand portion.

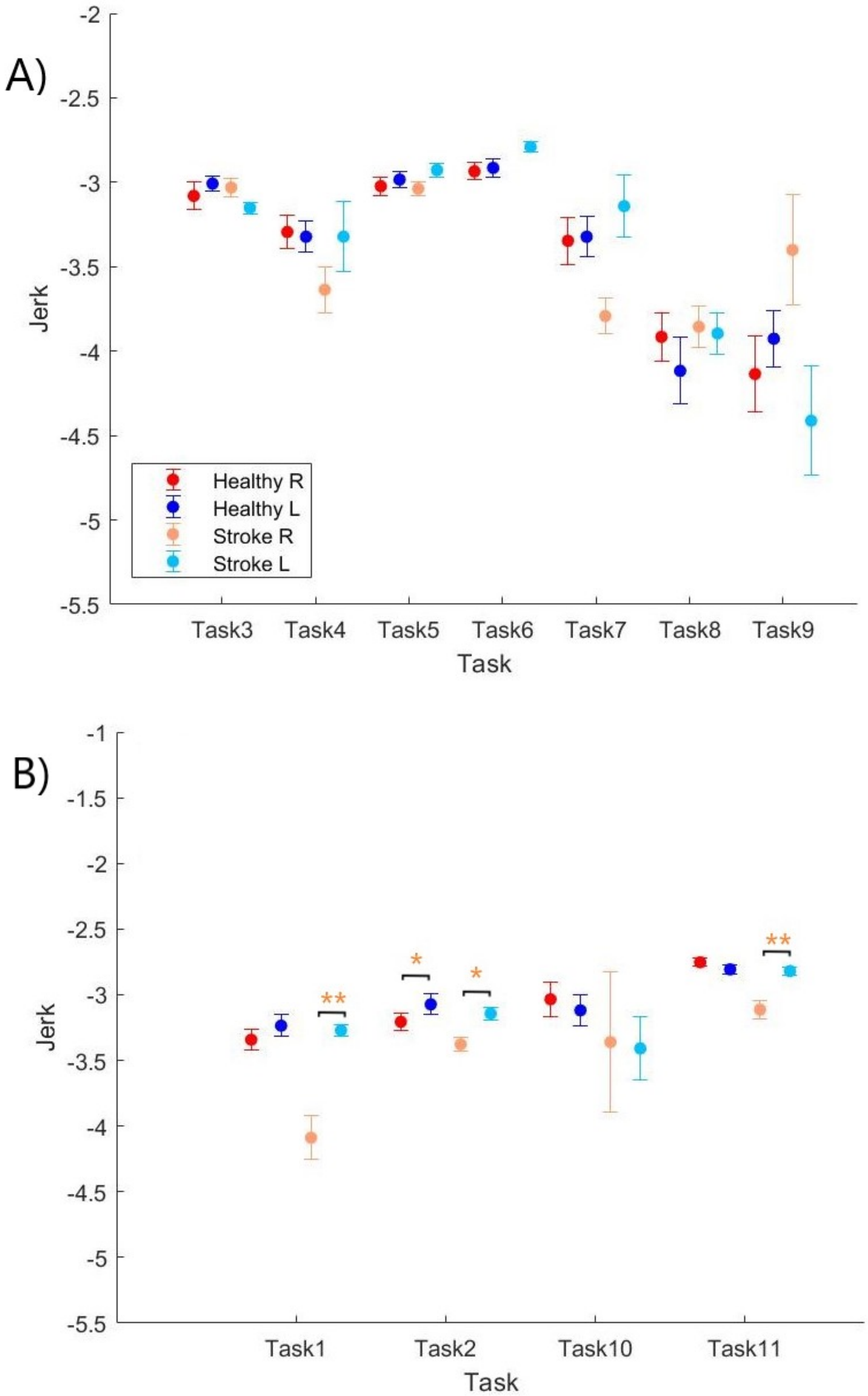

FIGURE 4.3: Mean and Standard Error representation for Jerk. A)Simple movements. B)Complex movements.

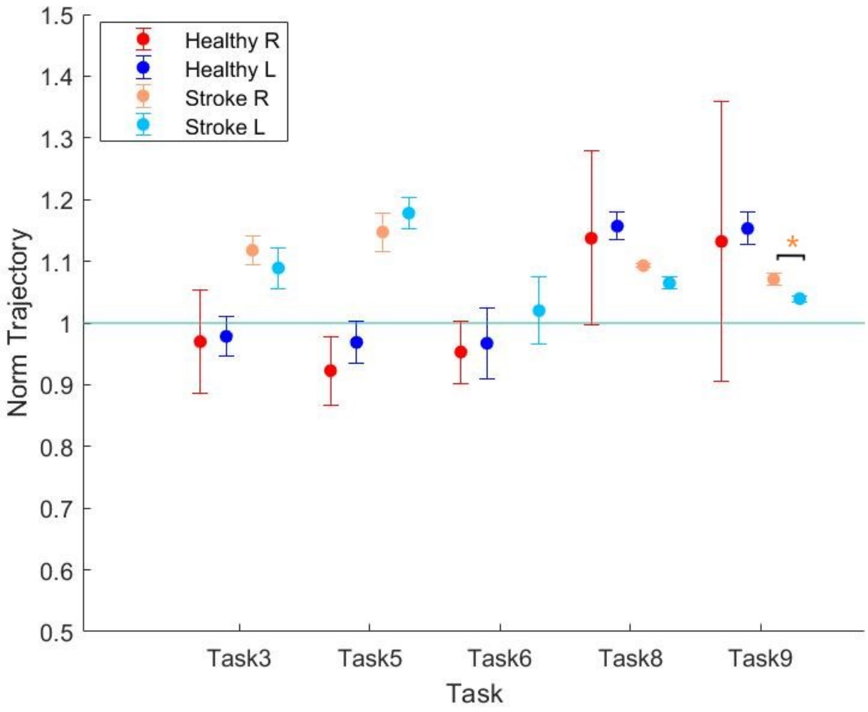

FIGURE 4.4: Mean and Standard Error representation for Normalized trajectory - simple movements.

Shoulder and Elbow angle

Also those two metrics were computed only for the simple movements (figure 4.5). The green line is used for indicating the reference value specific for each task. Shoulder angle was computed for all the simple tasks. It is possible to notice that the values for both healthy subjects and stroke patient are near the reference. Only for tasks 3)Shoulder flexion 0°-90° and 5)Shoulder abduction 0°-90° there is a more significant difference. This is probably linked to the fact that the final value of the angle reached in the execution of those tasks is not always exactly 90°. At the same time, in those tasks there is a more clear difference between stroke subject and healthy population.
Elbow angle was computed for all the simple tasks except for tasks 4 and 8. Here the values obtained are all around the reference value, considering both healthy and stroke subjects.
It is possible to conclude that from those parameters it is not possible to hightlight so much the impairment level of the patient that participated to the study always because it was more related to wrist and hand segment.

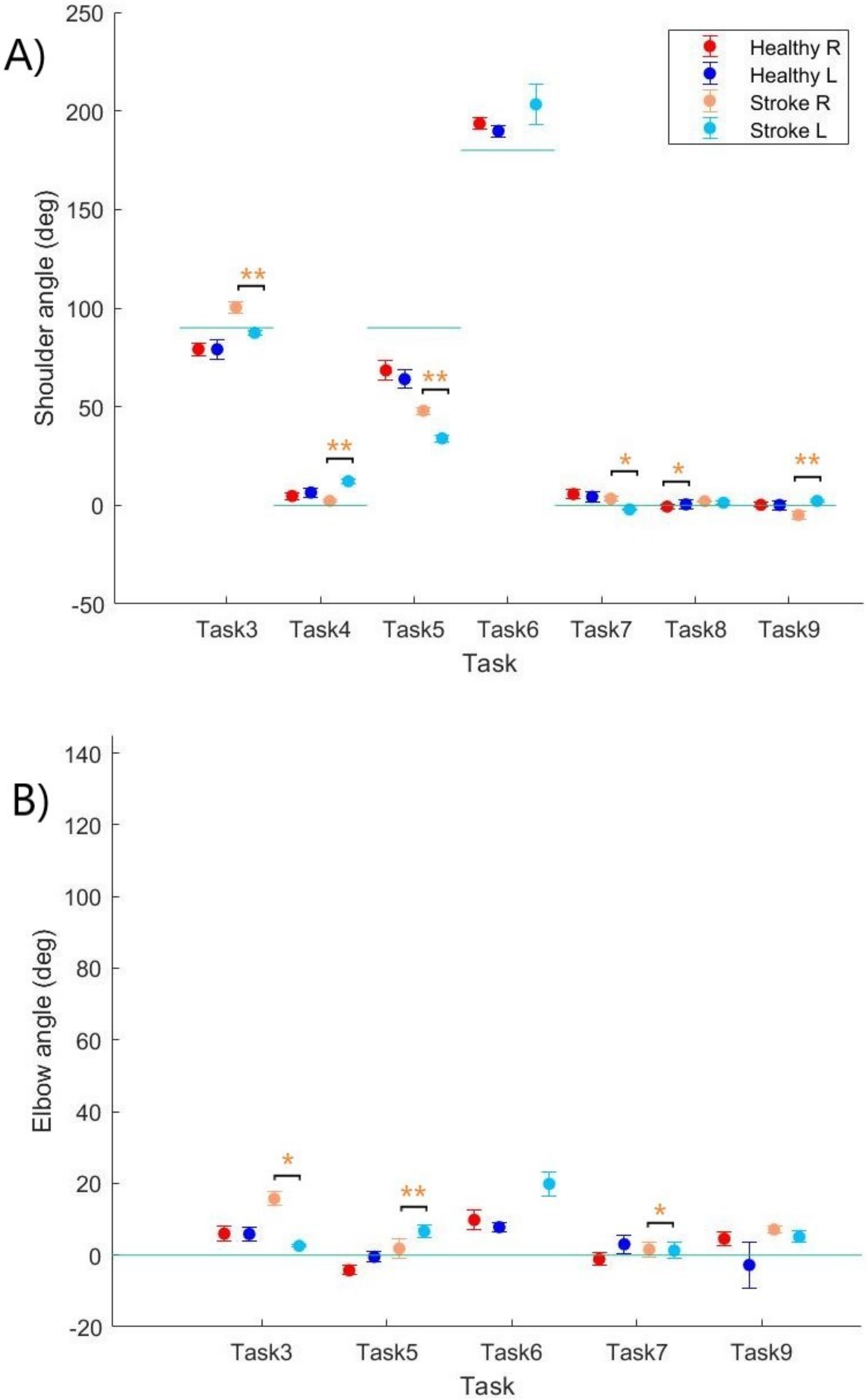

FIGURE 4.5: Mean and Standard Error representation for simple movements. A)Shoulder. B)Elbow.

4.1.2 2D Correlation coefficient

The correlation coefficient was calculated for both simple and complex movements and was obtained using data from several segments. The mean value and standard error were computed between the correlation coefficients obtained from the comparisons between subjects.
Also in this case data from the right and left arm were taken into account separately:

- *Healthy R* represent the result of the comparison between healthy subjects using right arm.
- *Healthy L* represent the result of the comparison between healthy subjects using left arm.
- *Stroke R* is the result of the comparison between healthy subjects and stroke patient both using right arm.
- *Stroke L* is the result of the comparison between healthy subjects and stroke patient both using left arm.

The results obtained for the correlation coefficient are illustrated in figure 4.6.
Considering the healthy subjects, it is possible to observe that all the values obtained are above 0.6 for both *Healthy R* and *Healthy L*. This means that there is an high correlation between healthy participants for all the exercises, both simple and complex movements.
For the stroke patient, the values obtained are lower than those of healthy subjects in case of the less affected arm (*Stroke L*) and even more considering the affected arm (*Stroke R*). This trend is valid for all the items. The fact that the correlation coefficients obtained for the stroke are lower, means that there is a minor similarity between the patient and the healthy subjects, so there is a difference in the execution of the exercises. This difference can be linked to the arm used for performing the task or to some compensatory strategies using thorax and/or controlateral shoulder. In fact correlation coefficient was computed considering also those joints: it gives a more complete information about the overall upper body movement with respect to the previous features.

4.1.3 Principal Component Analysis (PCA)

PCA was performed considering the information from different joints, so also this analysis was made for having a more complete description about strategies adopted by the subjects. Only complex tasks were considered in this phase.
Examining the first two Principal Components for the healthy and the stroke subjects, it is possible to observe the different contribute given by the joints considered in performing the same task. The PCs considered represent the most significant synergies and those synergies are different in healthy subjects and stroke patient. An example is shown in figure 4.7 for Task 1)Flexor synergy: hand from controlateral knee to ipsilateral ear. It can be noticed that the Shoulder end/exo rotation is less pronounced for the more affected arm of stroke patient looking at the first PC. In the same way, there is an activation of thorax segment looking at the second PC for stroke subject, while for healthy subjects it is practically non-existent.

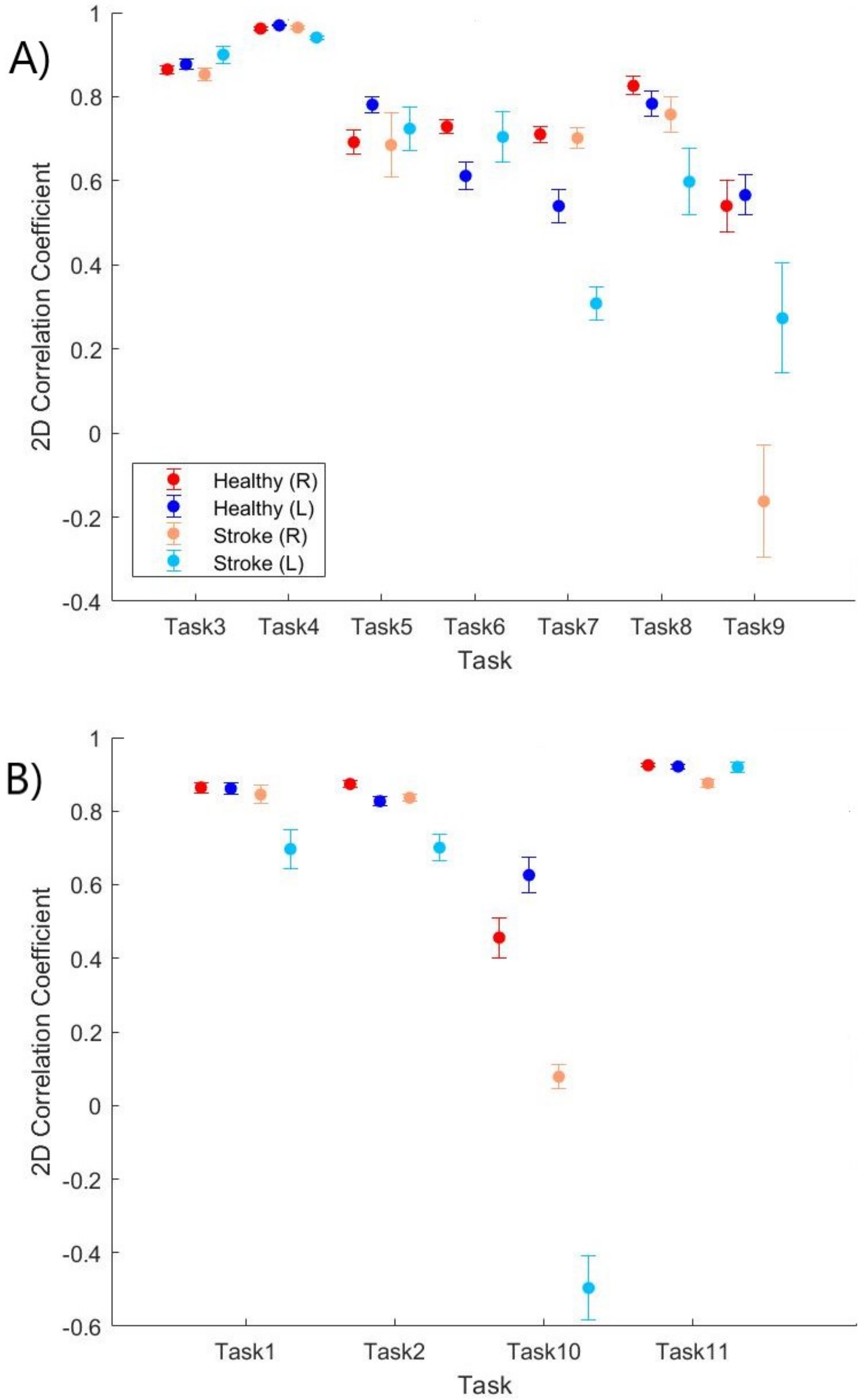

FIGURE 4.6: Mean and Standard Error representation for Correlation Coefficient. A)Simple movements. B)Complex movements.

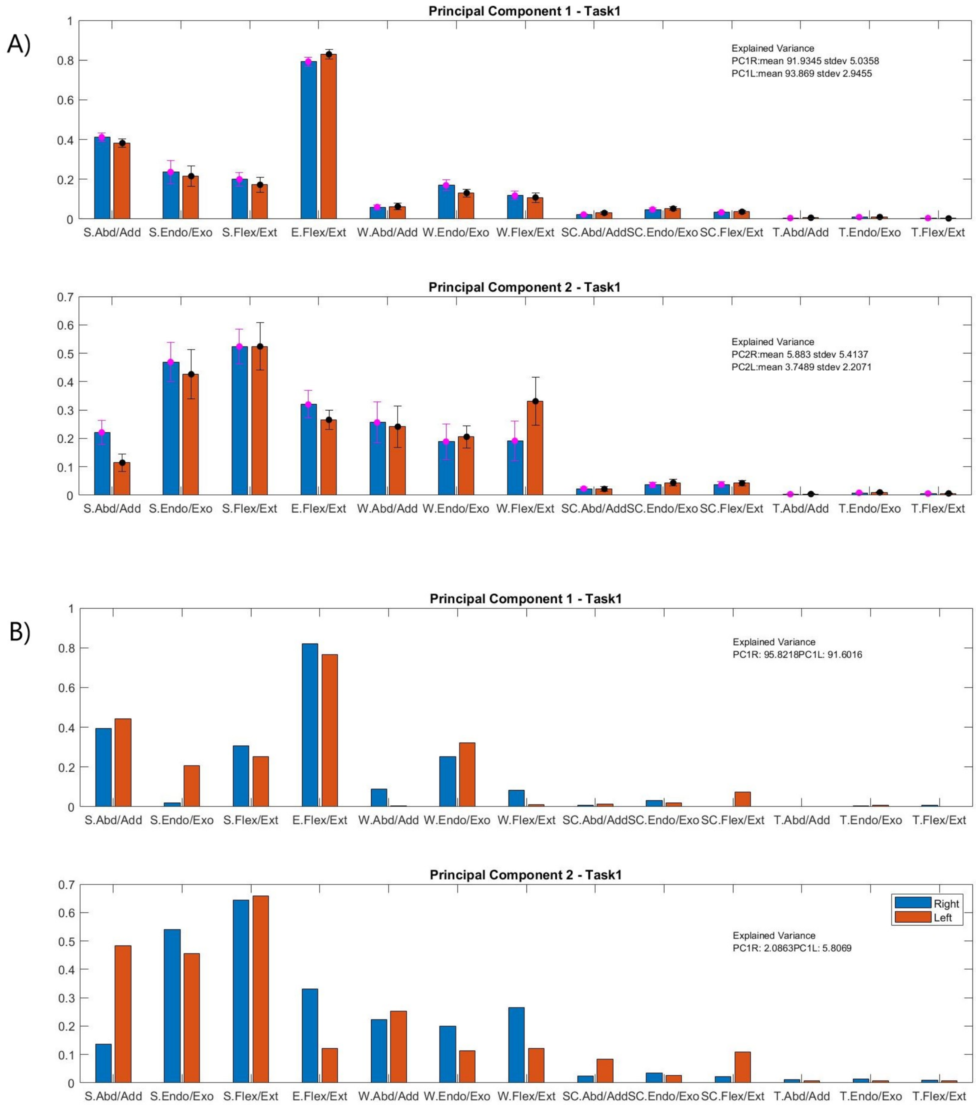

FIGURE 4.7: Principal Components for Task 1 - Flexor Synergy for healthy and stroke subjects. A) Healthy subjects. Representation of explained variance with also mean and standard deviantion for both left and right arm. B)Healthy subjects. Representation of explained variance for both left (less affected) and right (more affected) arm.

Then three kinds of comparisons were done for estimating the similarity intra and inter-subjects. Those are presented in the following.

Comparison between different subjects for the same task

This comparison was done considering separately right and left arm, following the same rules of the correlation coefficient (figure 4.8).
Starting from the results for healthy subjects, they show an high similarity. The values of VAF are all above the 80%, demonstrating that the PCs associated to the $j-th$ subject are able to describe in a proper manner the exercises executed by the $i-th$ subject with which the comparison is done. The values of Principal Angle are all under the 60° and those obtained for Projected Variance are all near 0.1. The lower the value of the last two parameters, the higher the similarity between subjects for a certain task. Moreover the standard error obtained is low for all the three parameters, indicating a low variability between results obtained from different couples of subjects.
Observing the results for the stroke patient, it is evident that the values obtained for the VAF are lower, expecially for tasks 2)Hand to lumbar spine. and 10)Circumduction. In general, for Principal angle the values are higher than 60° and those of Projected Variance are higher than 0.1. Also the standard error is higher for the three parameters. This shows a lower similarity between the stroke patient and the healthy subjects.

Comparison between left and right arm for the same subject

For each subject, a comparison was done between right and left arm. Results obtained for the healthy subject are presented using mean and standard error, while for the stroke patient there is of course only one value (figure 4.9).
The average values obtained for healthy subjects are all above 90% for the VAF, all under 50% for the Principal Angle and all under 0.1 for the Projected Variance. This indicated that the healthy subjects tend to perform the tasks in the same way with both left and right arm.
The trend of results for the stroke patient is in general opposite. In fact, lower values were obtained for the VAF, all under 90%; the Principal Angle assumes higher values than those obtained for healthy subjects in all exercises. Also the values obtained for the Projected Variance are higher in all cases. This shows how different is the behaviour of left and right arm for the stroke patient.

Comparison between different tasks for the same subject

For each subject, a comparison was done between different tasks. Also in this case, results obtained for healthy subjects are presented using mean and standard error, while for the stroke patient there is only one value (figure 4.10).
It is possible to notice from the results of healthy subjects that all the tasks are very different from one to the other. This is coherent with the fact that different tasks are performed using different synergies.
For the stroke subject this difference is even more evident for every task. Values of VAF are all under 80%, the Principal angle shows values above 50° and the Projected

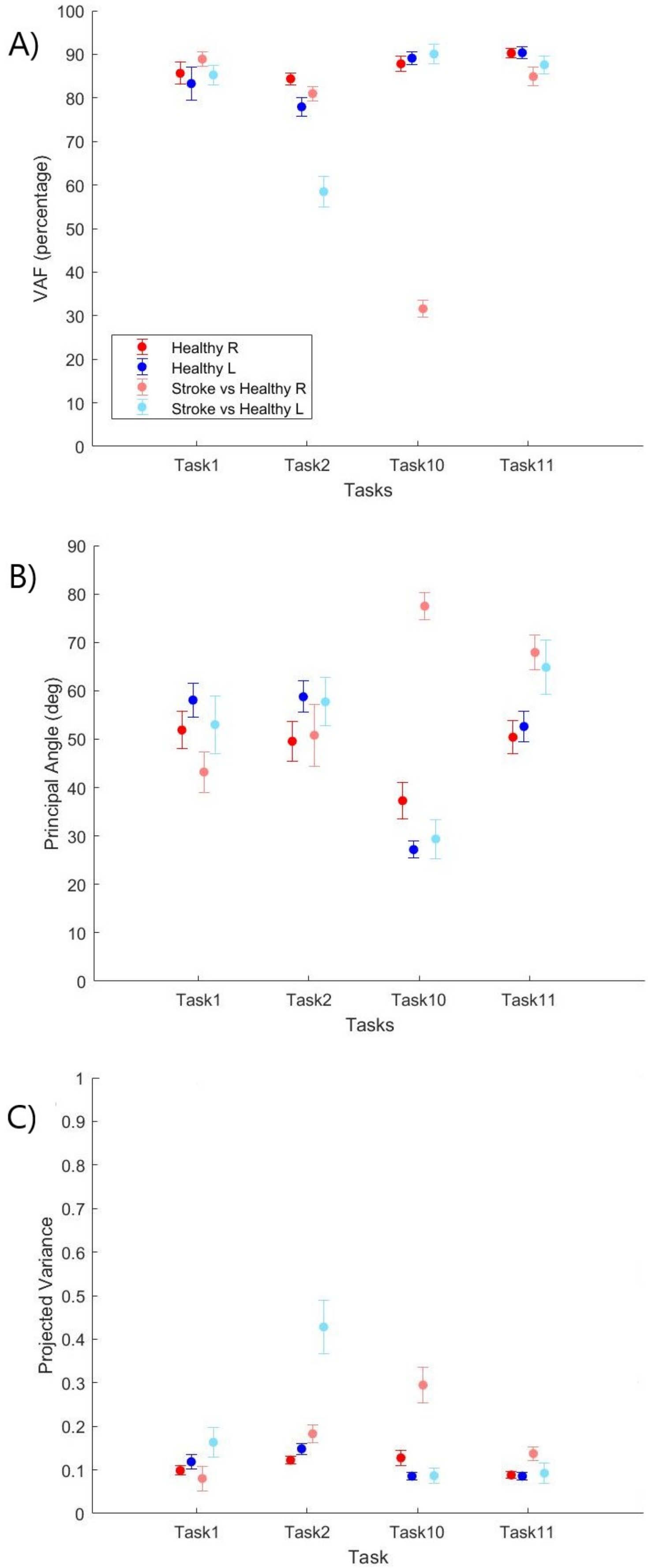

FIGURE 4.8: Results of comparison between different subjects for the same task in therms of VAF, Principal Angle and Projected Variance. A)Variance Accounted For (VAF). B)Principal Angle. C)Projected Variance.

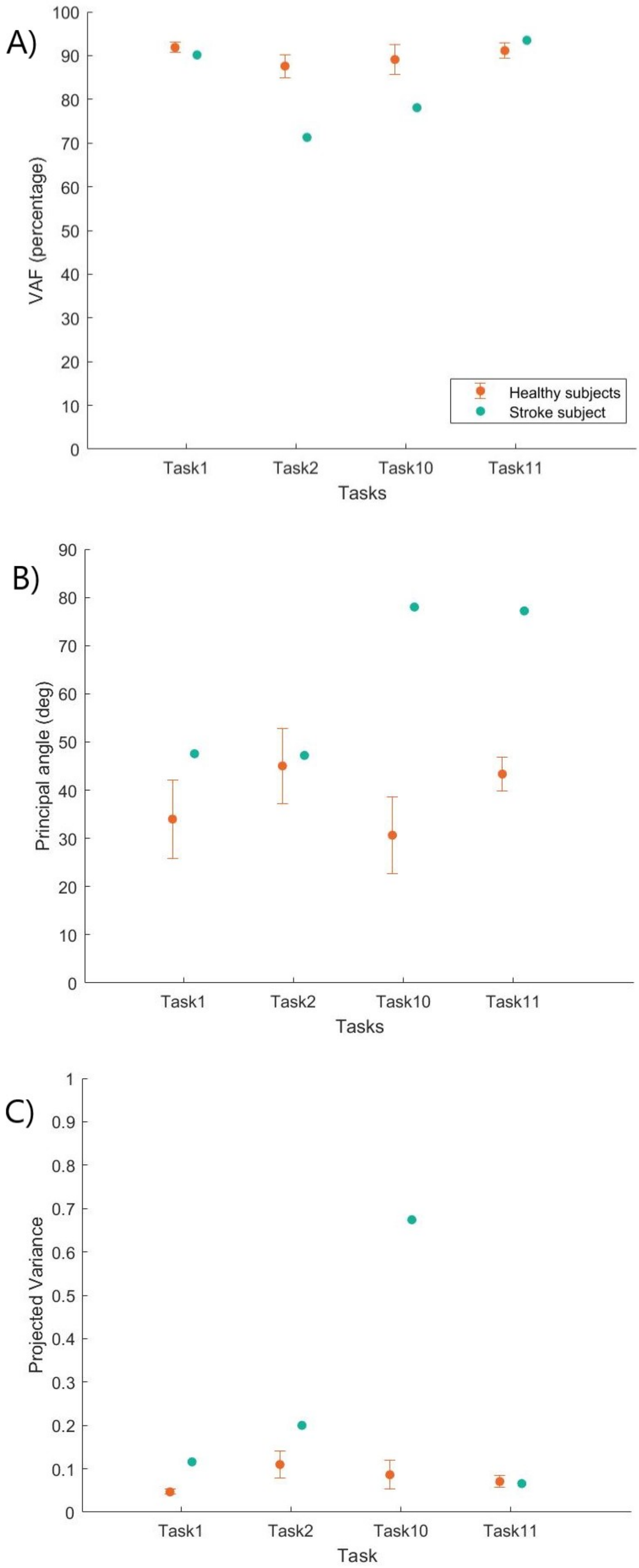

FIGURE 4.9: Results of comparison between left and right arm for the same subject in therms of VAF, Principal Angle and Projected Variance. A)Variance Accounted For (VAF). B)Principal Angle. C)Projected Variance.

Variance is in all cases above 0.2.

4.2 EMG results (exploratory analysis)

Results from EMG exploratory analysis are presented in this paragraph. The first parameter computed was the RMS value, then the 2D Correlation Coefficient and finally the PCA on complex movements.

4.2.1 RMS value

RMS value was computed for each repetition of every task for all the eight channels. This procedure was repeated for the three healthy subjects. As an example, the results obtained for exercise 3)Shoulder flexion 0°-90° and exercise 11)Coordination/Speed are illustrated in figure **??**.

It is possible to observe that for task 3, which is a simple task, the muscle activation is localized in a limited number of channels. On the contrary, for task 11, which is a complex task, the muscular activation is spread in all channels. This is coherent with the fact that more simple tasks involve the action of a lower number of muscles than complex tasks. The muscular synergies characterizing the two movements are different. Moreover, the activation pattern obtained for the three subjects is similar for both simple and complex movements.

4.2.2 2D Correlation Coefficient

Correlation coefficient was calculated considering the data from the eight channels for each task and the comparison between subjects was done (figure 4.12).

It is possible to observe that for the majority of the exercises, the correlation value is above 0.5. However, the results obtained are different from those of the kinematic analysis: in general the correlation coefficient values are lower. This may depend from the fact that the information given by the Myo armband is limited to the forearm, while for the kinematics several joints were considered. This is demonstrated by the lower values of correlation coefficients obtained for tasks 8,9 and 10, which involved the wrist, and the other complex tasks involving more joints. Of course the information extracted from the forearm is not sufficient for well describing those tasks.

4.2.3 Principal Component Analysis (PCA)

PCA was performed for complex movements considering the data from the eight channels as variables. In this case two comparisons were performed: between different subjects for the same task and between different tasks for the same subject.

Comparison between different subjects for the same task

Results obtained for PCA from EMG data are different from those obtained from kinematic data (figure 4.13). The VAF is under 90% for all the exercises. The principal angle assumes values all above the 30° degrees, reaching almost the 90° for task 2)Hand to lumbar spine. Also values obtained for the Projected Variance are almost

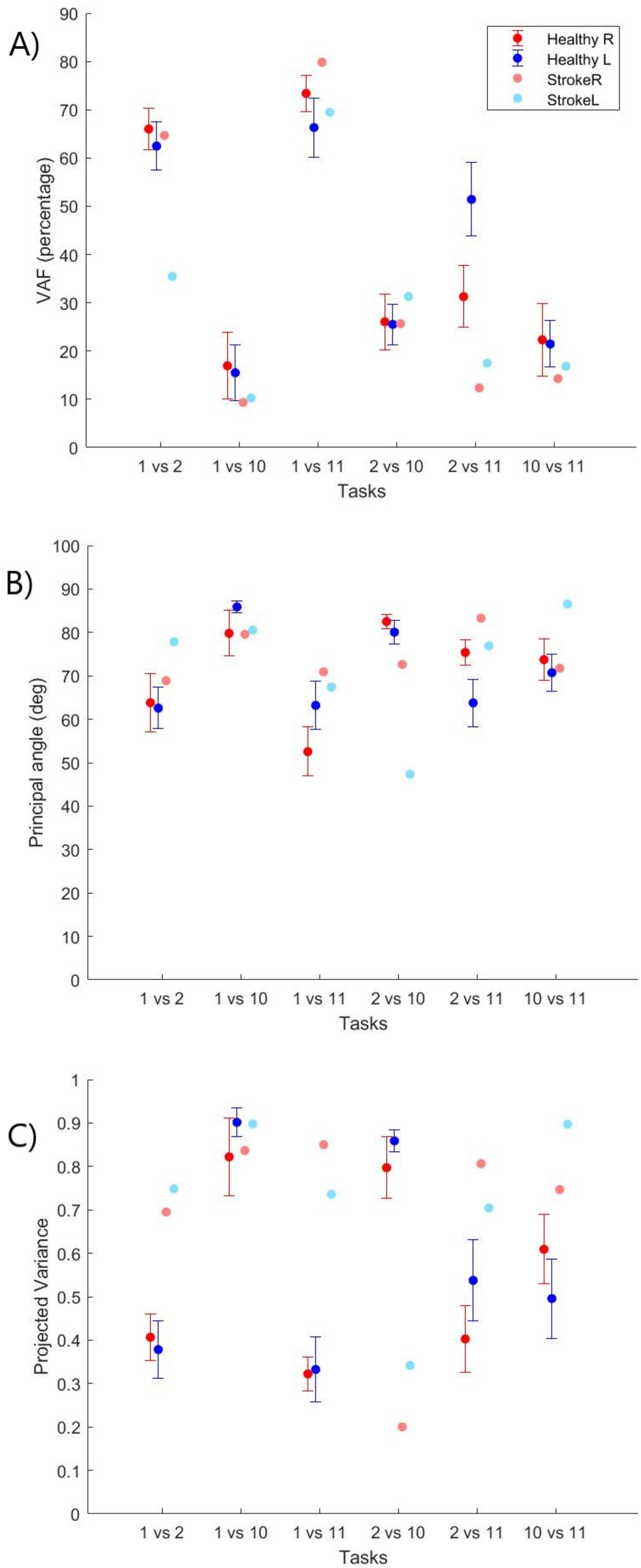

FIGURE 4.10: Results of comparison between different tasks for the same subject in therms of VAF, Principal Angle and Projected Variance. A)Variance Accounted For (VAF). B)Principal Angle. C)Projected Variance.

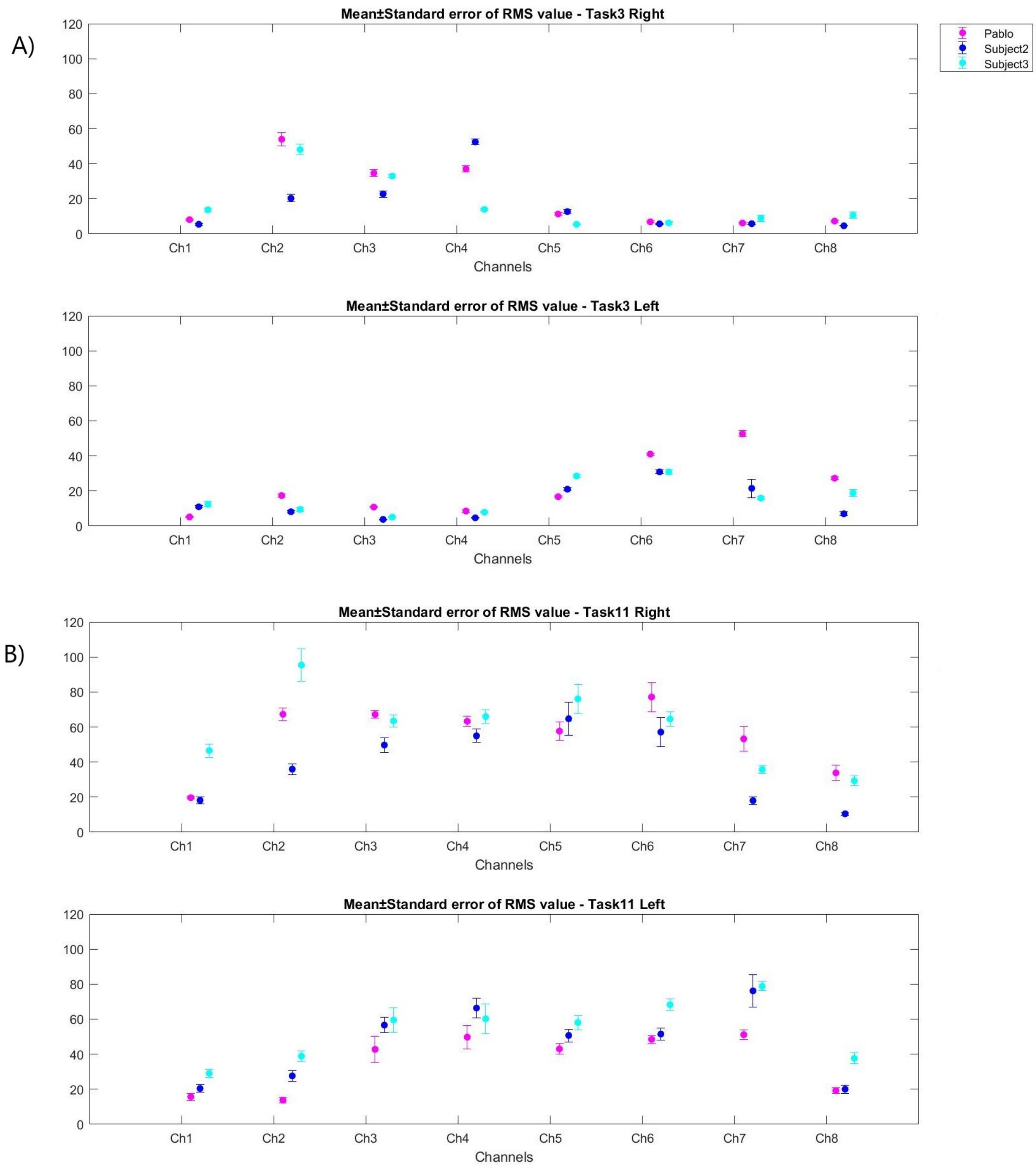

FIGURE 4.11: Example of RMS value for one simple movement and one complex movement. A)Task 3 (simple). B)Task 11 (complex).

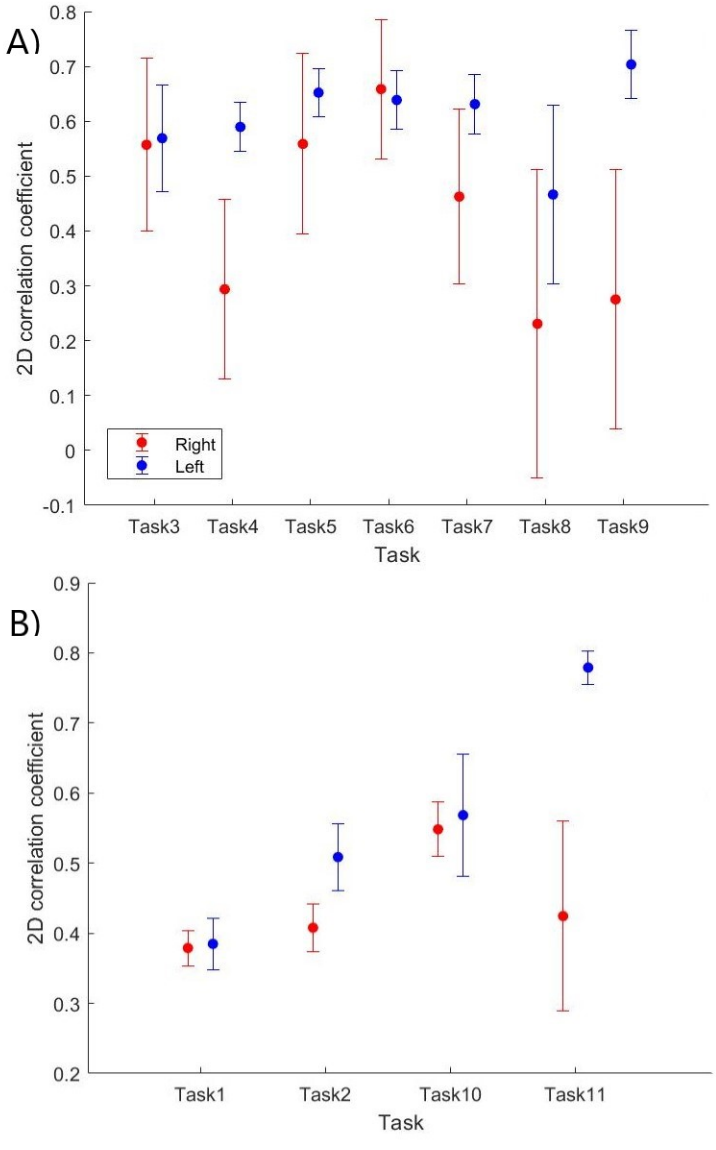

FIGURE 4.12: 2D Correlation Coefficient for simple and complex movements. A)Simple movements. B)Complex movements.

all above 0.3. This means that the information provided by the EMG recordings is different with respect to that obtained from kinematic data for two main reasons:

- The Myo armband was able to record signals only from forearm muscles, according to its positioning. On the other side, XSens records signals from hand, forearm, upper arm, controlateral upper arm and thorax. In fact the information provided by the second system is more complete, since it takes into account more segments.
- The PCA applied to EMG signal gives an information on muscular synergies, while that applied to IMU signals gives the information about kinematic synergies. The first ones are related to the way muscles are correlated and act together, the second ones are related to the coupling between joints. The control strategies applied to muscles and joints are different, so of course the information provided by the two analysis is different.

Comparison between different tasks for the same subject

PCA using EMG data was also performed for making the comparison between different tasks done by the same subject (figure 4.14).
The results show that there is a low similarity between different tasks. In fact the VAF is under 70% in all cases; the Principal angle assumes values above 40° and also the Projected Variance is high for all the comparisons, above 0.2.
Also in this case the trend is different from that obtained from the kinematic analysis. The reasons are the same explained for the comparison between different subjects for the same task.

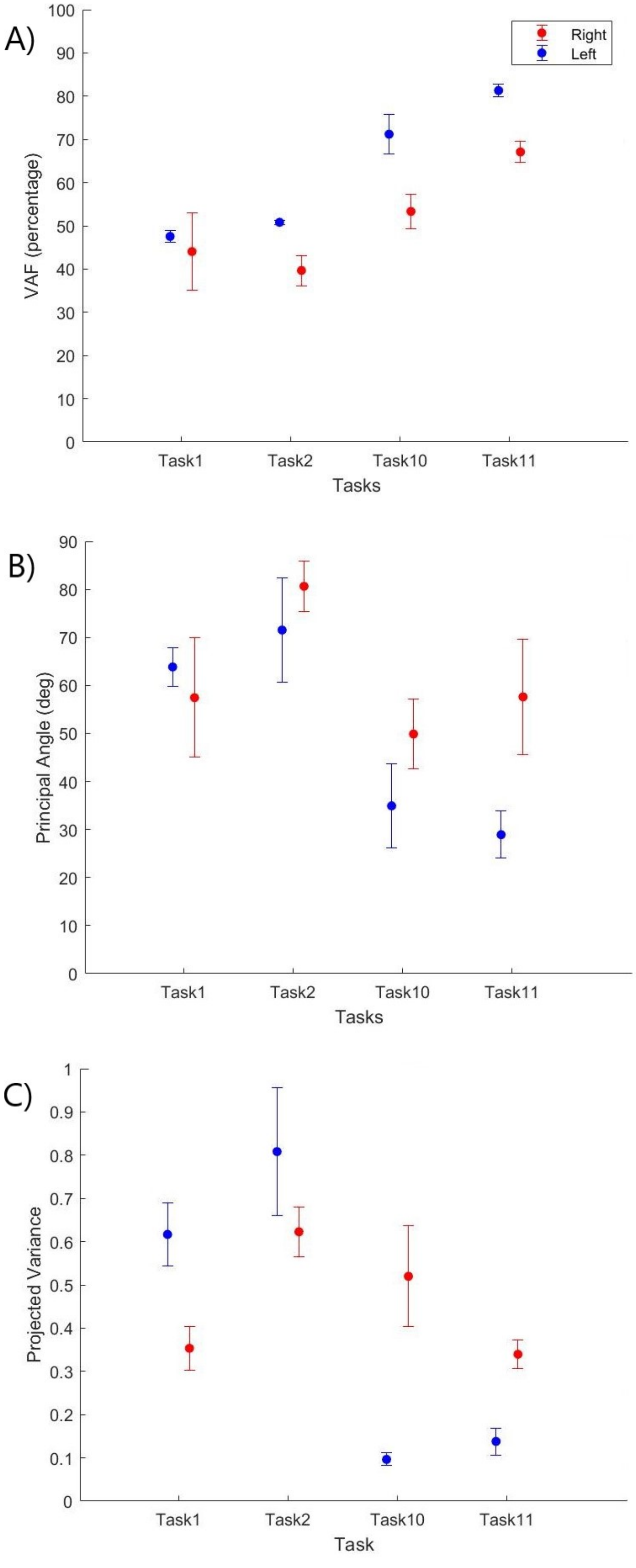

FIGURE 4.13: Results of comparison between different subjects for the same task in therms of VAF, Principal Angle and Projected Variance. A)Variance Accounted For (VAF). B)Principal Angle. C)Projected Variance.

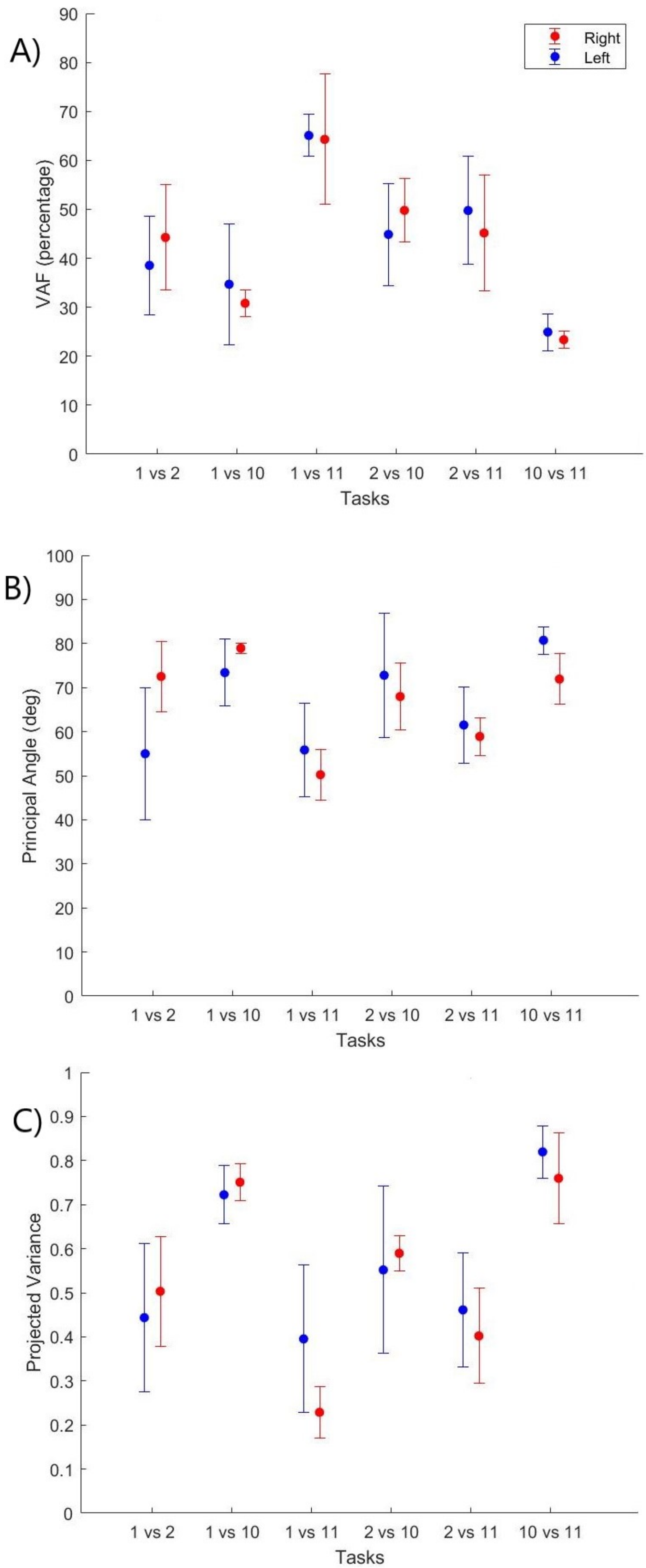

FIGURE 4.14: Results of comparison between different tasks for the same subject in therms of VAF, Principal Angle and Projected Variance. A)Variance Accounted For (VAF). B)Principal Angle. C)Projected Variance.

Chapter 5

Conclusions and Future Perspectives

In this Chapter, the work presented in this thesis is discussed, starting from the aim till the results achieved and already described in the previous Chapter. Advantages and limitations are illustrated looking at the future perspectives.

The aim of this thesis was finding a set of parameters for a quantitative analysis of upper-extremity impairment in post-stroke patients, using data collected with wearable sensors. This could be used for overcoming the limits of clinical scales, in particular the UE-FMA, which is the most used performance measure for stroke patients. In fact, as already discussed, this clinical assessment is clinician-dependent, the evaluation is qualitative (based only on the observation of a therapist) and the description of the impairment is partial, since it is reduced to a score. Moreover, the score ranges only between 0 and 2, so the Fugl-Meyer Assessment results to have a low sensitivity to mild impairment.

To the best of our knowledge, works found in literature were all based on the automation of clinical scales, extracting features to be used as input for a classifier, giving as output the scores. Only two works proposed a new approach based on the evaluation through parameters: the first one was focused on Multiple Sclerosis patients; the second one was focused on post-stroke patients. In both those works only one IMU sensor was used, positioned near the wrist, so the information obtained was limited to forearm segment. Moreover, in the work related to stroke patients, only 5 items of 33 from UE-FMA were tested.
For all those reasons, the work proposed the use of XSens Awinda, in order to collect the kinematic data not only from the forearm on the affected side, but from several segments, including the controlateral part. This was useful for making a more complete analysis and achieving information also on possible compensatory strategies and abnormal synergies. Moreover, Myo armband was used for recording EMG data from the forearm portion for making an exploratory analysis. A total of 11 tasks were selected from UE-FMA for testing a good part of this clinical scale.
The system was tested on 9 healthy subjects and 1 stroke patient. Several parameters were extracted, including some features deriving from a single segment and more detailed analysis (2D Correlation Coefficient and PCA) made considering several segments. In particular, the last ones were useful for assessing the contribution of different joints during the performance of the observed tasks.
Results achieved showed that the selected paramenters are able to point out the differences between healthy subjects and stroke patient. Moreover they allow to observe that not only the more affected arm behaves differently with respect to the limb of healthy population, but also the less affected arm shows some differences.

This means that stroke has an influence also on the so called "unaffected arm".
It is also important to notice that this new approach is able to quantify the impairment of the stroke patient who participated to the study even if it is mainly related to the wrist/hand portion. So the sensitivity to mild impairment is higher than that of the Fugl-Meyer clinical scale.
Summarizing, there are several advantages deriving by the use of the proposed metrics:

- The evaluation is quantitative, since it is based on parameters obtained from data recorded with sensors.
- For the same reason the evaluation is objective and it does not depend on the clinician of course.
- The description of the impairment is more complete and detailed because it is not reduced to a single number.
- The set of parameters allows to describe in a satisfactory way also mild impairment, without losing information.
- The sensors system chosen is able to collect data from the entire upper body, so that eventual compensatory strategies can be examined.

This work as also some limitations:

- The analysis is performed offline
- The Myo armband only records data from forearm segment
- The system was tested only on one stroke patient
- The Myo armband was used only on healthy subjects

Those limitations can be obviously overcomed. Future perspectives are illustrated in the following:

- Using more than one Myo armband positioned on forearm and upperarm on both arms. Alternatively, using an EMG electrodes positioned on the entire upper extremity in order to obtain the information from more muscles.
- Using a glove sensor for also evaluating the hand impairment
- Testing the system on other stroke patients
- Collect data from an age-matched testing group
- Building a classifier for discriminating the movements and then compute the analysis. This can be useful for obtaining a system working online.

In particular, we are already moving in the direction described in the last point: a classifier able to discriminate the movements was built and tested on the data from some healthy subjets. Some details about this work are illustrated in Appendix A.

Appendix A

Classifier for movements discrimination

In this appendix the building of a classifier for discriminating movements using QDA (Quadratic Discriminant Analysis) is briefly described.

A.1 QDA classifier

QDA classifier [50] was built using data collected from three healthy subjects. A total of 20 recordings were executed on the same subject, simulating the performance of 20 different subjects, in order to have a sufficiently big dataset. The other two subjects performed only one recording session. In this case only XSens Awinda was used for obtaining data.
Kinematic data were then filtered and segmented according to the steps described in Chapter 3.
A series of features were extracted for each repetition of every task to be used as input of the classifier:

- Shoulder angles (x,y,z)
- Elbow angles (x,y,z)
- Wrist angles (x,y,z)
- Forearm position (x,y,z)
- Hand position (x,y,z)

Each feature was extracted looking at the end of forth movement.
The classifier was built using Matlab function *fitcdiscr* and specifying discriminant type. It was trained considering 70% of data from the 20 recordings on one subject. Then it was tested on the remaining 30% and on the recordings of the other two healthy subjects.
Classifier resulted to have an accuracy of 98% and was able to correctly classify all the exercises (figure A.1).

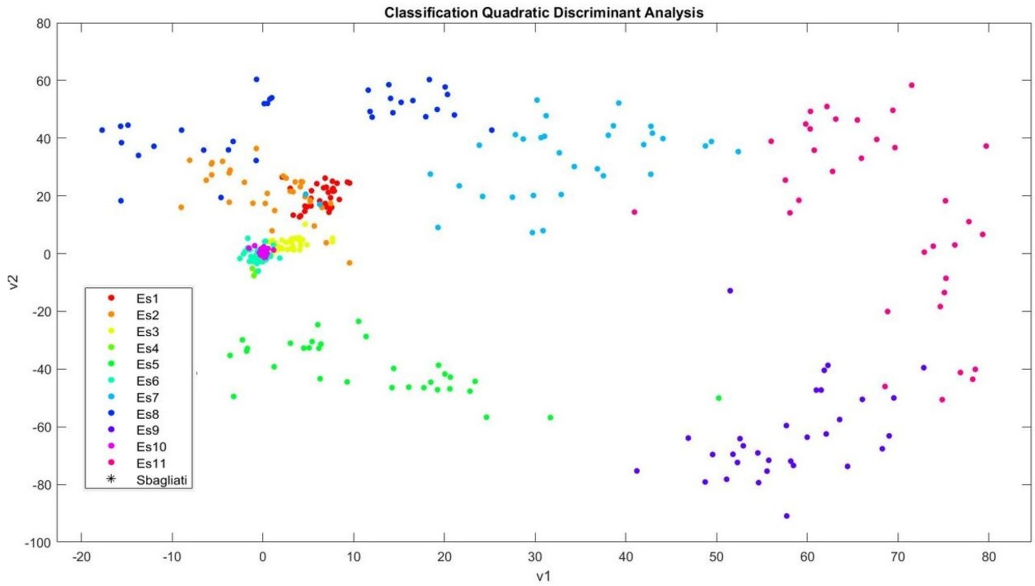

FIGURE A.1: Scatter plot showing QDA classifier results. All exercises are correctly classified.

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