UNIVERSITA' POLITECNICA DELLE MARCHE

FACOLTA' DI INGEGNERIA

Corso di Laurea in Biomedical Engineering

ASSESSMENT OF TEMPORAL PARAMETERS OF GAIT IN HEMIPLEGIC CHILDREN BY MACHINE LEARNING APPROACH

Relatore:
Prof. Francesco Di Nardo

Tesi di Laurea di:
Alessandro Paoloni

Correlatore:
Prof. Christian Morbidoni

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ABSTRACT

Hemiplegia is a pathology caused by a neurological disorder and is quite frequent in children with cerebral palsy. A lot of methods have been proposed to perform gait analysis in order to understand how muscles activate during walking activity, so that it is possible to understand how hemiplegia affects muscular recruitment. To this aim, there are techniques based on the use of classi sensors, but the most recent approaches consist in using machine/deep learning techniques. In the present work, artificial neural network was employed with the aim of classifying the two main gait phases (stance and swing periods) and to predict foot-floor contact signals from surface electromyographic (sEMG) signals in hemiplegic children. To this purpose, sEMG signals from the main leg muscles and foot-floor-contact signals were acquired during walking at self-selected pace of 20 hemiplegic children. These data were then fed as input to a feed-forward multi layer perceptron (MLP) neural network. Successively, prediction evaluation was performed to assess the goodness of the chosen model for the neural network. Sensitivity analysis of classification and prediction performances to the processing parameters was also performed. Results show as acceptable levels of accuracy in gait-phases classification and gait-event prediction were reached both for learned and unlearned subjects. Although there is still work to be done, deep learning approach was proved to be a reliable tool for gait analysis, also in this preliminary attempt. The fact that with deep learning approach gait events are extractable from sEMG signals is useful because in this way it is possible to avoid the use of foot-switch sensors and, consequently, to perform gait analysis with a smaller number of sensors and thus with reduced costs, time-consumption, and patient invasiveness.

1 - INTRODUCTION

Hemiplegia is a pathology that can be congenital or develop as a consequence of a stroke: in both cases it is caused by a cerebral dysfunction that is due to brain damages. These damages are located in one of the two hemispheres and the consequence is that the contralateral part of the body is paralyzed while the other one keeps well functioning [1]. This disorder provokes a really serious asymmetry which prevents subjects to perform easily all common tasks of everyday life, above all walking.

Hemiplegia occurs in different shapes, for example it can be characterized by an anatomical deformity, like drop foot and equinism. Since this pathology can affect, besides adults, 2 per 1000 children since birth, scientists are working very hard on research in order to understand how to develop more and more efficient rehabilitation programs so that adults who have experienced stroke can come back as earlier as possible to live a normal life and children with congenital cerebral palsy can grow like the other ones[2]. Among these rehabilitation programs, for example there is the electrical stimulation of muscles, which is a method consisting in stimulating electrically the activity of those muscles that are not sufficiently innervated by the nervous system and thus cause the anatomical deformity [3].

The development of these programs was possible only by using methods that could analyze efficiently the neuromuscular system activity because it is necessary to understand how and when muscles activate both in normal and pathological conditions in order to treat the pathology successfully. One of these methods is the electromyography (EMG) which consists in recording the electrical activity of muscles: this method is largely used first of all because it is non-invasive so it is absolutely safe for the patient; moreover during experiments, this technique often showed very reliable results that gave a good explanation of the electrical activity of muscles during different motor tasks. By applying this approach in laboratory with healthy and hemiplegic subjects who are requested to walk, it is possible to get useful information for the rehabilitation program.

During walking it is fundamental to correlate EMG signals to kinematic parameters in order to reach a reliable spatial-temporal identification of muscle activation patterns. This kind of approach appears particularly important to characterize and interpret potential disorders' functional effects. Thereby, gait cycle is commonly divided in a 0-100% scale to correctly partition each of sub-phase. Every single of them, characterized by a synergic movement schema, has a specific role in walking activity. Overall, the full sequence can be divided in two macro-stages: stance and swing phases that, respectively, occupy 60% and 40% of the whole gait cycle. The stance phase identifies the whole time frame when the foot is in contact with the ground, while the swing phase comprehends the remaining period when the foot is suspended in the air. In order to identify correctly gait phases it is important to individuate transitions between a stance and the following swing phase and viceversa: the transition between a swing and a stance is called heel-strike (HS) while the other one is called toe-off (TO).

A lot of methods have been proposed in order to identify gait phases. In [4] force platforms and pressure measurement systems have been used to perform gait analysis: by measuring ground reaction forces and pressure under each foot, researchers have succeeded in identifying stance and swing phases. In another study [5] a pressure sensor and an inertial measurement unit (IMU) sensor were used for the measurement of the angle variation of the ankle joint; with this procedure, researchers have succeeded in identifying transitions phases (heel-strike and toe-off) and also stance and swing periods. In last decades researchers focused their efforts trying to use machine and deep learning approach to improve the reliability of gait analysis.

In [6], acceleration sensors have been applied on ankles, knees and hips, and then recorded data have been processed by utilizing assembled classifiers in combination with a deep learning algorithm in order to classify gait phases with the highest accuracy: once the best classifier was found, it was combined with the deep learning algorithm.

In [7] researchers tried to classify gait types by recording gait data with pressure, acceleration and gyro sensors installed in a smart insole. After acquisition, a multiple deep convolutional neural network has been constructed and consequently gait features were extracted: the final classification has given very good results. All these methods have been proposed in order to perform gait analysis as more accurately as possible, so that researchers can elaborate rehabilitation protocols which vary depending on the type of pathology affecting walking, like hemiplegia.

Machine learning approaches were also satisfactorily implemented for the estimation of gait events from both kinematic data [8,9,10,11] and electromyographic (EMG) signals [11,12,13,14] during walking. The success of machine learning approaches has opened a novel perspective for reducing the complexity of experimental set-up. Predicting gait events from only EMG signals could remove the need of further sensors or systems (foot-switch sensors, pressure mats, IMUs, stereo-photogrammetry) for the direct measurement of temporal data. This would be particular suitable for specific fields where measuring myoelectric signals is strongly recommended, such as the analysis of neuromuscular pathologies such as hemiplegic cerebral palsy.

In the present work, a new method based on deep learning approach has been proposed: an artificial neural network for classification of the two main gait phases in children affected by hemiplegic cerebral palsy, by using only sEMG signals. Further aim was the prediction of basographic signals, i.e. those signals which contain the sequences of gait events (including heel-strike and toe-off timing).

2 - MUSCLE RECRUITMENT DURING WALKING

Walking is a very common activity in normal life of all people but the way in which it works and it is possible from an anatomically point of view is not so easy to understand.

First of all walking is defined as a repetitive sequence of movements of the lower limbs (legs) that allow the advancement of the body without losing the maintenance of the balance; every sequence of movements from the heel contact on the ground until the following heel contact of the same foot identifies the so called “gait cycle”. During the advancement, one limb acts as a support for the body while the other one moves forward until it touches the ground; in this precise moment both feet are in contact with the ground but one of them is going to detach from it; when the rear limb is lifted up, body weight is transferred on the leaning foot until the other foot finishes its progress coming in contact with the ground; then another cycle can begin.

So gait cycle can be subdivided in two big phases: the stance, which identifies the time frame in which the foot is in contact with the ground; the swing, that is referred to the remaining part of the gait cycle where the foot is suspended in the air. The precise moment in which stance begins is called “heel strike” while the corresponding moment to swing beginning is called “toe off”.

Gait cycle begins when both feet lean on the ground, that is a very short gait period known as “double initial stance” and for each foot is equivalent approximately to the 10% of the gait cycle, so the total lean is equal to the 20%; the resting part of the cycle is constituted by single lean (40%) and swing (40%).[15]

Walking activity is made possible by a complex organization of muscles activity and bones in legs and feet. Bones are kept united by joints that play a fundamental role in allowing the performance of all movements which are very important for the gait cycle. Muscles are attached to bones through tendons and thanks to their continuous activation, movements can be performed.

In the present section, firstly a description of ankle-joint and knee-joint muscles is provided, then gait cycle and gait analysis methods are explained in details.

2.1 - ANKLE-JOINT MUSCLES

The ankle is a joint that connects the leg and the foot: it is subdivided into two smaller joints that are the talocrural joint (also called tibio-talar joint), which connects tibia and talus, and the subtalar joint which connects talus and calcaneus.

The talocrural joint can generate two movements of the foot that are dorsiflexion and plantarflexion: the first is intended as the upward movement of the foot while the second represents the downward movement of the foot. These two movements are very important during walking because they permit the advancement of the body and the correct impact absorption when the foot has to sustain body weight. Dependently on the phase of the gait cycle, the talocrural joint produces different movements.[16][17]

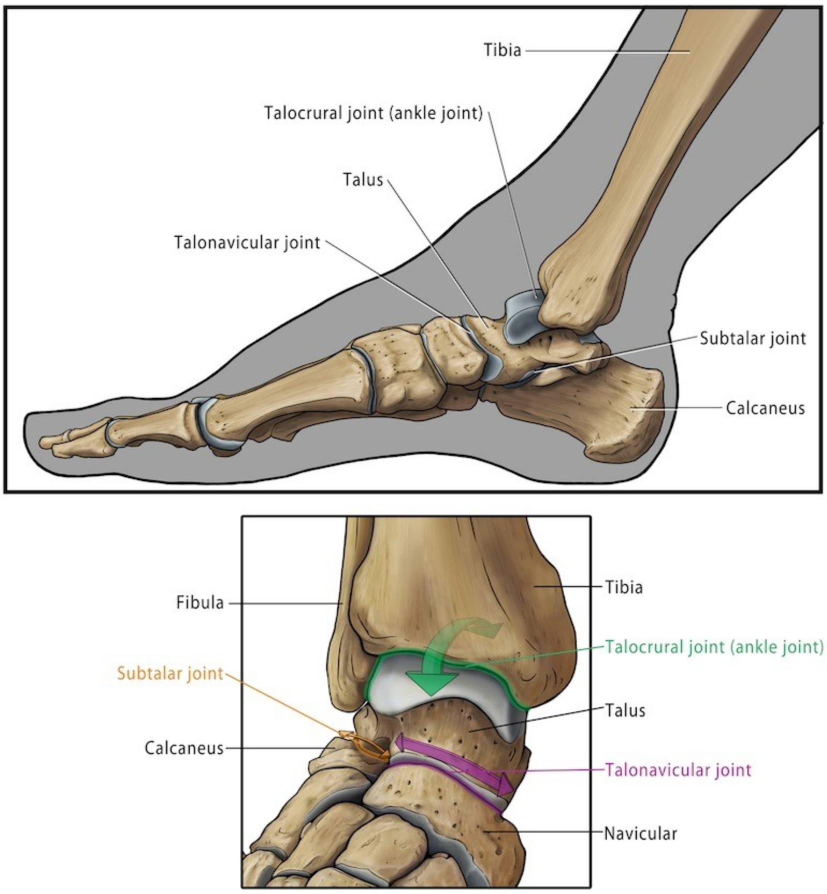

Figure 1: The main joints of the foot: in particular the talocrural joint between the talus and the tibia

When the heel contact occurs, the talocrural joint is in a neutral position or at most it shows a plantarflexion of only 3-5 degrees; after that, there is the real first plantarflexion movement which is caused by the response to the transfer of body weight (phase known as loading response).

Then, when also the forefoot comes in contact with the ground, plantarflexion is substituted by dorsiflexion; for a small second fraction, the foot is in a stationary position while the tibia moves forward producing dorsiflexion movement which continues for all time the foot remains completely leaned on the ground: in this brief phase the maximum angle is reached, that is 10° and is kept until the end of the single stance.

After that, when also the other foot comes in contact with the ground, there is a sudden plantarflexion movement of the talocrural joint that can reach a maximum angle of 30° at the end of the stance; then with the beginning of the swing phase, the talocrural joint performs its last movement during the gait cycle, that is the dorsiflexion. After that, in the central part of the swing, the dorsiflexion angle decreases until it reaches the neutral position (0°) which will be maintained for the resting part of the swing phase.

So, as it is possible to notice, the talocrural joint performs dorsiflexion and plantarflexion movements that alternate each other during gait cycle. These two movements are generated by two kinds of muscles, which are plantar flexion and dorsal flexion muscles.

Anteriorly with respect to the talocrural joint there are three main dorsal flexor muscles: tibialis anterior, the extensor digitorum longus and the extensor hallucis longus. Here below, a figure showing dorsal flexor muscles of the foot is reported:

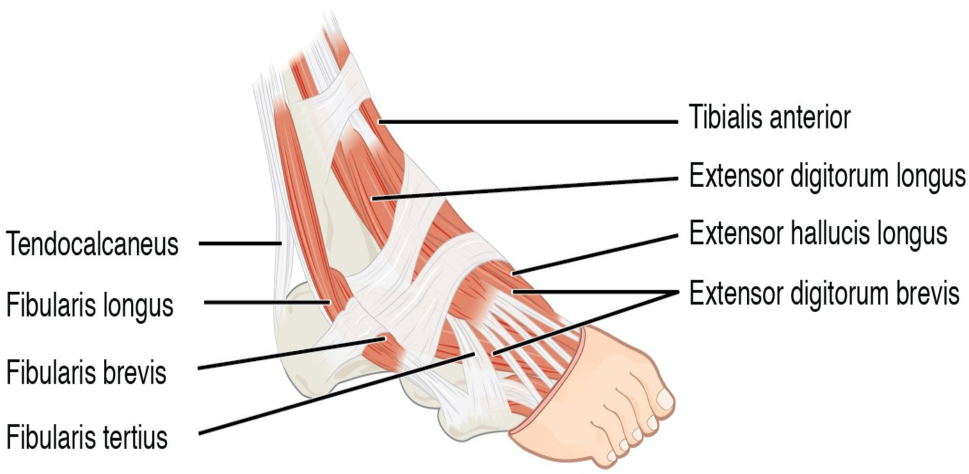

Figure 2: Dorsal flexor muscles of the foot[18]

The tibialis anterior has a larger section with respect to the other two muscles and, as a consequence, it has a greater mass, so it is more efficient in exerting a dorsiflexion action.

Dorsal flexor muscles activate at the end of the stance: the first muscle that begins its action is the extensor hallucis longus. After that, in the central part of swing phase, the tibialis anterior and the extensor digitorum longus activate; the intensity of the activity of both muscles grow continuously also during the final part of the swing in which tibialis anterior plays a fundamental role in positioning the foot for the stance.
All three muscles reach a high level of activity with the initial contact and they all deactivate temporarily before the ending of the loading response. They reach their peak of intensity during the first part of the swing and the loading response phase.
Posteriorly with respect to the talocrural joint, there are 7 muscles that are responsible of the plantar flexion movement so they are named plantar flexion muscles. These muscles are the soleus, the gastrocnemius and 5 perimalleolar muscles: tibialis posterior, flexor hallucis longus, flexor digitorum longus, peroneus longus and peroneus brevis; among them the first two have a bigger section so they contribute together to the execution of plantar flexion movements in a way that is much more considerable than the other ones.
Perimalleolar muscles surround the medial and lateral malleoli but are much smaller than the soleus and the gastrocnemius so they give a much lower contribution to plantar flexion movements. Among them, the flexor hallucis longus gives the greatest contribution to these movements.[19]
In the following page, a figure showing plantar flexor muscles is reported.

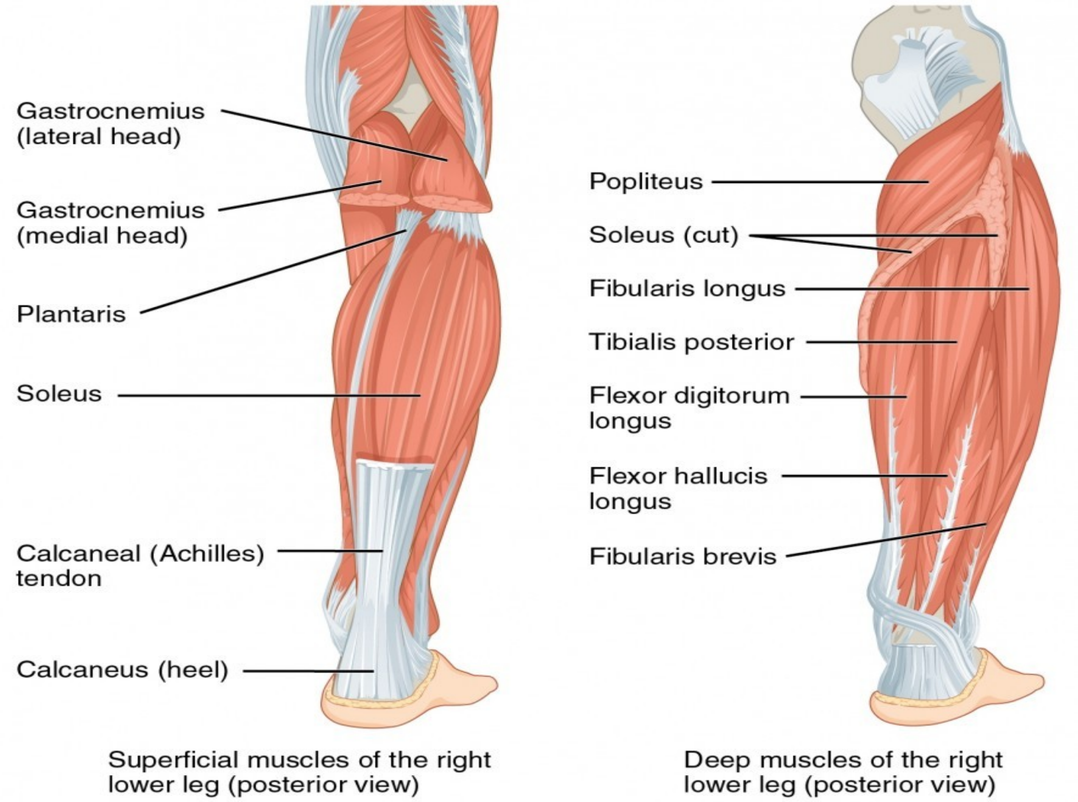

Figure 3: Plantar flexor muscles [20]

Soleus activates after the end of the loading response (8% of the gait cycle) and keeps its activity steady for all the central part of the stance; when the final part of the stance phase begins (45% of the gait cycle), soleus increases rapidly and importantly its activity, after that its action decreases quickly until the beginning of the double stance phase in which it stops completely.
Gastrocnemius activates immediately after soleus (12% of the gait cycle) but its action grows slowlier and less. During the final part of the stance, the gastrocnemius increases suddenly its action intensity and finally, as the soleus, it decreases quickly its activity until the end of the stance, in which it stops definitely. However during electromyographic recordings it is frequent to notice an activation of the gastrocnemius also during the central part of the swing but nowadays it's still not clear the reason of this activation.
For what concerns the other plantar flexor muscles, the perimalleolar ones, they activate differently from soleus and gastrocnemius: actually one of them, the tibialis posterior, activates immediately with the intial stance (0% of the gait cycle) and remains active during the entire single stance;

immediately after the end of the tibialis posterior activity, the flexor digitorum longus begins its action (10% of the gait cycle) and subsequently flexor hallucis longus does the same (25% of the gait cycle).

Peroneus longus and peroneus brevis muscles activate in the final part of the stance, and terminate their action in the central part of the swing (55-58% of the gait cycle). From electromyographic recordings it is possible to notice that peroneus longus and peroneus brevis muscles activate with similar intensity and modality.[21]

So the action of all these muscles, dorsal and plantar flexors, is fundamental for the modulation of the talocrural joint movements, actually their activation during gait cycle generate those movements that are very important so that walking activity can be performed correctly.

2.2 - KNEE-JOINT MUSCLES

The knee is the joint which connects femur and tibia, i.e. two long bones that represent (with the foot) the segments of the lower limb. The knee plays a fundamental role in locomotion during both stance and swing: during stance it maintains the stability of the lower limb, while during swing it allows through its flexion the advancement of the limb.

Like the ankle, also the knee can perform two movements in order to favor the stability and the advancement of the body during walking: flexion and extension. These two movements can be performed thanks to the action of 14 muscles which regulate knee movements by contracting at precise instants during gait cycle in order to allow progression.

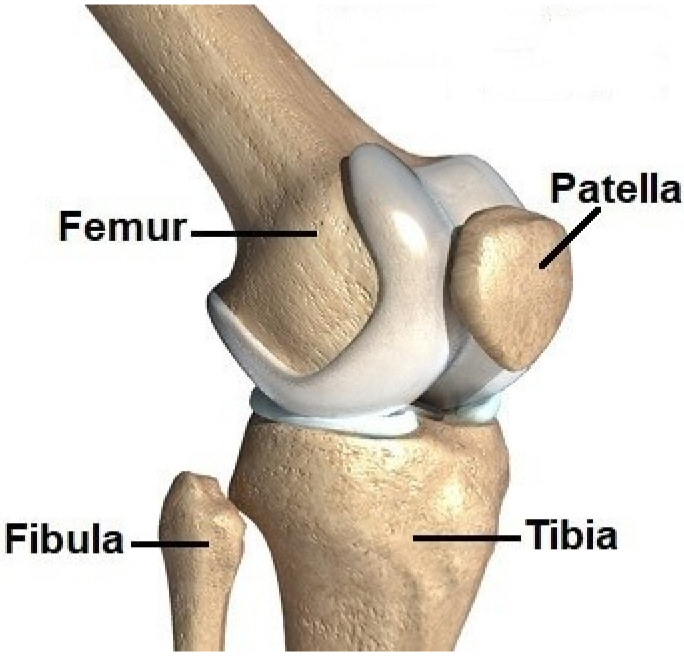

Figure 4: The knee joint[22]

During stance, extensor muscles activate to slow the knee flexion, while during swing firstly extensor muscles and then flexor muscles activate in order to favor the correct progression of the limb.

For what concerns extensor muscles of the knee, there are 4 muscles which act exclusively on the

knee joint: vastus intermedius, vastus lateralis, vastus medialis longus, and vastus medialis obliquus. A fifth muscle, the rectus femoris, contributes to knee extension but differently from the other ones it doesn't act only on the knee but also on the hip. These 5 muscles compose the quadriceps.
The activity of all vasti muscles begins in the final part of the swing and increases rapidly in the following stance period when body weight is loaded on the leaning foot. Their action intensity remains high until the central part of the stance where it decreases very quickly going to zero.
Rectus femoris activates much differently from vasti muscles: its action is quite short, actually it is comprised between the end of the stance and the beginning of the swing; moreover its action intensity is lower with respect to vasti muscles, so rectus femoris gives a smaller contribution to locomotion.
For what concerns flexor muscles of the knee, there are two mono-articular muscles which act uniquely on the knee and determine directly its flexion: the short head of the biceps femoris and the popliteus.
The short head of the biceps femoris activates at the beginning of the swing and continues its action until 2/3 of the swing period; in some cases, it can activate also in the final part of the stance period. The popliteus is active for all gait cycle phases, except the part of the swing period in which the short head of the biceps femoris is active; the popliteus action reaches its maximum intensity during the final part of the swing; another period of the gait cycle, in which popliteus activity is quite intense, is the final part of the stance.
Besides the two mono-articular muscles just described, there are the hamstring muscles (semimembranosus, semitendinosus and the long head of the biceps femoris) which are located in the posterior part of the thigh but contribute significantly to the knee flexion. All 3 hamstring muscles reach the maximum intensity of their action in the final part of the swing: their activity start decreasing with the beginning of the following stance and cease when body weight begins to be transferred on the limb.
Another important muscle that contributes to knee flexion is the gastrocnemius. This muscle acts principally on the talocrural joint but it exerts also a flexion action on the knee and begins its action when the foot has just leaned completely on the ground. Gastrocnemius increases its action intensity during stance until the heel is lifted up and terminates its activity just before the beginning of the swing.[23]
So thanks to the activity of these muscles, the knee can perform three important tasks during gait.

Two of these tasks are performed during stance: the impact absorption when body weight is transferred on the front limb and the stability during extension in order to sustain body weight. The third task is performed during swing: the knee must flex rapidly to favor the progression of the limb.

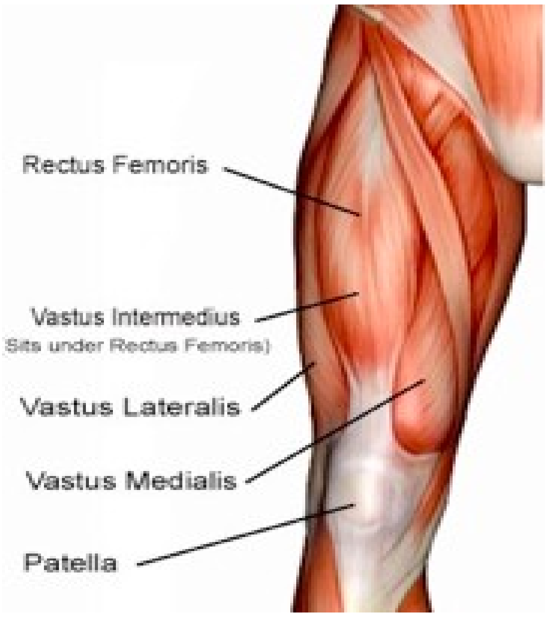

Figure 5: Quadriceps muscles

2.3 - GAIT PHASES

Gait cycle is constituted by two big phases, stance and swing, but by analysing in detail walking phases, it is possible to define 8 phases.
The first 5 are comprehended in the stance period and are:

- Initial contact
- Loading response
- Mid-stance
- Terminal stance
- Pre-swing

The other 3 phases are included in the swing period and are:

- Initial swing
- Mid-swing
- Terminal swing

In the following a figure showing all gait cycle phases is reported:

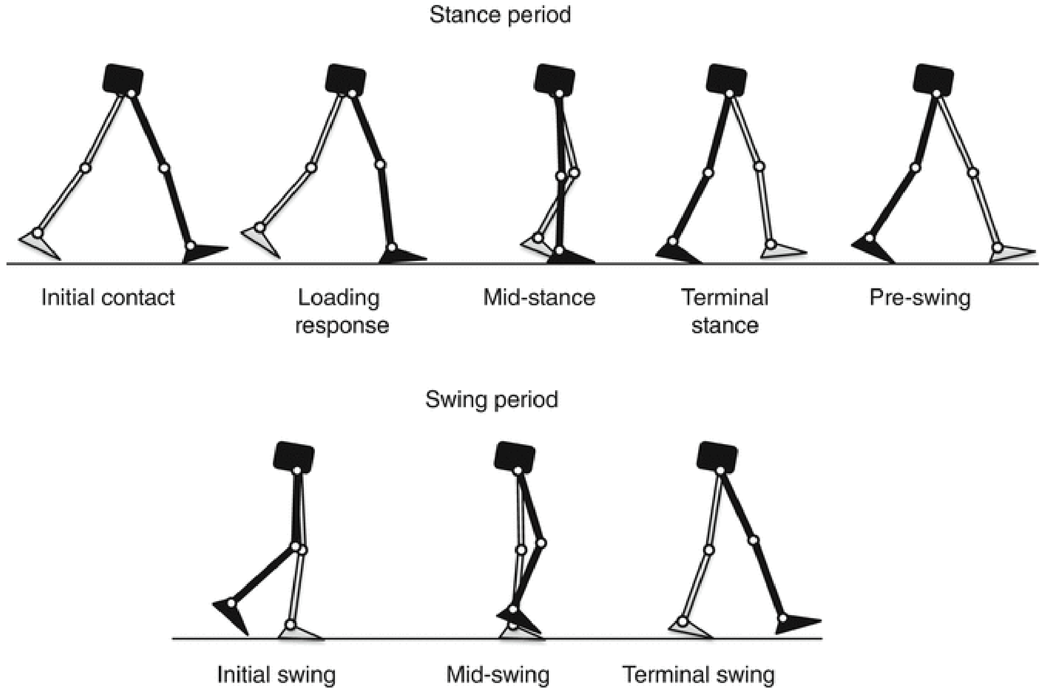

Figure 6: the eight phases of the gait cycle [24]

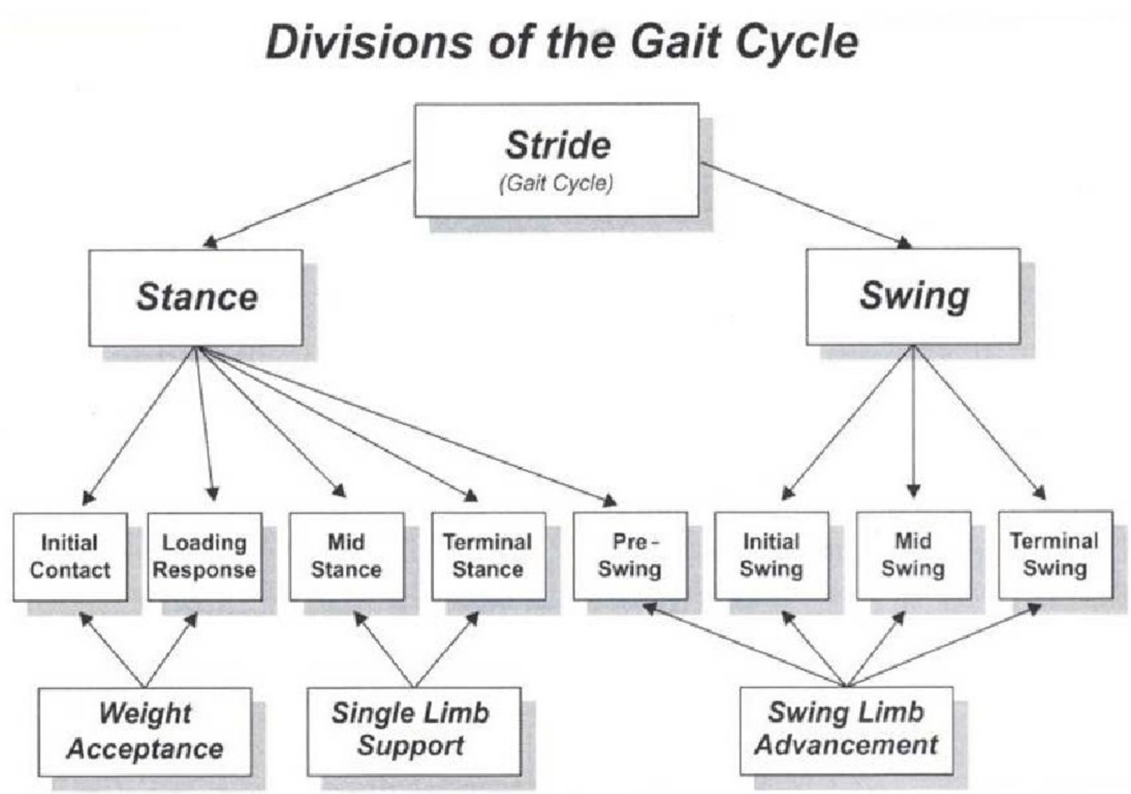

Figure 7: block scheme of gait cycle phases[25]

In the following pages a brief description of the 8 gait phases is reported.

2.3.1 - INITIAL CONTACT

Initial contact begins when the heel of the front foot comes in contact with the ground. Once the contact has occurred, the so called “body vector” is generated: this vector represents the reaction force of the ground to the stance. In this initial phase, body vector is behind the talocrural joint and this is very important for the following loading response in order to keep the progression.

The talocrural joint forms a right angle with the foot so that the forefoot is turned upward and in this way the calcaneus can support the load and then roll in the following phase. For the support funtion the dorsal flexion action exerted by pretibial muscles is fundamental.

Sometimes the talocrural joint can be subjected to a very little plantar flexion (3°-5°) but this doesn't affect the walking activity. Simply it follows that the calcaneus will perform a smaller rolling movement.

Initial contact is the shortest phase of the entire gait cycle and its period corresponds to the 0-2% of the total cycle.[15]

Figure 8: Initial contact[25]

2.3.2 - LOADING RESPONSE

Loading response (2-10% of the gait cycle) begins when the load is transferred on the front foot: this implies that not only the heel but also the forefoot is in contact with the ground.

When body weight is transferred on the front foot, the talocrural joint performs a plantar flexion movement and the calcaneus begins to roll so that the forefoot moves downward on the ground and load can be successfully supported. The rolling of the calcaneus is very important because it also allows the correct advancement of the body; in the same way, also the plantar flexion movement of the talocrural joint is fundamental because if the angle between the tibia and the foot remained equal to 90° then the tibia would follow the foot in its complete movement and finally body weight wouldn't be supported and the subject would fall down.

In order to have the correct progression in this phase, it's necessary the action of two pretibial muscles (tibialis anterior and extensor digitorum longus) which control and slow the plantar flexion movement of the talocrural joint. In this way, while the foot is leaning completely on the ground, the tibia advances normally (not too quickly) without any risk of falling for the subject.

So at the beginning of the loading response (2% of the gait cycle), there is a rapid movement downward of the foot which is favored by the talocrural joint flexion; then pretibial muscles activate and slow the plantar flexion movement so that the forefoot comes in contact with the ground more slowly and the impact can be absorbed correctly.

When the forefoot has finished to move downward, the movement of the talocrural joint changes radically becoming dorsal flexion movement; so in order to allow the progression of the body, the foot stays motionless on the ground and the tibia moves forward by means of the rotation of the tibio-talar joint.

For what concerns the end of the loading response, there isn't a precise moment in which this phase finishes: its end depends on walking speed of the subject.[15]

Figure 9: Loading response[25]

2.3.3 - MID-STANCE

Mid-stance (10-30% of the gait cycle) begins when the rear foot detaches from the ground with the consequent total transfer of the body weight on the other foot: with the support of the load on only a foot, it's possible to have the progression. In this phase of the gait cycle, the talocrural joint is subjected to a dorsal flexion movement that allows the tibia to rotate and to advance with respect to the foot.

During the progression of the tibia, it is fundamental the action of the soleus which performs the task of controlling the rapid dorsal flexion that occurs at the beginning of the phase and to slow the advancement of the tibia which initially is quite quick; this is important in order to maintain stability during walking, actually if soleus doesn't activate correctly (due to a pathology for example) the tibia advances so rapidly that the subject could fall down. The soleus activates at the beginning of mid-stance and increases its activity progressively until it reaches its maximum at the 25% of the gait cycle and continues till the end of the phase.

Also other muscles activate during mid-stance: these are all dorsal flexion muscles and are the gastrocnemius, the tibialis posterior and the two peronei muscles. The gastrocnemius doesn't act directly on the tibia because it departs from the distal femur and so it contributes more to the knee flexion. For what concerns the other muscles, they are behind the malleolus so they can't act importantly on the tibia in order to modulate its movement.

Conversely the soleus binds tibia and calcaneus, and is also greater than the other upper mentioned muscles, so its action is much more considerable.[15]

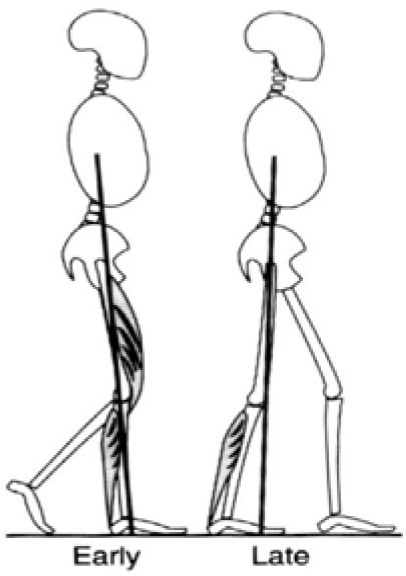

Figure 10: Mid-stance[25]

2.3.4 - TERMINAL STANCE

The terminal stance (30-50% of the gait cycle) begins when the heel of the rear foot rises up and terminates when the other foot comes in contact with the ground. In this phase the body vector has reached the forefoot and the talocrural joint doesn't move anymore, actually its movement is blocked by the soleus and the gastrocnemius.

The advancement of the body produces, as already said, a displacement of the body vector which arrives to the metatarsal heads of fingers and, as a consequence, it provokes the rotation of the forefoot that results in the calcaneus raising and in a further dorsal flexion of the talocrural joint: this moves just a little because it is subjected to the action of the soleus and the gastrocnemius which reach both a very high level of activity that is more or less 3 times greater with respect to the mid-stance phase.

The talocrural joint is then controlled by plantar flexor muscles and thanks to their action the foot and the tibia can rotate correctly and the progression of the body can occur in good conditions without the risk that walking stability is lost. This stability is favored by the fact that the rotation center is fixed on the metatarsal phalangeal articulations of fingers.[15][26]

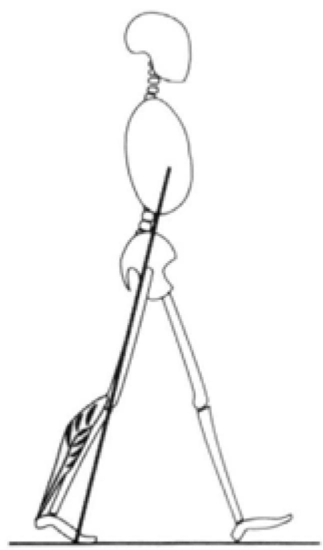

Figure 11: Terminal stance[25]

2.3.5 - PRE-SWING

Pre-swing (50-60% of the gait cycle) represents the beginning of the second half of the gait cycle. This phase begins when the second foot comes in contact with the ground and lasts until the first foot doesn't begin to swing.

At the beginning of pre-swing, the body weight is quickly transferred on the anterior foot: this means that the posterior foot doesn't need to be stabilized at the level of the talocrural joint, so consequently both the soleus and the gastrocnemius decrease very quickly their intensity action that previously reached a very high level; also the other plantar flexion muscles (the perimalleolar muscles) reduce their action and this generates a rapid plantar flexion of the talocrural joint of circa 20°. However the quick transfer of the body weight to the anterior foot doesn't mean that the other foot isn't anymore subjected to a weight force, actually during double stance period the body weight is supported by both feet but not equally: the major part of body weight is supported by the anterior foot.

With the reduction of soleus and gastrocnemius activity, the posterior foot can perform the plantar flexion movement thank also to the fact that the body vector has its application point at the level of the metatarsal phalangeal articulations. The remaining action of plantar flexor muscles provokes a forward displacement of the tibia while fingers rest in contact with the ground and knee undergoes a rapid flexion so that it is ready for the imminent beginning of the swing.

At the end of the pre-swing, tibialis anterior and the extensor digitorum longus start activating in order to prepare the control of the talocrural joint for the moment in which swing will take place. [15]

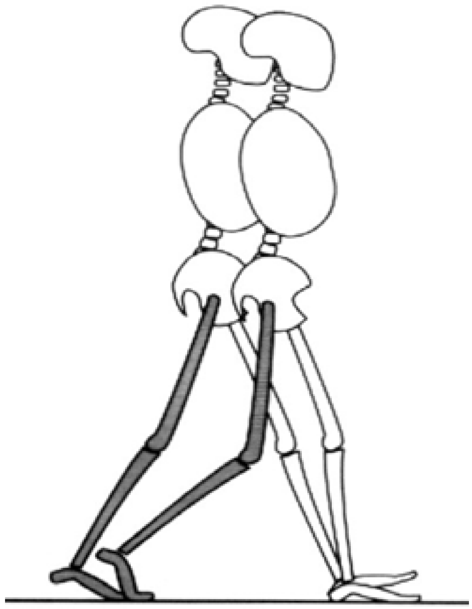

Figure 12: Pre-swing[25]

2.3.6 - INITIAL SWING

The initial swing (60-73% of the gait cycle) begins when the posterior foot detaches from the ground and terminates when the suspended foot is parallel to the other one. In the precise moment in which swing starts, the talocrural joint is in a plantar flexion position of 20°. Initially, this position is not impairing for walking progression, but very soon the tibialis anterior muscle activates and controls the talocrural joint which must perform a dorsal flexion movement because otherwise the correct advancement of the body is not possible, actually fingers would creep on the ground in the following phase, the mid-swing.

For this reason, pretibial muscles increase immediately their action intensity (at 5% of the initial swing) provoking the raising of the foot with a plantar flexion angle of 5°; when tibialis anterior and extensor digitorum muscles are both active, fingers perform a dorsal flexion movement which allows the normal progression of the body.[15]

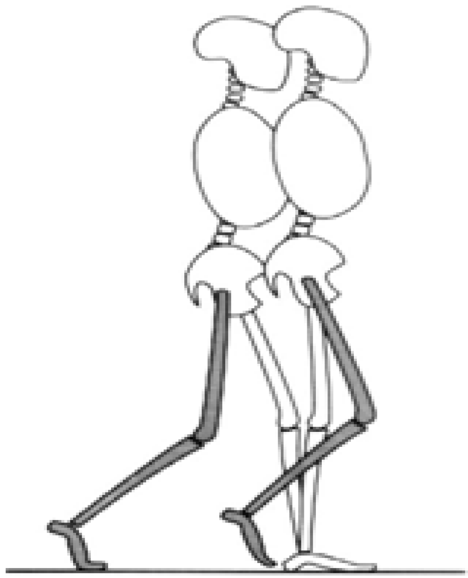

Figure 13: Initial swing[25]

2.3.7 - MID-SWING

Mid-swing (73-87% of the gait cycle) begins when the swinging limb passes in front of the other one and terminates when the tibia of the advancing limb is in vertical position with respect to the ground. During mid-swing the most important thing is that the foot performs a dorsal flexion movement because the knee extends due to the progression, so the foot must move in this way in order to avoid the contact with the ground that would destabilize the subject.

In the first part of mid-swing, the tibialis anterior and the extensor hallucis longus increase sensitively their activity: in this way they favor the dorsal flexion movement of the talocrural joint until the foot forms a right angle with the tibia.

In the second part of this phase, muscles reduce their activity because it's not necessary a great action in order to keep the talocrural joint in the neutral position in which the foot is at right angle with the tibia.[15]

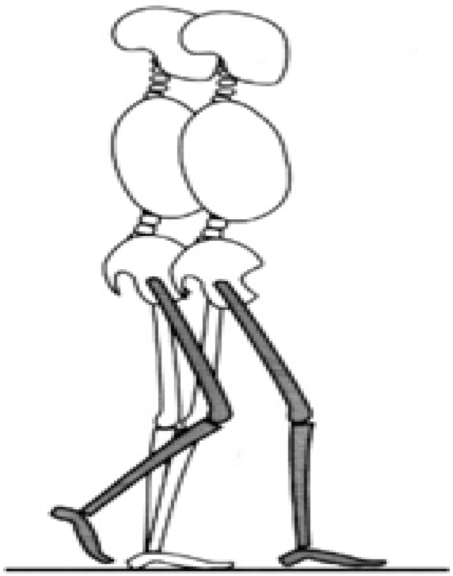

Figure 14: Mid-swing[25]

2.3.8 - TERMINAL SWING

The terminal swing is the last phase of the gait cycle (87-100%): it begins when the tibia is in vertical position and terminates when the heel touches the ground.

During this phase it's very important that the right angle between the foot and the tibia is kept in order to favor the following initial contact with which another gait cycle can start: so it's necessary that the pretibial muscles increase again their activity (their action was reduced in the second part of the mid-swing) but they don't succeed in maintaining the talocrural joint in the neutral position, actually it's frequent that it is subjected to a plantar flexion movement between 3° and 5°.

Pretibial muscles keep high their action intensity not only at the beginning of terminal swing but also in the final part because they must be prepared to face the load that after the initial contact will be transferred on the advancing foot.[15]

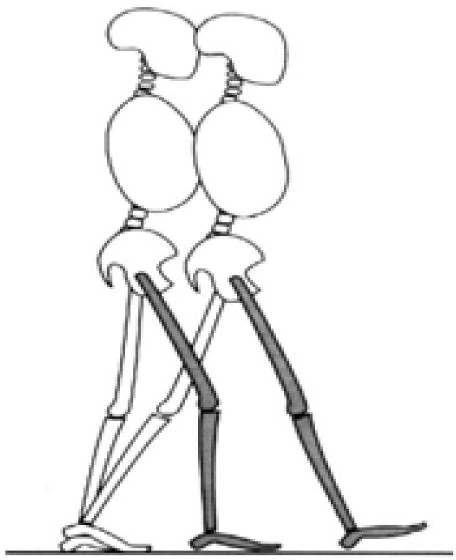

Figure 15: Terminal swing[25]

2.4 - METHODS FOR GAIT ANALYSIS

Human gait study began some thousands of years ago: according to historical documentations, it seems that Aristotle (the philosopher of the ancient Greece) was one of the first pioneers of gait analysis.[27]

Successively a lot of other scientists tried to study human gait attempting to explain how it works from a bio-mechanical point of view, the phases that compose it and what are the differences between the gait of a normal subject and the gait of a pathological one, but only with the arrival of photography and cinematography it was possible to notice some aspects of human gait sequences that earlier were not noticeable with naked eyes; so the development of film cameras, at the beginning of 1900s, represented an important progress step.

Another fundamental improvement occurred in the 1970s with the development of video camera systems which were able to provide much detailed images regarding the gait of every subject with the advantage of a great reduction of costs and time constraints. The development of these new technologies was very important in order to analyze successfully also gait of pathological subjects like those affected by cerebral palsy, Parkinson's disease and other neuromuscular disorders and to make a comparison with healthy subjects' gait.

Then in the early 1980s new progresses were made for what concerns analysis instrumentation, actually researchers began to use computer based systems in their laboratories; in the mid-1980s also infrared camera systems were developed in order to improve further the efficiency of the gait analysis.[28]

Successively also machine learning approach began to be used in the clinical context. Now the discussion will be focused on the presentation of the main gait analysis methods: stereophotogrammetry, floor sensors, surface electromyography, inertial measurement units and objective analysis techniques.

2.4.1 - STEREOPHOTOGRAMMETRY

Stereophotogrammetry is a technique that permits to estimate the 3-Dimensional position of a point from images obtained by means of two or more cameras. This method is used in order to determine the three spatial coordinates of points that are moving in space in any instant: in this way it is possible to have a representation of the path of all points.

There must be at least two cameras which have to be placed in precise points of the laboratory with a definite orientation dependently on the path of the object under observation. The position and the orientation of cameras are fixed and represent the so called "calibration parameters" that are fundamental to determine the spatial coordinates of points. Each camera has an own cartesian reference system which is used to compute image coordinates, i.e. points coordinates with respect to the camera system.

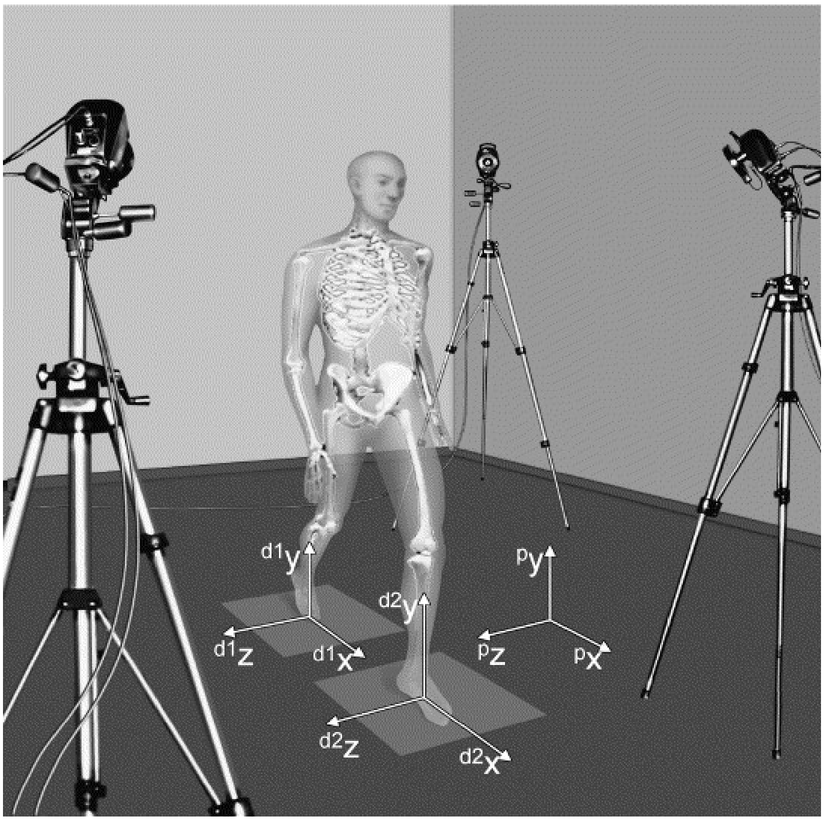

Figure 16: Stereophotogrammetry application

Once calibration parameters and image coordinates are known, their values are fed in input to a system of equations: the resolution of these equations gives the three spatial coordinates of points for each instant in which cameras have acquired images.

Stereophotogrammetry has proved to be a good method in computing the coordinates of points in space and for this reason it is largely used to perform gait analysis. For this purpose it's necessary to place markers on ankles, knee and hips according to a standard protocol. After that the protocol has been chosen and markers have been correctly placed on the subject, gait analysis can be performed. So the subject walks and at each instant cameras acquire images of all markers that change position and orientation: in this way it is possible to recognize linear and angular movements of leg joints and to understand when these movements occur and how large they are.

Nowadays stereophotogrammetry is one of the most used methods to perform gait analysis.[29]

2.4.2 - ANALYSIS WITH FLOOR SENSORS

This analysis method consists in placing electrical sensors on the floor, precisely on the so called “force platforms” in which gait information are recorded by force or pressure sensors and moment transducers that activate when subjects under examination pass on them.

For this analysis technique it is possible to use two kinds of floor sensors: force platforms and pressure measurement systems. Force platforms perform the task of measuring ground reaction forces (GRF) produced by body force vectors applied on them, while pressure measurement systems are used to detect the center of pressure under each foot and to quantify pressure components generated by normal forces but not those ones produced by shear forces.

In the following page a figure showing two force platforms is reported :

Figure 17: Two force platforms (one for each foot) used for posture and gait analysis[39]

Floor sensors were used in a lot of studies and often gave very reliable and accurate information about gait parameters and for this reason researchers carry on using them. These devices measure ground reaction force and, moreover, monitor the way in which the pressure of the foot varies from the initial contact to the end of the stance; in this way, if the analysis is focused on a pathological subjects, it is possible to understand from the foot pressure evolution which is the impairment of the patient and to make diagnosis.[4]

2.4.3 - SURFACE ELECTROMYOGRAPHY

Surface electromyography (sEMG) is a non-invasive procedure that consists in recording the electrical activity of muscles by means of surface electrodes that are applied on patient's skin. Muscles activation is the result of the nervous system action which emits electrical signals that, after passing through the spinal cord, arrive to motor neurons which provoke muscles contraction; when muscles activate, their cells produce an electric potential.

Muscular activity is recorded through surface electrodes that catch electrical potentials generated by muscle cells. In order to record signals in the correct way, first of all it's necessary to dry skin and removing hairs which create an electrical impedance that decreases the signal-to-noise ratio; after that a conductive gel layer must be applied on the skin surface where electrodes are then placed, so that electrical impedance between the skin and the electrodes is decreased and signal quality is less

affected.
Then it is possible to apply electrodes on the skin: they must be made of a conductive material, like silver chloride, so that signal-to-noise ratio is high and consequently the recording is more accurate. Here below a figure showing electrodes placed on the lower limbs is reported:

Figure 18: Representation of an electromyographic exam

Once the skin has been adequately treated and the electrodes have been correctly placed, the electrical activity of muscles can be recorded: electrical signals are caught by electrodes, then are amplified and converted in digital signals in order to generate on a monitor the electromyographic track, i.e. the graphical representation of the electrical activity of muscles. In this graph the vertical axis represents the amplitude of the electrical potential measured in millivolt (mV), while the horizontal axis represents the time in seconds of muscles activity.
But the quality of electrical signals can be affected by some noise sources, like movement artifacts and electromagnetic noise. Movement artifacts are caused by the fact that when muscles activate, their length decreases, so a movement of electrodes with respect to the skin is generated and, as a consequence, the signal-to-noise ratio is lowered. Electromagnetic noise is caused by

electromagnetic sources (for example mobile phones or other electrical devices) which are too close to the subject under examination and thus affect signals quality.

Because of the frequent presence of noise artifacts, it's necessary to process acquired signals by means of numerical filters in order to remove noisy components; the processing procedure allows to clean signals quite well.

Thus, with surface electromyography it is possible to obtain a quite reliable explanation of muscles activity, i.e. how and when they activate. For this reason, this analysis method is also used in the medical field on unhealthy subjects (like for example those having walking problems) in order to make diagnoses of pathologies.[30]

2.4.4 - INERTIAL MEASUREMENT UNITS

Inertial measurement units (IMU) are electronic devices composed by a combination of one or more accelerometers and one or more gyroscopes in order to detect the acceleration and the angular rate of a specific body. These devices are very useful to perform gait analysis, actually with them it is possible to compute gait parameters, like velocity that is calculated by integrating the acceleration; with a further integration, displacement can be obtained. Thank to the presence of gyroscopes, it is also possible to measure the angular velocity of joints then, with integration, angle variations are computed.

Inertial measurement units can be used in different ways to perform gait analysis: it is possible to detect gait phases by placing a single device on the knee or on the ankle or even on the subject's back if it is put sufficiently close to the center of mass; in this last case gait events can be detected by computing the vertical acceleration of the center of mass with reliable results.

These devices are good also because with them it is possible to find gait abnormalities that permit to diagnose pathologies, like hemiplegia.[31]

2.4.5 - OBJECTIVE ANALYSIS TECHNIQUES

Objective gait analysis methods consist in using different devices for the measurement of gait parameters. There are two main objective analysis methods for gait: image processing and wearable sensors.[32]

2.4.5.1 - IMAGE PROCESSING

This method is typically constituted by a system of many analog or digital cameras with lens which are used to take information about gait: data can be acquired for example by converting images into black and white and then calculating the number of light and dark pixels; this technique gives very good results for what concerns gait recognition, so it is largely used to identify people from the way they walk.

Image processing can be applied in different ways and one of them is based on depth measurement (also called range imaging) with which it is possible to get important details from an image with an optimal and quick real-time process. Depth measurement can be performed by using different techniques, like Time-of-Flight method and infrared thermography.

Time-of-Flight method consists in using a system of cameras that illuminate the observed scene (i.e. the walking subject) with near infrared light which after reflection is projected onto a complementary metal oxide semiconductor sensor that, by using signal modulation, measures the phase-shift in order to quantify the distance covered by the subject; in this way it is possible to get information about gait.[33]

Infrared thermography is based on the process of creating visual images from surface temperatures. Thanks to the very high skin emissivity (close to 1), which doesn't depend on pigmentation, the great absorptivity (close to 1) the low reflectivity (close to 0) and the null transmissivity it is possible to measure the infrared thermal intensity of the human body; in this way, who uses infrared thermography can, for example, analyze muscles activation and obtain important information about gait.[34]

2.4.5.2 - WEARABLE SENSORS

Wearable sensors, as suggested by the name, are sensors that are placed on the human body: to perform gait analysis, these devices are located on feet, knees and hips and are largely used by clinicians. The main devices that are included in this category of sensors are: force sensors, inertial sensors and goniometers.

2.4.5.2.1 - FORCE SENSORS

Force sensors are located beneath each foot and measure the ground reaction force that is generated during the stance period of the gait. These devices are composed by force transducers, like piezoelectric and capacitive transducers:

- piezoelectric sensors: these sensors are constituted by 3 deformation meters that measure orthogonal deformations in 3 different directions.
- capacitive sensors: these devices are used to measure forces and pressures. These sensors can't work singularly but need to be coupled with another capacitive sensor.

2.4.5.2.2 - INERTIAL SENSORS

Inertial sensors are electrical devices used to measure the acceleration, velocity and orientation of an object. The main sensors included in this category are accelerometers and gyroscopes.

The accelerometer measures acceleration along its sensitive axis. It is composed by a proof mass which is attached to a spring; when the accelerometer undergoes an acceleration, the mass moves causing a compression or an elongation of the spring and this displacement gives the acceleration experienced by the sensor. Accelerometers can measure acceleration only along one direction, so in order to have complete spatial characterization, it's necessary to use 3 accelerometers.

The gyroscope is used to measure the angular velocity; for what concerns gait analysis gyroscopes can be used to measure quite well angular variations and angular velocity of lower limb joints, so that it is possible to detect gait phases. Gyroscopes are often used in combination with accelerometers to perform gait analysis.

2.4.5.2.3 - GONIOMETERS

These devices are used to measure angle variations for hips, knees, ankles and metatarsals. One of them is the strain gauge-based goniometer which gives the measure of the angle dependently on how its resistance varies due to the flexion experienced. A flexion causes an increase of resistance, actually current takes more time to travel along the sensor; this resistance enhancement is proportional to the flexion angle.

3 - HEMIPLEGIC WALKING

Hemiplegia is a pathology that causes the paralysis of one whole half of the body ("hemi" is a Greek word that means "half", while "plegia" means "weakness"). This paralysis is caused by brain damages which are located in one of the two cerebral hemispheres (left and right) and that provoke the total inability to execute correctly movements with the contralateral half of the body: this means that if damages affect the left cerebral hemisphere, then paralysis involves the right half of the body and viceversa.

This pathology sometimes develops during pregnancy (or birth) but in most of cases it is caused by a stroke with symptoms that are sudden and unexpected: recovery time can change dependently on the entity of the pathology and on the patient's age. The main symptom is a reduced or even null ability to move the body parts involved due to the malfunctioning of the upper motor neurons that transmit a too weak electrical potential to the spinal cord and thus also to lower motor neurons; as a consequence, muscles aren't correctly innervated and even the most common movements are inhibited, actually their preparation and coordination is strongly affected.

Another important symptom is a considerable change of the sensitivity which is another consequence of brain damages, actually it is provoked by a malfunctioning of proprioceptors and nociceptors: proprioceptors, also known as sensory receptors, are responsible of the monitoring of limbs position in space; nociceptors are receptors mostly located under the skin that activate when an external stimulus is potentially harmful for tissues. In hemiplegic patients both proprioceptors and nociceptors don't work in the right way, so the consequence is that patients don't realize in which position their limbs are and they could feel pain even with a small contact or conversely they couldn't perceive anything if they are touched or hit.

Sometimes subjects affected by hemiplegia have also other symptoms like language difficulties, lower view capability and even respiratory problems.[35][36]

As already said, hemiplegia can also be congenital, so in this case it affects children since birth causing a lot of problems to their physical and psychological development. Winters et al. have proposed a classification of this pathology in 4 types: Winters' type 1 in which there is a lower innervation of ankle dorsiflexors in the hemiplegic side, resulting in a difficulty in pulling up the foot with the consequence that stance phase is much shorter.

Winters' type 2 is more serious than the first one, actually is characterized by the so called “clubfoot” that is a foot which is rotated inward and downward;[4] what can happen during walking is a hyperextension of the knee in stance phase. Winters' type 3 in addition to the previous ones presents a decreased knee flexion during swing phase, while Winters' type 4 is characterized by a lower motion of the hip.[37]

Even if a classification of hemiplegia types has been provided, there are still a lot of questions without any answers for what concerns this pathology. Scientists, nowadays, are still working very hardly by means of research and experiments with newer and more efficient measurement instrumentation in order to understand as much as possible when and how leg muscles activate during gait cycle with the aim to develop new rehabilitation protocols.

In last decades researchers have tried also to look for new solutions against this highly impairing pathology: they didn't simply think about the rehabilitation based only on physiotherapy, but they also tried to project a particular instrumentation that can stimulate electrically those muscles which aren't sufficiently innervated by motor neurons due to the neurological dysfunction provoked by hemiplegia.

But researchers have still a lot of work to do, actually nowadays even if this pathology has already been classified by Winters et al. there are some studies which have pointed out that two hemiplegic subjects who belong to the same Winters' class could show different gait and muscle activation patterns.[38]

The most frequent hemiplegic forms are Winters' type 1 and 2 which, as previously said, are characterized respectively by drop foot and equinus foot.[39]

Drop foot is among the most recurrent anatomical abnormalities in hemiplegic children: scientific studies have pointed out that drop foot is caused by a reduced force of ankle dorsiflexor muscles which is provoked by a lesion or an insufficient maturation of the motor cortex of the corticospinal tract. The consequence of this physical deformity is that the subject can't raise upward the foot because dorsiflexion muscles can't activate with enough intensity in order to control the talocrural joint which can't perform the dorsal flexion movement: so the foot remains in a plantar flexed position and is turned downward.

In the following page, a figure showing the drop foot is reported:

Figure 19: Comparison between a normal foot and a drop one

Due to the low activity of dorsiflexor muscles, particularly the tibialis anterior, the talocrural joint is not controlled in its movements, so the subject can't walk normally and the effects on the gait cycle are easily visible: for the subject it's quite difficult to lift up the toe, so the swing period is very short; moreover there is another important consequence that is the difficulty in beginning a new gait cycle, actually without dorsal flexion movements of the talocrural joint, the heel-strike can't occur and so gait cycle doesn't begin regularly.[40]

Another common physical deformity that is largely diffused among hemiplegic subjects is the so called equinus foot (or clubfoot): according to researchers, this congenital deformity is the most frequent among hemiplegic subjects, actually statistic data show that it concerns unless 1 over 1000 newborns.[41]

Clubfoot is a foot which is rotated inward and downward and it doesn't lose its deformity without treatment;[42] besides the abnormal rotation, the foot sometimes can be also smaller than the other one.[43]

In the following page, a figure showing the difference between a normal foot and a clubfoot is reported:

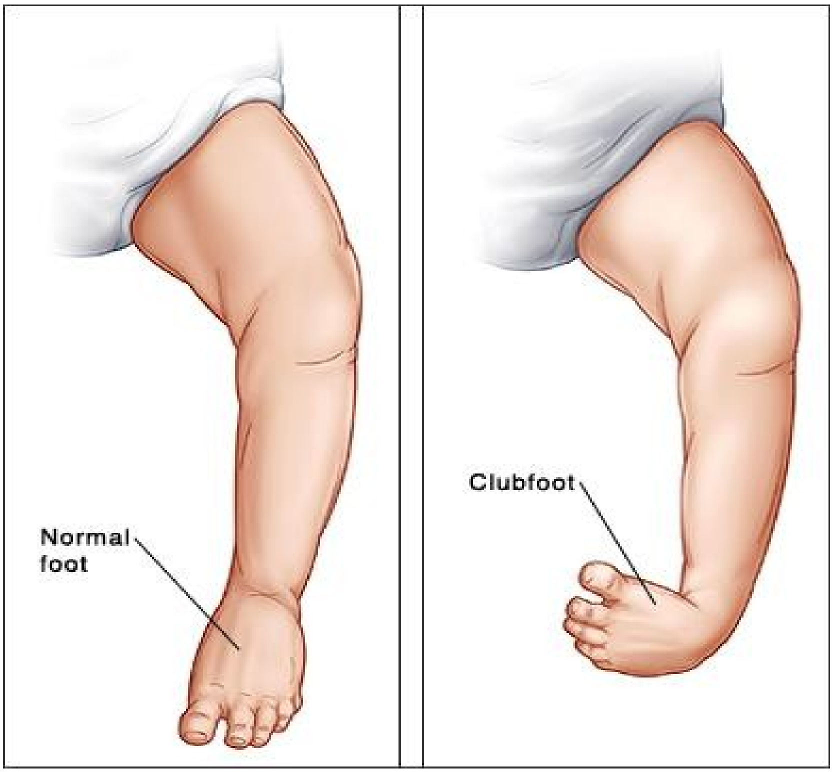

Figure 20: comparison between a normal foot and a clubfoot

The clubfoot deformity is mainly caused by a limited ankle motion which is due to the tightness of calf muscles (soleus and gastrocnemius) or of the Achilles tendon. Sometimes it could also happen that a fragment of a broken bone (derived for example from an injury) can block the ankle motion; other times, but it is less frequent, clubfoot can also be provoked by spasms of the two calf muscles which are probably due to neurological disorder.

This deformity induces the patient to load a lot of weight on the other foot in order to compensate the limits of the hemiplegic foot: these compensation trials, unfortunately, can cause the development of problems in the healthy foot, like heel pain, inflammation of the Achilles tendon, ankle pain and arthritis of the midfoot.[44]

The presence of the clubfoot and the associated effects, including pain, affect heavily the gait cycle of the subject that can't be regular.

During walking the most evident and frequent effects of the ankle-foot complex dysfunction are a longer cycle time, a shorter stride length and a shorter swing phase. The differences are particularly

evident for the cycle time and the stride length: actually cycle time can be twice longer with respect to normal conditions, and the stride length can be also less than the half. For what concerns the swing phase, differences are not so evident.
The talocrural joint is subjected to a lower dorsiflexion action during stance period;also for what concerns plantar flexion movement, the angles variation is reduced.[45]
Among children, there is also a particular form of hemiplegia that is quite diffused: the spastic hemiplegia. This pathology is a kind of cerebral palsy which is characterized by a neuromuscular disorder that provokes a continuous and uninterrupted contraction of muscles of one half of the body: this is due to the fact that brain damages cause a continuous transmission of action potentials to neuromuscular junctions on the unhealthy half of the body.[46]
Here below is reported a figure of a subject with spastic hemiplegia:

Figure 21: Subject with spastic cerebral palsy

Obviously the constant stimulation of muscles has important consequences on gait performance: first of all gait cycle is longer, walking speed is smaller and there is also a longer support phase, i.e. the healthy lower limb must support body weight for more time; since the healthy lower limb must compensate for the other limb, it shows a shorter swing period.
Moreover there a lot of differences from healthy subjects also for what concerns the angle

variations of the hip, knee and the ankle joints at the moment of the initial contact and during foot extension. During walking, subjects with spastic hemiplegia must incline their upper body a little backward in order to compensate their inability to lift up the affected lower limb and the reduced capacity to flex the hip; moreover they also contract their abdominal muscles continuously to compensate their inability to flex the hip.
Another important aspect that it is possible to notice from the spastic hemiplegic subject walking is that when the ankle terminates its extension, the knee starts extending immediately: this is much different from healthy subjects.[47]
Since anatomical deformities caused by hemiplegia are not so rare and can't be corrected without any treatment, researchers have elaborated different rehabilitation techniques: one of the most important is the functional electrical stimulation.

Functional electrical stimulation (FES) is a rehabilitative technique which was elaborated to correct foot drop deformity in hemiplegic subjects classified as Winters' type 1. This rehabilitative method can be applied correctly only by knowing well gait parameters of normal people, actually it was thought to relearn gait patterns of healthy subjects.
First of all, it's necessary to apply pressure sensors under shoes and inertial sensors on feet, shanks and hips in order to get immediately information about the gait of the hemiplegic subject: data are sent to a computer that elaborates them and, after having identified the beginning of the swing phase, it activates a wireless inertial sensor placed on the foot which stimulates electrically the tibialis anterior and dorsiflexor muscles. The stimulation occurs by generating an electrical current which excites motor neurons, weakly activated because of brain damages, so that muscles can be correctly innervated to perform dorsiflexion movement.
This rehabilitative technique, together with voluntary effort, showed very good results in correcting drop foot during walking.[3]

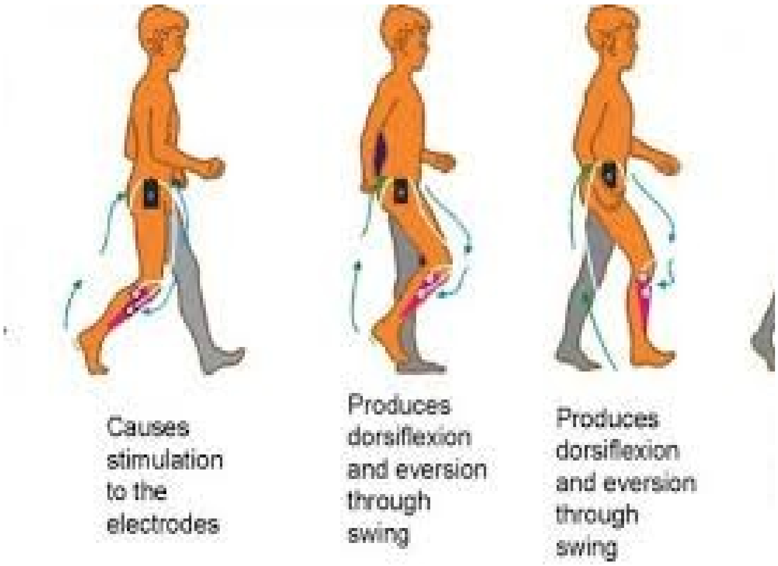

Figure 22: Functional electrical stimulation

4 - ARTIFICIAL NEURAL NETWORK

An artificial neural network (ANN) is a computational system that is inspired to biological neural networks, i.e. those organizations of neurons that are connected each other by synapses; biological neurons receive external stimuli (mechanical, thermal, chemical ecc.) in form of electrical signal, then elaborate information and after that they transmit it to the other neurons which perform another elaboration in order to generate a response to stimuli.[48]

Artificial neural networks functioning is similar to biological ones, actually they are constituted by an interconnection of little units, called artificial neurons; these units receive signals, process them and finally transmit to the other units, in a way that is similar to biological neurons. But artificial neural networks are much simpler than biological ones: for this reason these models can't be used in order to represent and understand biological neural networks.[49][50]

Originally, ANNs were thought by scientists in order to develop mathematical models that can explain the information processing activity of biological neurons; but very soon researchers understood that these models couldn't be applied to biological nerve cells for the previously exposed reason. So they decided to try to use artificial neural networks in order to perform tasks which don't concern biology. In this way they discovered that there were a lot of contexts in which these revolutionary models could be utilized successfully. Some of them are for example computer vision, speech recognition, machine translation and even something that has always been considered performable only by humans, like painting.[51]

Here below a figure showing the structure of an ANN is reported:

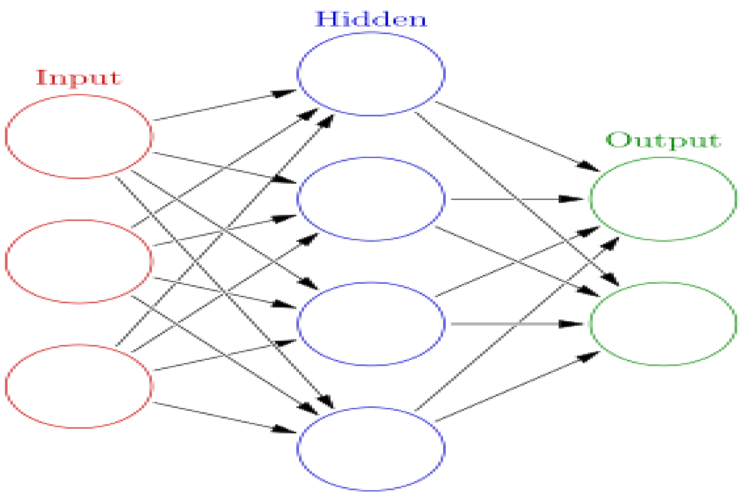

Figure 23: Schematic representation of an artificial neural network

In this figure every circle represents an artificial neuron (also said node) and arrows represent all connections between the output and the input of a couple of neurons. Each of these links allows signals to travel from a neuron to the next one: each neuron can receive more input signals and give more output ones.[52]
So ANNs are typically organized in three principal neurons layers: the first one is called “input layer” and receives information from the outside; the second one is called “hidden layer” and is responsible for the major part of internal processing and performs the task of patterns extraction; the third one is called “output layer” and produces ANN outputs.[53]
There is great quantity of different artificial neural networks and their complexity varies above all on the base of the number of neurons layers which compose them. This means that an ANN can be constituted by more neurons layers that are located between the input and the output one and are all comprised in the hidden layer.
The complexity of an ANN doesn't depend uniquely on the quantity of neurons layers but also on the type. Sharma and Copra[54] provided an important description of the two main types of ANN which are the feed-forward neural networks (FFNN) and the recurrent neural networks (RNN).
In the figure below, there is the schematic representation of both networks:

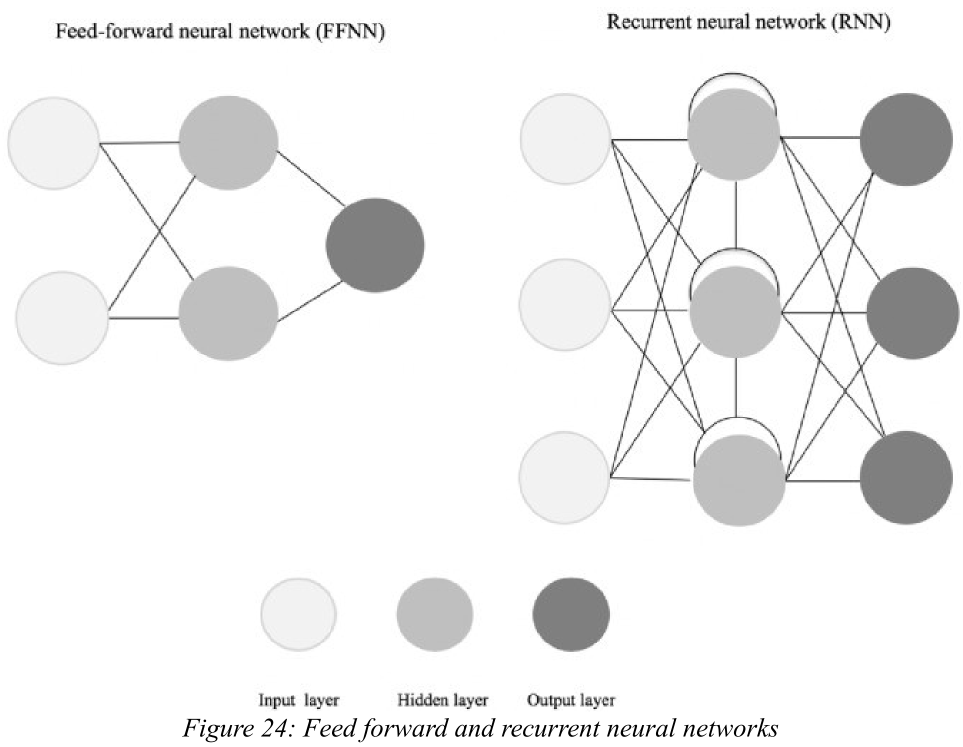

Figure 24: Feed forward and recurrent neural networks

FFNNs can have a unique layer or multiple ones but in both cases the information flow is unidirectional, i.e. data are transferred only from the input layer to the hidden one (that, as already said, can be composed by multiple layers) and finally to the output one: this means that signals can't in any way be transmitted in the opposite direction; moreover neurons of each layer can transmit signals only to neurons of the following layer: so in a single layer, neurons don't communicate and thus they don't exchange data in any way.

RNNs work in a totally different manner, in fact information are not processed only once. For example hidden layer neurons can send back data for a further processing and in this case neurons of the inputs layer receive the so called "feedback inputs"; in the same way, as it is possible to notice from the previous figure, information can be transmitted back also from output layer neurons to the hidden layer and then they can come back even to input layer for a new processing.[55]

Whatever kind of ANN is used, it's necessary to perform repetitively a training procedure in order to find the best configuration.

The training of an ANN consists in giving continuously data in input to the network, so that unit connections can be optimized: in this way errors in prediction phase can be sensitively reduced and it can be possible to reach an optimal level of accuracy.[7]

If we consider the simplest ANNs, i.e. with a single hidden layer, training process can be divided in six steps: firstly data are passed to the input layer which, after the elaboration, passes the output to the hidden layer and, during the transfer, all data are multiplied by the first set of connection weights; secondly, when signals arrive to the hidden layer, they are summed, are elaborated again and, after having been multiplied by the second set of connection weights, are transferred to the output layer; thirdly, signals arrive to the output layer, are summed and undergo the last elaboration, so that the network output is generated; fourthly the output is compared with the expected value and the difference between them is computed; fifthly, after the difference entity has been evaluated, connection weights are opportunely modified; lastly the modification of connection weights is saved for a new training, in which new data are given in input to the network.[56]

By applying the training process, and so by correct appropriately connection weights, ANNs can perform quite well a lot of tasks and thus can be very useful. Actually for their great efficiency, they are used also for medical diagnosis, and researchers continue to work with them in order to elaborate more and more efficient models.

5 - MATERIALS AND METHODS

5.1 - DATASET

Gait data regarding hemiplegic children were provided by retrospective studies performed at the Laboratory of Gait Analysis, Ospedale Santa Croce, Moncalieri(TO), Italy. The database included a total of 20 subjects: 10 Winters' group I (W1, 6 females and 4 males), of age ranging from 5 to 13 years, mean height (± SD) = 129 ±14 cm, mean mass = 28.7 ±8.4 kg; and 10 Winters' group II (W2, 5 females and 5 males), of age ranging from 4 to 10 years, mean height (± SD) = 120 ±18 cm, mean weight 22.7±11.8 kg.

All subjects who presented another pathology, although they had however difficulties in walking, were excluded from experiments.

For the present work hemiplegic children classified as Winters' type 1 and as Winters' type 2 were recruited because these two forms of hemiplegia are not so serious that subjects aren't able to walk. The present study respects all regulations and ethical principles decided by the Helsinki Declaration and has been approved by an institutional committee. Moreover all subjects' parents have given their consent to the execution of the test.

5.2 - SIGNAL ACQUISITION

In order to do experiments of classification and prediction, surface electromyographic and basographic signals of all 20 hemiplegic were acquired: the acquisition was performed by means of sEMG probes (5 for each lower limb, which record the activity of 5 different muscles) and 3 foot-switches sensors that were applied under each foot, one beneath the heel and the others under the first and the fifth metatarsal heads; these sensors activate continuously during subject walking giving information about gait cycle and the temporal duration of each phase. Both for electromyographic and basographic signals acquisition, a multichannel recording system (with resolution: 12 bit; sampling rate: 2kHz) has been used.

All sEMG probes were allocated on both lower limbs skin in order to record the electrical activity of 5 muscles: tibialis anterior, gastrocnemius lateralis, vastus medialis, rectus femoralis and hamstring.

Signals recording has been performed by respecting specific rules which were provided by the

European concerted action SENIAM (surface EMG for a non invasive assessment of muscles): these regulations regard the placement of electrodes which have to be located in some precise points of the skin by considering some important aspects like motor points of the limb and muscular fiber orientation.[57]
After the correct positioning of probes and foot-switch sensors, all 20 hemiplegic children were requested to start walking on the floor for 2 minutes and 30 seconds with their own pace without requiring them to accelerate or slow in any moments, so walking was performed in absolutely natural conditions by all young subjects.

5.3 - PRE-PROCESSING

After acquisition, electromyographic and basographic signals were submitted to a pre-processing procedure in order to remove electrical noise which would affect the reliability of data giving distorted results.
Electromyographic signals were processed by means of two linear-phase FIR filters: a high-pass and a low pass filters with cut-off frequency respectively equal to 20 Hz and 450 Hz. After that, all surface electromyographic signals were further processed with a second-order Butterworth low-pass filter with cut-off frequency equal to 5 Hz in order to extract the envelope.
In the following page, two figures putting in comparison an acquired signal and an envelope one obtained with pre-processing are reported:

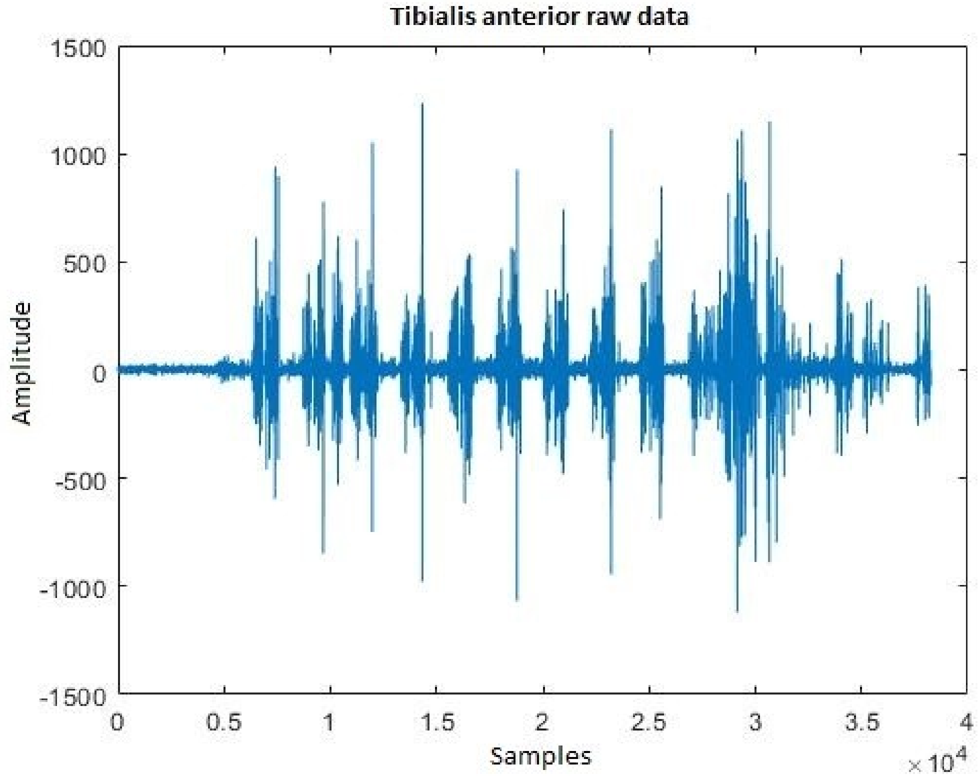

Figure 25: Tibialis anterior signal not processed

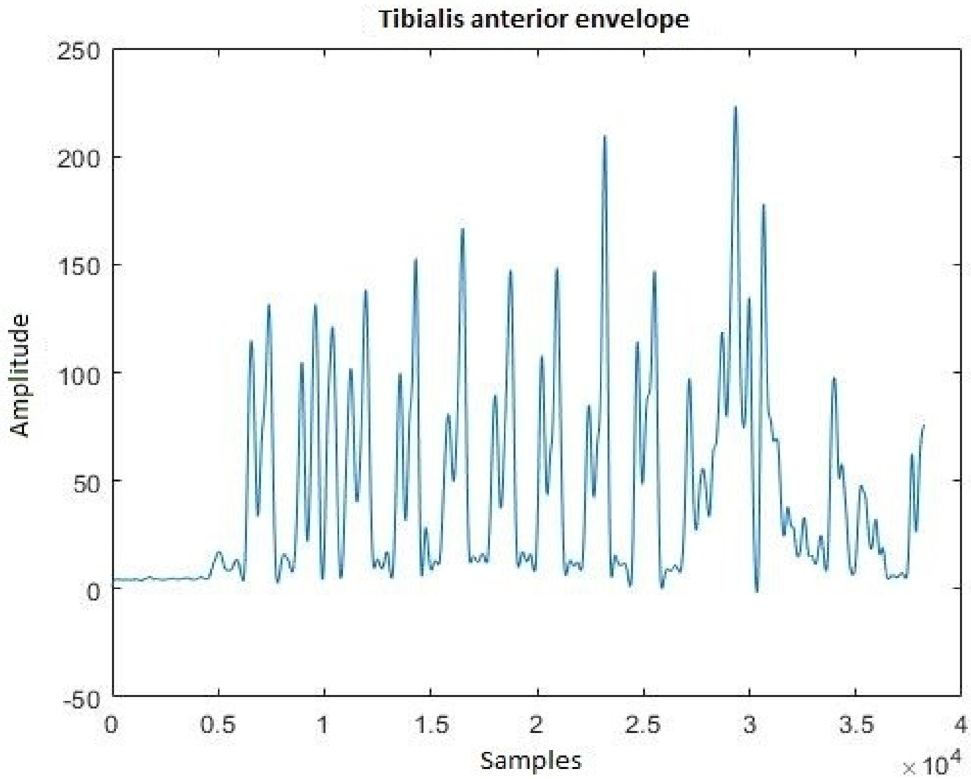

Figure 26: Tibialis anterior signal processed with envelope extraction

For what concerns basographic signals they have been processed in order to identify the start and the end of each gait cycle, and also to detect stance and swing phases that are identified by means of two binary numbers: 0 for stance and 1 for swing. This purpose was reached by applying an anti-causal anti-bounce filter so that spurious spikes, which were caused by switch bounces, are removed.

With this procedure it was possible to individuate also the beginning of the stance (heel-strike) and the swing (toe-off).

5.4 - DATA PREPARATION

After that pre-processing has been correctly performed, data regarding each muscle need only to be normalized in order to have values comprised in the [0-1] interval. After the normalization procedure, data are structured in this way: for each of the 20 subjects there is a file that is composed by 5 columns, each of which contains values (that are rational numbers between 0 and 1) that represent the electrical activity of a specific leg muscle which was recorded by means of probes; from the first to the fifth column, muscles are reported in the following order: Tibialis anterior, gastrocnemius lateralis, vastus medialis, rectus femoralis and hamstring.

Every file contains also a 6th column reporting integer values (0 and 1) which were derived from ground truth signals, i.e. basographic signals recorded with foot-switch sensors. These values identify the phase of the gait cycle: 0 represents the stance phase, i.e. the time frame in which the foot is in contact with the floor, while 1 represents the swing phase, that is the period in which the foot is suspended in air. This last label is the one on which the analysis is focused in order to predict gait events (heel-strike and toe-off).

Once data are acquired, they need to be prepared adequately before being given in input to the neural network for the training procedure. First of all it's necessary to divide each signal in windows of samples in order to obtain vectors of elements which will be used to feed the classifier.

In order to understand with which windows gait phases classification and gait events prediction are optimized, experiments have been performed on windows of 20, 50, 100 and 200 samples. So if for example we choose to produce 100 samples windows, what we get is a big vector that is composed by 100 sequences, each of which contains 5 elements. So in total this vector has 500 elements and is structured in this way: the first 5 elements represent the sample values of the 5 muscles in the first time-sample; the following group of 5 elements constitutes the values of the second sample and so on until the hundredth sample.

After that samples windows have been generated, it's possible to go on with folds creation, that is a procedure with which 20 folds, each of which contains windowed data of 19 subjects for the network training and 1 for the test. For each fold it is possible to distinguish two categories of subjects: learned subjects who are used to perform the training of the neural network; unlearned subjects who are utilized for the test of the neural network in which gait events prediction is performed.

So, in few words, every fold is composed by windowed data regarding 19 learned subjects (LS set) and 1 unlearned subject (US set). Moreover for each fold there is a different subject for the test: this means that a subject is used as test subject in a fold, while in all the other folds it is used as training subject.

Since the purpose is to measure the phase classification performances not only for unlearned subjects but also for learned ones, the LS set has been divided into training set (LS-train) and test set (LS-test). LS-train contains the 90% of the windowed of each train subject, while LS-test includes the remaining 10%.

Once all 20 folds have been created, it is possible to proceed with the following step of the work: the network training.

5.5 - NEURAL NETWORK

There are a lot of types of artificial neural networks that can be used in order to classify gait phases and to predict foot-floor contact signal. As already said in the previous chapter, the main types of artificial neural network are two: the feed-forward neural network (FFNN) and the recurrent neural network (RNN).

In the present work, all experiments have been performed by using a feed-forward multi layer perceptron neural network with 3 hidden layers (FF5 model). Each of these layers is composed by a set of units (the first one has 512 units, the second one has 256 units, the third one has 128 units), called artificial neurons, which perform the task of elaborating incoming signals from the previous layer. After the entire elaboration, the output signals was fed to a sigmoid function and then a 0.5 threshold is utilized in order to get a binary output: if the output has a value that is lower than 0.5 the label 0 is assigned; otherwise the label 1 is assigned.

For what concerns experiments, a stochastic gradient descent (SGD) was used as optimization algorithm so that connection weights between two neurons layers are optimized; moreover a binary cross entropy (BCE) has been utilized as the loss function.
For what regards the choice of the learning rate, the value 0.01 was experimentally considered the best learning rate for FF5 model and for this reason it was used in all experiments of the present work. After that the learning rate has been chosen, it is possible to proceed with the ANN training that was performed by means of an early stop technique which consists in training the network for at most 100 epochs: if the accuracy on the validation set didn't increase for 10 consecutive epochs, then the network training is stopped.
At the end of the procedure, the best learned parameters were taken for the following evaluation of the neural network performance over LS-test and US sets with the basographic signal that is used as ground truth signal.

5.6 - GAIT EVENTS TIMING DETECTION

After that the neural network training has been performed, it's possible to proceed with the test procedure, which consists in testing the neural network by predicting the basographic signals and comparing them with the original ones in order to verify the efficiency and the precision of the selected model.
With prediction, 20 basographic signals were obtained, one for each subject: so for every subject there is an array containing sequences of 0 and 1 that represent respectively the stance and the swing period. These sequences allow to identify easily HS, i.e. the transition from 1 to 0, and TO, that is the transition from 0 to 1.
After predicted basographic signals have been obtained, it's necessary to perform the cleaning of each one. Actually these signals, after prediction, can show very short phases (short sequences of 0 or 1) that absolutely can't represent correctly the stance and the swing period: in order to optimize the performance in gait events prediction, it's necessary to clean as much as possible every signal by choosing an adequate threshold so that superimposition of phase transitions on some tolerance intervals can be avoided. This cleaning procedure allows to cancel false HS inside each swing period (every 0 between two 1) and false TO inside each stance period (every 1 between two 0).
So, in order to understand which threshold allows to obtain the best gait events prediction, all predicted basographic signals have been cleaned with 5 different thresholds: 25, 50, 150, 250 and

300 milliseconds (ms).

If for example you choose a threshold equal to 300 ms, the first HS is detected and then the following 600 samples are scanned to find and, eventually, remove those having value equal to 1; when the 600th sample has been reached, the successive HS is identified and then the same procedure is repeated until the last sample is reached.

For what concerns toe-off events, the procedure is identical: initially the first toe-off is identified and then the following 600 samples are scanned in order to individuate and take off those samples assuming the value of 0; after that the 600th sample has been scanned, the following toe-off is identified and then the same process is repeated and so on.

5.7 - PREDICTION EVALUATION

After that signals have been cleaned, it's possible to proceed with the last step of the work: the evaluation of the basographic signal prediction. This is the final part of all experiments and it's crucial in order to understand the reliability of phase transitions prediction. For that purpose, since signals prediction was performed by a classifier of EMG signals segments, it's necessary to evaluate the performance of the machine in assigning the right value to every EMG segments (0 for stance and 1 for swing).

This purpose is reached through the computation of 4 statistical parameters: accuracy, precision, recall and F1 score. Unfortunately this procedure is not so easy and rapid as it can seem, actually the calculation of these parameters doesn't give reliable information about the evaluation of the basographic signal prediction: for example if errors are located in proximity of phase transitions, also a high accuracy could give unsatisfactory results for what concerns the time error of transition instants.

For this reason, predicted basographic signals given by the classifier were further processed (after the cleaning process) with the aim to remove imprecise prediction information and to improve the performance quality.

So in order to perform another signals processing it's necessary to introduce an important statistical parameter: the tolerance. This is a temporal parameter that allows to classify all predicted gait events as true positives or false positives. For that purpose, after having consulted scientific literature, tolerance was set to 600 milliseconds.

This means that, by comparing signals acquired by means of foot-switches sensors (ground truth signal) with basographic predicted ones, if a predicted HS (or TO) event is sufficiently close (less than 600 milliseconds) to the corresponding gait event in the ground truth signal, it will be considered a true positive. More precisely a true positive will be found if, by taking into consideration the instant at which a gait event has been predicted and the instant at which the same event appears in the ground truth signal, the absolute value of the difference between these two instants is lower than the chosen tolerance; otherwise, the predicted gait event is considered a false positive.

After that, precision, recall and F1 score can be measured; for all true positives, also the mean average error (MAE) was computed: this value is defined as the average time difference between the predicted gait event and the one, of the same type, in the ground truth signal.

Precision, recall, F1 score and MAE are so defined:

- precision = tp/(tp+fp)
- recall = tp/tp+fn
- F1 score = 2*(precision*recall)/(precision+recall)

where:

- tp = true positives
- fp = false positives
- fn = false negatives

In the present work, basographic signals prediction evaluation was performed by using other tolerance values: 100, 200 and 300.

Then the corresponding values of the computed parameters are compared among them in order to understand at which tolerance gait events prediction gives the most reliable results.

6 - RESULTS

In the present work, experiments have been performed in order to optimize classification and prediction performances of the used neural network. Firstly, gait phases classification was performed both for learned and unlearned subjects; then gait events prediction was performed on unlearned subjects and so basographic signals were obtained.

After that, these signals were cleaned with 5 different thresholds: 25, 50, 150, 250 and 300 milliseconds. Then the prediction performance was evaluated by processing predicted signals in order to remove false prediction. For that purpose, 4 different tolerance values were tested in the experiments: 100, 200, 300 and 600 milliseconds. At the end, signals prediction was evaluated by computing precision, recall, F1 score and mean average error both for HS and TO.

In the following pages, there are some tables and graphical representations reporting results obtained from experiments.

GAIT PHASES CLASSIFICATION RESULTS

Here below there is a table showing the average values, calculated over the 20 folds, of accuracy (acc), precision (P), recall (R) and F1 score (F1) regarding the classification of stance (0) and swing (1) performed for learned (L) and unlearned (U) subjects, considering windows with 20, 50, 100 and 200 samples (spw means "samples per window"). For each of these parameters, the corresponding standard deviation (SD) is reported on the right side.

Table 1: Gait classification results

FF5 model	Avg (spw=20)	SD (spw=20)	Avg (spw=50)	SD (spw=50)	Avg (spw=100)	SD (spw=100)	Avg (spw=200)	SD (spw=200)
Acc_U	76,79	9,79	79,39	8,93	80,09	10,47	80,89	9,68
Acc_L	84,10	1,92	82,05	0,68	82,35	0,88	82,35	0,78
P_0_U	76,59	16,12	78,81	16,05	81,17	16,21	81,59	16,28
R_0_U	75,62	19,42	79,50	17,35	78,49	21,54	79,71	19,36
F1_0_U	72,62	14,77	76,10	13,04	75,62	18,31	77,17	14,89
P_1_U	80,04	15,99	82,65	15,47	82,93	16,24	83,34	16,18
R_1_U	81,05	12,12	82,36	12,00	84,68	12,00	85,00	11,32
F1_1_U	78,64	9,71	80,69	9,31	81,80	9,73	82,38	9,67
P_0_L	83,92	2,62	81,61	1,98	82,56	1,32	83,52	1,53
R_0_L	80,33	2,99	78,10	2,58	77,26	2,46	76,64	2,00
F1_0_L	82,05	2,25	79,76	0,92	79,79	1,21	79,90	0,97
P_1_L	84,31	2,00	82,50	1,56	82,27	1,45	81,55	1,27
R_1_L	87,20	2,39	85,35	2,14	86,53	1,53	87,17	1,56
F1_1_L	85,71	1,72	83,86	0,69	84,33	0,79	84,25	0,75

RESULTS FOR WINDOWS WITH 20 SAMPLES

In the table below, it is possible to see the mean values of precision, recall, F1 score and MAE (with the corresponding standard deviation) computed by evaluating gait events prediction, considering windows of 20 samples at different tolerances and thresholds for HS. All these values were obtained by calculating the average of values of all 20 folds: for every fold, precision, recall, F1 score and MAE were computed, then these values were averaged and the standard deviation was calculated.

Table 2: Results of the gait events prediction for HS considering windows of 20 samples

Threshold	Tolerance	Precision HS		Recall HS		F1 HS		MAE HS	
		AVG	SD	AVG	SD	AVG	SD	AVG	SD
25	100	29.4	17.9	52.9	26.8	37.2	21.2	45.7	12.0
50	100	31.6	20.1	50.4	26.8	38.3	22.8	46.0	12.1
150	100	33.1	25.8	39.1	27.6	35.4	26.4	43.3	13.3
250	100	34.5	27.1	35.0	27.1	34.3	26.8	43.6	17.3
300	100	35.4	27.8	33.2	27.1	33.7	27.0	43.5	17.4
25	200	44.9	16.7	80.7	19.0	56.6	17.7	80.7	32.4
50	200	47.4	18.3	75.8	19.1	57.3	18.6	79.9	33.7
150	200	50.4	25.0	60.0	26.4	54.1	25.1	80.6	34.3
250	200	51.4	27.2	52.0	27.3	51.1	26.8	80.7	36.8
300	200	52.9	27.9	49.4	27.7	50.2	27.2	80.9	37.9
25	300	54.5	16.7	98.8	18.4	69.0	17.3	108.3	43.4
50	300	57.1	18.0	92.1	16.9	69.3	17.7	106.3	46.1
150	300	60.3	24.6	71.8	24.9	64.8	24.4	108.2	46.4
250	300	60.5	25.9	61.0	26.0	60.0	25.7	107.5	51.0
300	300	61.6	26.9	57.2	27.0	58.4	26.5	105.1	48.8
25	600	75.5	16.6	100.0	28.9	86.1	17.6	198.8	64.9
50	600	77.3	17.0	100.0	24.6	87.2	17.1	193.1	68.3
150	600	80.4	20.4	95.9	20.4	86.5	19.6	195.4	91.3
250	600	78.0	20.6	77.6	20.1	77.0	20.3	185.5	93.9
300	600	77.8	20.9	70.3	22.6	72.6	21.5	179.0	94.9

In the following table, there are the mean values of precision, recall, F1 score and MAE (with the corresponding standard deviation) calculated for TO, over the 20 folds, considering windows of 20 samples.

Table 3: Results of the gait events prediction for TO considering windows of 20 samples

Threshold	Tolerance	Precision TO		Recall TO		F1 TO		MAE TO	
		AVG	SD	AVG	SD	AVG	SD	AVG	SD
25	100	26.4	15.0	47.3	23.5	33.3	17.6	51.5	10.2
50	100	28.0	16.2	44.9	23.0	33.9	18.5	49.6	13.0
150	100	34.2	21.5	40.2	23.4	36.5	22.2	50.1	15.2
250	100	38.1	23.9	36.9	21.7	37.1	22.6	46.7	17.9
300	100	38.7	23.9	33.2	19.9	35.0	21.0	45.7	16.9
25	200	42.2	21.0	75.1	29.8	53.0	23.7	89.5	23.4
50	200	44.8	23.0	71.1	29.0	54.0	25.0	90.4	25.8
150	200	54.4	28.7	63.4	28.9	57.9	28.6	93.3	31.0
250	200	59.7	30.1	57.9	27.9	58.1	28.8	92.6	31.0
300	200	61.3	30.9	53.0	27.1	55.6	28.1	93.8	31.8
25	300	50.0	21.2	90.5	29.8	63.1	23.4	118.3	43.4
50	300	52.9	22.9	85.2	27.7	64.1	24.2	118.7	46.5
150	300	64.4	27.0	75.3	25.0	68.6	26.0	120.6	51.3
250	300	70.8	27.5	68.1	25.3	68.5	26.2	119.6	52.2
300	300	72.1	28.1	61.9	25.6	65.0	26.0	120.1	53.2
25	600	67.5	17.7	100.0	35.6	80.6	19.0	202.6	84.4
50	600	70.1	18.1	100.0	28.8	82.4	18.3	197.0	88.5
150	600	81.3	19.2	96.5	14.7	87.3	17.0	183.5	92.2
250	600	86.3	19.5	83.3	16.9	83.6	17.8	173.0	88.3
300	600	87.9	19.9	75.7	19.9	79.3	18.8	171.6	90.0

RESULTS FOR WINDOWS WITH 50 SAMPLES

In the following table you can see the average values of the same parameters (with the corresponding standard deviation) computed taking into consideration 50 samples windows for HS, over the 20 folds, at different tolerances and thresholds

Table 4: Results of the gait events prediction for HS considering windows of 50 samples

Threshold	Tolerance	Precision HS		Recall HS		F1 HS		MAE HS	
		AVG	SD	AVG	SD	AVG	SD	AVG	SD
25	100	40.3	18.5	62.8	20.7	48.4	19.4	44.0	10.7
50	100	42.4	19.9	61.5	21.2	49.5	20.5	43.9	10.7
150	100	44.4	25.4	50.7	26.9	46.7	25.7	44.5	11.8
250	100	45.4	27.2	45.0	26.8	44.5	26.4	45.0	12.1
300	100	47.0	27.1	43.8	26.9	44.4	26.3	44.9	11.4
25	200	54.5	17.1	86.4	13.0	65.8	15.9	70.6	24.6
50	200	56.4	18.3	83.6	14.4	66.4	17.1	69.5	25.1
150	200	59.1	25.0	67.8	25.4	62.5	24.8	71.0	25.9
250	200	59.4	26.6	58.5	26.6	58.1	26.0	70.5	26.8
300	200	61.9	26.3	56.7	27.4	57.9	26.3	70.8	26.9
25	300	62.1	17.0	99.6	12.4	75.3	15.5	92.2	36.2
50	300	63.4	18.0	95.0	13.8	74.9	16.5	88.8	37.7
150	300	66.2	24.5	76.2	23.6	70.0	23.8	91.9	38.6
250	300	65.7	25.2	64.5	25.4	64.2	24.7	90.8	42.5
300	300	67.9	24.6	61.8	26.6	63.3	25.2	90.0	43.1
25	600	81.0	15.7	100.0	23.1	89.5	15.6	174.9	60.6
50	600	81.7	16.0	100.0	20.8	89.9	15.1	169.2	64.2
150	600	84.6	17.6	97.2	14.2	89.5	15.7	169.7	98.9
250	600	82.1	17.6	79.2	17.6	79.6	17.2	161.4	102.2
300	600	80.8	17.4	71.5	21.6	74.1	19.0	145.5	94.9

Here below there is the table reporting the mean values of the same parameters calculated for TO, over the 20 folds, considering again 50 samples windows.

Table 5: Results of the gait events prediction for TO considering windows of 50 samples

Threshold	Tolerance	Precision TO		Recall TO		F1 TO		MAE TO	
		AVG	SD	AVG	SD	AVG	SD	AVG	SD
25	100	27.9	15.9	45.0	24.8	34.0	19.0	52.0	12.3
50	100	29.4	17.2	44.4	25.0	34.9	20.0	51.4	11.8
150	100	37.2	23.3	42.0	25.1	39.1	24.1	52.7	15.3
250	100	40.2	25.9	38.8	24.6	39.0	25.1	48.2	15.7
300	100	40.4	25.8	35.8	24.2	37.2	24.7	48.1	15.9
25	200	45.2	21.1	72.0	27.6	54.7	23.6	89.6	26.2
50	200	47.6	22.7	71.0	28.0	56.2	24.8	90.2	27.0
150	200	59.4	28.3	66.8	27.5	62.2	28.0	91.1	29.8
250	200	63.6	30.3	60.9	28.6	61.4	29.2	91.0	29.4
300	200	64.4	30.7	56.1	29.0	58.6	29.2	90.8	28.2
25	300	54.0	19.9	86.5	22.0	65.4	20.7	117.6	44.0
50	300	56.5	21.1	84.7	22.4	66.8	21.6	117.6	46.4
150	300	69.8	25.1	78.9	21.5	73.3	23.6	116.5	48.9
250	300	75.8	25.4	72.0	23.2	72.9	23.9	118.1	50.4
300	300	77.7	25.6	66.6	24.8	69.9	24.1	119.3	50.1
25	600	68.8	17.1	100.0	23.0	81.5	16.8	187.0	74.7
50	600	71.1	17.5	100.0	20.9	83.1	16.7	181.8	76.8
150	600	82.8	19.3	94.8	13.6	87.4	16.7	164.1	81.5
250	600	87.6	20.1	83.4	17.7	84.4	18.4	157.2	78.8
300	600	89.3	20.1	77.1	22.2	80.7	20.1	157.2	77.6

RESULTS FOR WINDOWS WITH 100 SAMPLES

Here below there is a table reporting mean values of precision, recall, F1 score and MAE regarding HS: these values were computed at each tolerance and threshold, over the 20 folds, considering windows of 100 samples.

Table 6: Results of the gait events prediction for HS considering windows of 100 samples

Threshold	Tolerance	Precision HS		Recall HS		F1 HS		MAE HS	
		AVG	SD	AVG	SD	AVG	SD	AVG	SD
25	100	40.9	18.8	60.3	23.0	47.8	20.5	45.7	8.0
50	100	44.4	20.8	58.1	23.3	49.4	22.0	45.2	8.1
150	100	46.4	24.2	50.4	25.3	47.6	24.7	46.1	8.5
250	100	47.7	25.0	46.3	25.7	46.3	25.3	46.8	10.2
300	100	49.9	24.6	45.5	25.8	46.6	25.3	46.4	9.5
25	200	57.0	17.3	84.1	19.5	66.3	17.5	74.2	23.3
50	200	60.6	19.1	79.5	19.9	67.3	19.1	72.3	23.8
150	200	63.4	23.5	69.0	24.4	65.0	23.7	73.1	23.8
250	200	64.5	23.3	62.3	25.4	62.2	24.3	72.9	24.9
300	200	67.0	22.8	60.9	26.3	62.4	25.0	72.6	24.8
25	300	65.3	18.0	96.5	18.7	76.0	17.6	95.4	35.2
50	300	68.3	19.4	90.0	19.0	75.9	18.9	91.3	36.3
150	300	71.2	23.3	77.7	23.6	73.1	23.3	92.4	36.5
250	300	72.2	22.4	69.5	25.0	69.7	23.8	92.0	38.4
300	300	75.0	21.1	67.7	26.1	69.6	24.4	91.9	39.3
25	600	81.3	16.4	100.0	26.4	89.7	18.4	164.9	56.6
50	600	83.3	16.7	100.0	21.4	90.9	17.5	156.1	62.7
150	600	85.6	16.9	93.3	17.4	87.9	16.8	153.0	84.7
250	600	83.7	15.9	79.5	20.5	80.1	18.4	138.7	77.9
300	600	84.6	15.4	74.9	22.7	77.4	19.8	128.7	68.7

Here below there is the table reporting the average values, calculated over the 20 folds, of precision, recall, F1 score and MAE concerning TO .

Table 7: Results of the gait events prediction for TO considering windows of 100 samples

Threshold	Tolerance	Precision TO		Recall TO		F1 TO		MAE TO	
		AVG	SD	AVG	SD	AVG	SD	AVG	SD
25	100	30.4	17.3	45.1	25.4	35.6	20.3	51.9	12.9
50	100	32.9	19.8	43.5	25.8	36.8	22.2	51.6	13.1
150	100	39.6	24.8	42.3	25.6	40.3	25.1	52.0	14.3
250	100	42.0	26.9	39.2	24.8	39.7	25.3	48.6	17.2
300	100	42.5	26.9	36.7	24.0	38.3	24.6	48.7	17.1
25	200	48.1	23.1	71.1	29.7	56.3	25.8	87.5	28.6
50	200	52.0	25.6	68.6	29.9	58.1	27.5	88.6	29.5
150	200	61.1	30.1	65.7	29.8	62.4	30.0	88.3	30.7
250	200	64.2	31.7	60.6	30.4	61.3	30.7	88.9	32.7
300	200	65.1	31.8	56.7	29.9	59.0	30.2	88.7	31.9
25	300	56.6	22.8	84.6	27.4	66.4	24.5	113.9	44.7
50	300	60.8	24.6	81.1	27.0	68.2	25.6	114.6	48.9
150	300	70.9	27.7	76.9	26.4	72.8	27.2	113.6	50.9
250	300	74.9	28.5	70.5	28.0	71.3	28.0	114.1	52.8
300	300	76.0	28.4	66.1	28.3	68.8	27.9	114.3	52.8
25	600	71.0	18.1	100.0	26.8	83.1	18.4	182.9	81.4
50	600	74.5	18.8	99.7	22.7	83.2	18.2	174.6	85.8
150	600	83.7	20.4	90.5	18.4	85.5	19.0	162.6	89.2
250	600	87.4	20.7	81.7	21.9	82.7	20.9	158.9	89.9
300	600	88.3	20.8	76.5	24.0	79.7	22.2	158.1	89.4

RESULTS FOR WINDOWS WITH 200 SAMPLES

In the following table there are the average values of precision, recall, F1 score and MAE computed over the 20 folds, considering windows of 200 samples. These values concern HS.

Table 8: Results of the gait events prediction for TO considering windows of 200 samples

Threshold	Tolerance	Precision HS		Recall HS		F1 HS		MAE HS	
		AVG	SD	AVG	SD	AVG	SD	AVG	SD
25	100	44.1	17.1	56.1	17.1	48.7	17.2	47.8	3.8
50	100	44.1	17.1	56.0	17.1	48.6	17.2	47.8	3.8
150	100	47.3	19.6	51.9	19.0	48.9	19.3	48.2	4.2
250	100	48.7	20.6	48.5	19.4	48.1	19.9	48.0	5.3
300	100	51.3	20.7	45.9	20.0	47.7	20.2	48.4	6.0
25	200	62.0	19.0	79.5	17.2	68.6	18.0	76.3	13.2
50	200	62.0	19.0	79.5	17.2	68.6	18.0	76.3	13.2
150	200	66.9	22.2	73.8	20.9	69.3	21.2	77.5	13.8
250	200	69.4	22.8	69.3	21.8	68.6	21.9	77.9	14.7
300	200	73.6	26.6	65.6	30.3	68.1	23.4	78.5	29.8
25	300	68.7	19.0	88.5	15.3	76.1	17.3	93.4	25.0
50	300	68.7	19.0	88.4	15.3	76.1	17.3	93.4	25.0
150	300	73.4	22.0	81.3	19.7	76.2	20.6	93.4	25.4
250	300	76.2	22.4	76.2	21.1	75.3	21.4	94.0	26.4
300	300	80.8	34.2	71.7	32.4	74.6	35.4	94.4	40.9
25	600	83.5	15.7	100.0	15.0	91.0	13.9	154.9	64.1
50	600	83.6	15.7	100.0	15.0	91.1	13.9	155.0	64.1
150	600	87.2	15.8	96.8	10.6	90.6	12.8	147.7	77.2
250	600	89.8	15.1	89.3	11.6	88.6	13.0	144.4	78.5
300	600	91.3	39.7	80.0	33.7	83.7	27.5	129.9	77.1

Here below there is the table reporting the average values, computed over the 20 folds, of the 4 parameters obtained for TO.

Table 9: Results of the gait events prediction for TO considering windows of 200 samples

Threshold	Tolerance	Precision TO		Recall TO		F1 TO		MAE TO	
		AVG	SD	AVG	SD	AVG	SD	AVG	SD
25	100	30.3	16.2	39.2	19.5	33.7	17.5	50.7	5.2
50	100	30.3	16.2	39.2	19.5	33.8	17.6	50.7	5.2
150	100	34.3	19.6	37.7	19.9	35.5	19.6	50.6	5.1
250	100	36.3	20.7	36.1	20.2	35.7	20.2	50.7	5.3
300	100	37.1	22.1	32.9	20.7	34.2	20.8	51.3	5.4
25	200	51.7	23.6	66.7	25.6	57.5	24.7	91.8	18.2
50	200	51.7	23.6	66.7	25.6	57.5	24.7	91.8	18.2
150	200	58.3	27.7	63.8	26.4	60.2	27.2	92.2	17.9
250	200	61.3	28.7	60.8	27.0	60.4	27.8	92.7	18.6
300	200	62.4	36.7	54.8	34.4	57.2	30.2	93.1	37.2
25	300	62.4	23.0	81.2	23.6	69.6	23.4	122.1	32.6
50	300	62.4	23.0	81.2	23.6	69.6	23.4	122.1	32.7
150	300	70.0	26.6	77.1	24.2	72.5	25.6	122.7	34.3
250	300	73.4	27.0	73.0	24.9	72.4	25.7	122.7	35.8
300	300	75.0	33.9	65.7	34.8	68.7	31.7	123.0	59.6
25	600	77.5	18.1	100.0	18.6	87.3	16.5	184.2	77.4
50	600	77.6	18.2	100.0	18.6	87.4	16.5	184.2	77.4
150	600	84.3	19.6	93.3	14.6	87.4	16.7	176.1	83.1
250	600	87.4	13.0	86.4	15.9	86.0	17.8	171.3	82.7
300	600	89.3	44.1	77.6	20.5	81.4	37.4	171.2	101.4

PRECISION

Here below there are graphical representations of precision values for HS and TO, so that it is possible to see how this parameter changes by varying the threshold used to clean predicted signals. All graphs show mean precision computed over the 20 folds with a tolerance of 600 milliseconds.

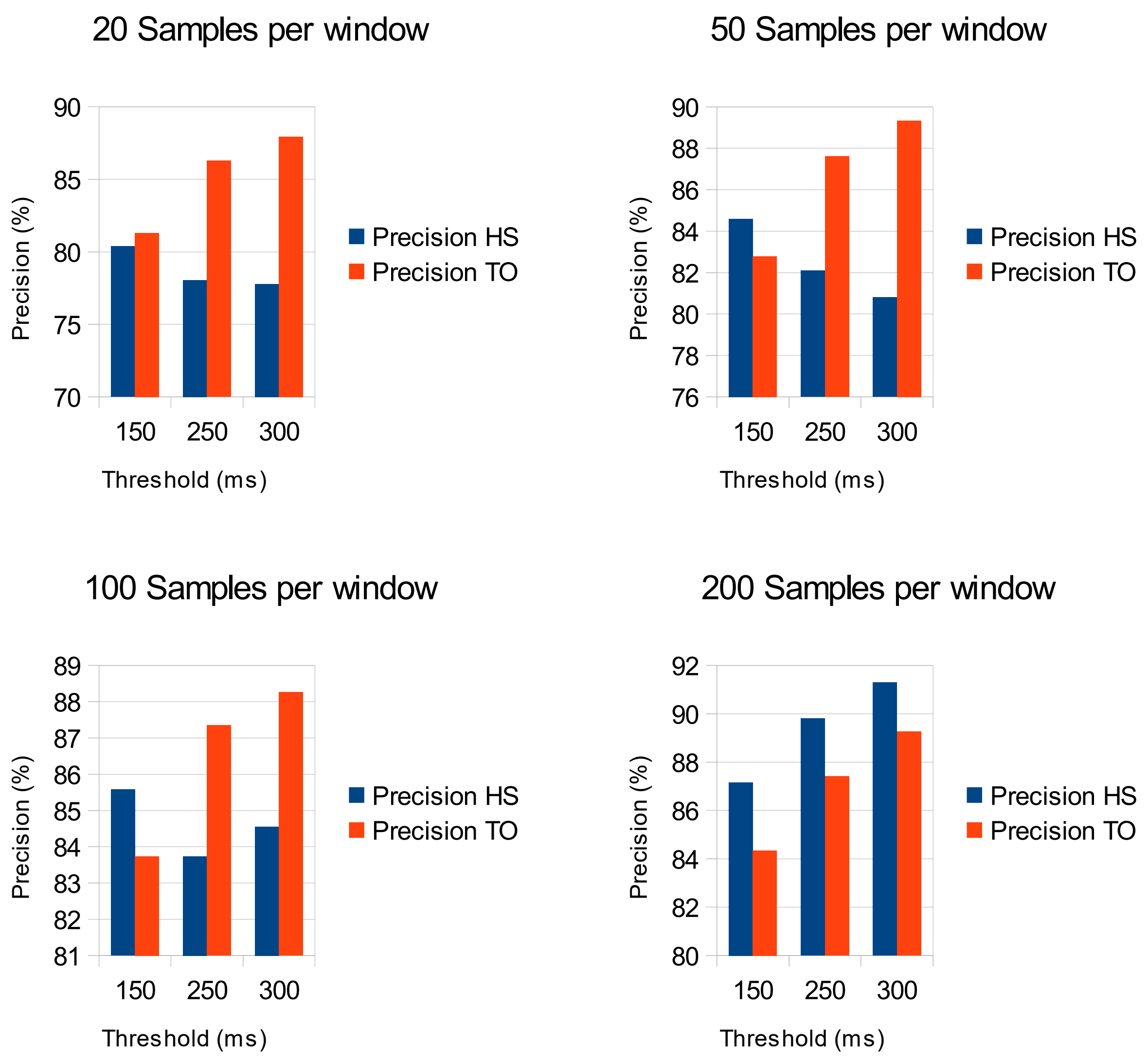

Figure 27: Precision values for different window size with tolerance of 600ms

In the following there are the graphical representations of mean precision values, obtained over the 20 folds, varying with tolerance at the fixed threshold of 300 ms.

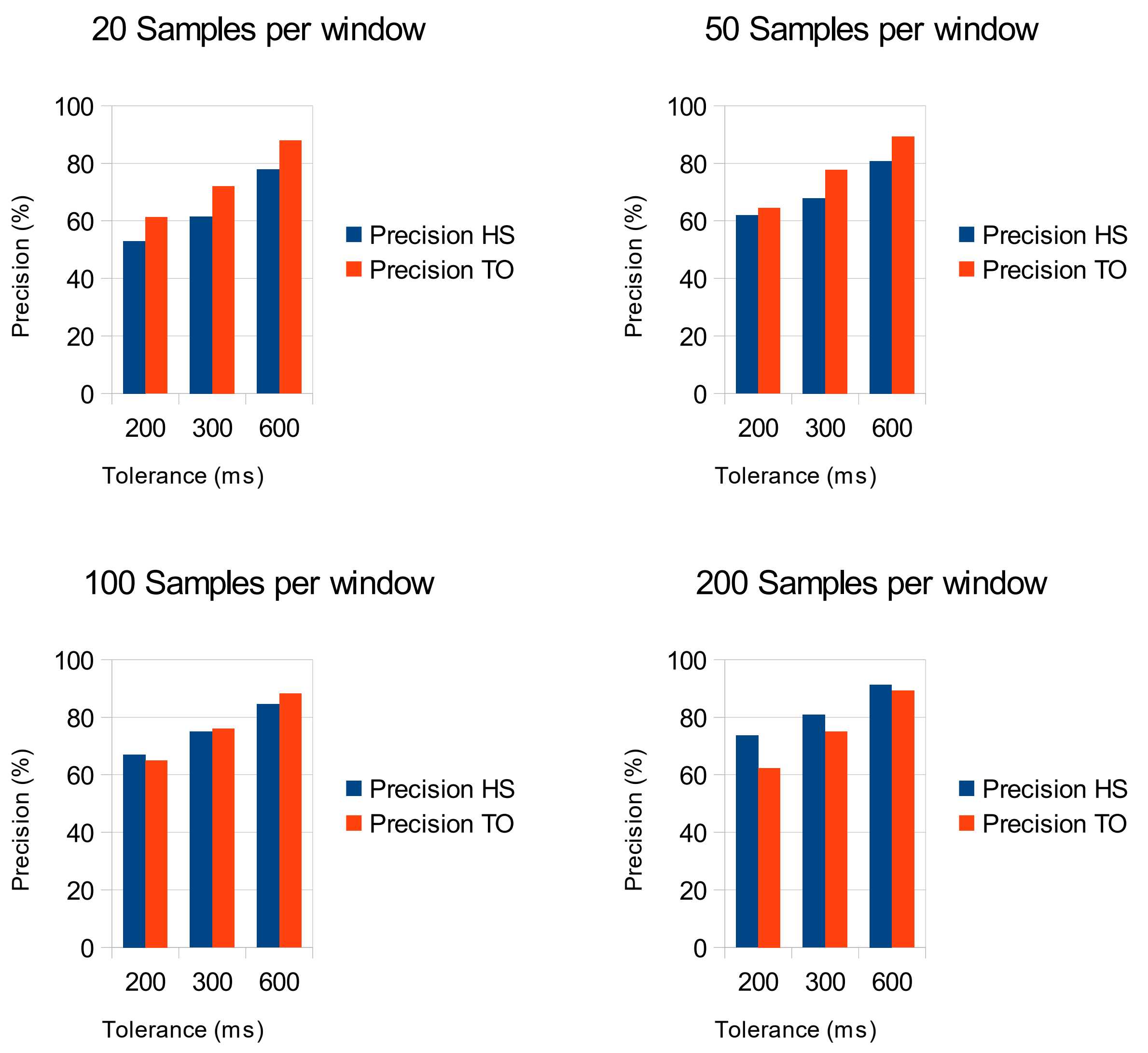

Figure 28: Precision values for different window size with threshold of 300ms

RECALL

Here below graphical representations of mean recall values for HS and TO are reported.

All graphs show mean recall values computed, over the 20 folds, with a tolerance of 600 milliseconds.

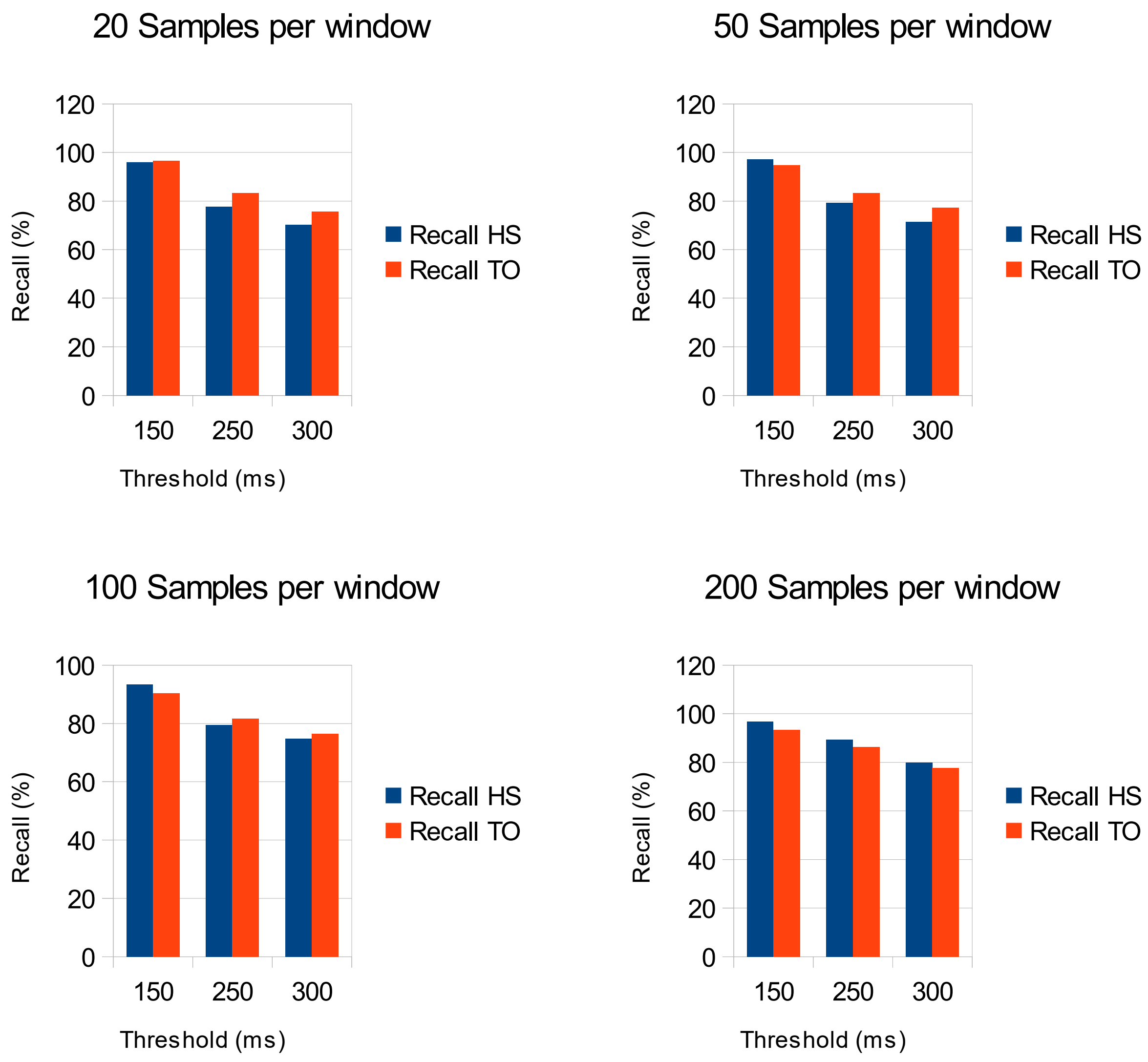

Figure 29: Recall values for different window size with tolerance of 600ms

In the following, there are the graphical representations of mean recall values varying, computed over the 20 folds, with tolerance at the fixed threshold of 300 ms.

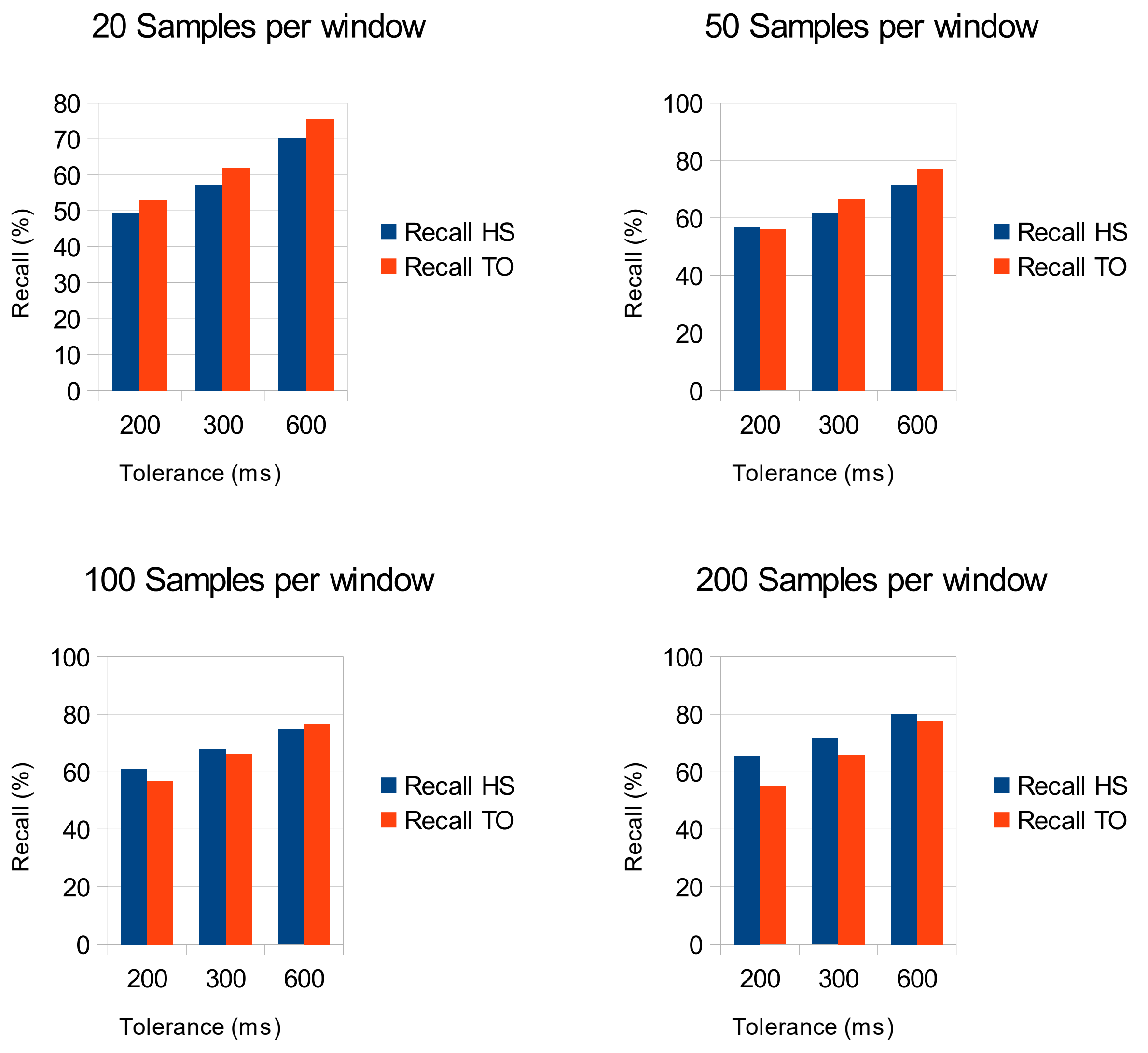

Figure 30: Recall values for different window size with threshold of 300ms

F1 SCORE

Here below there are graphical representations of mean F1 score values, computed over the 20 folds, for HS and TO,.

All graphs show F1 score computed with a tolerance of 600 milliseconds.

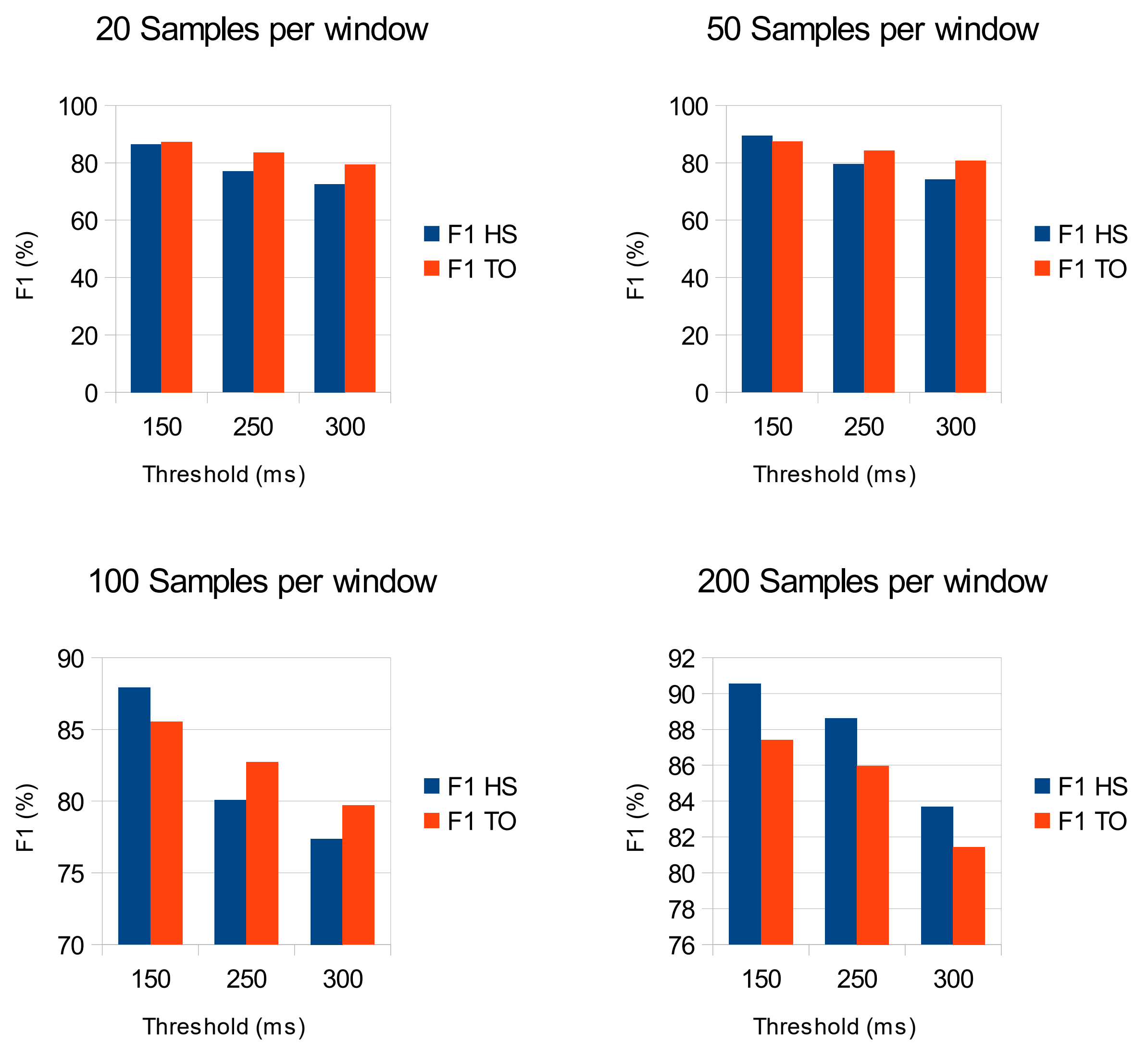

Figure 31: F1 Score values for different window size with tolerance of 600ms

In the following there are the graphical representations of mean F1 score values, computed over the 20 folds, varying with tolerance at the fixed threshold of 300 ms.

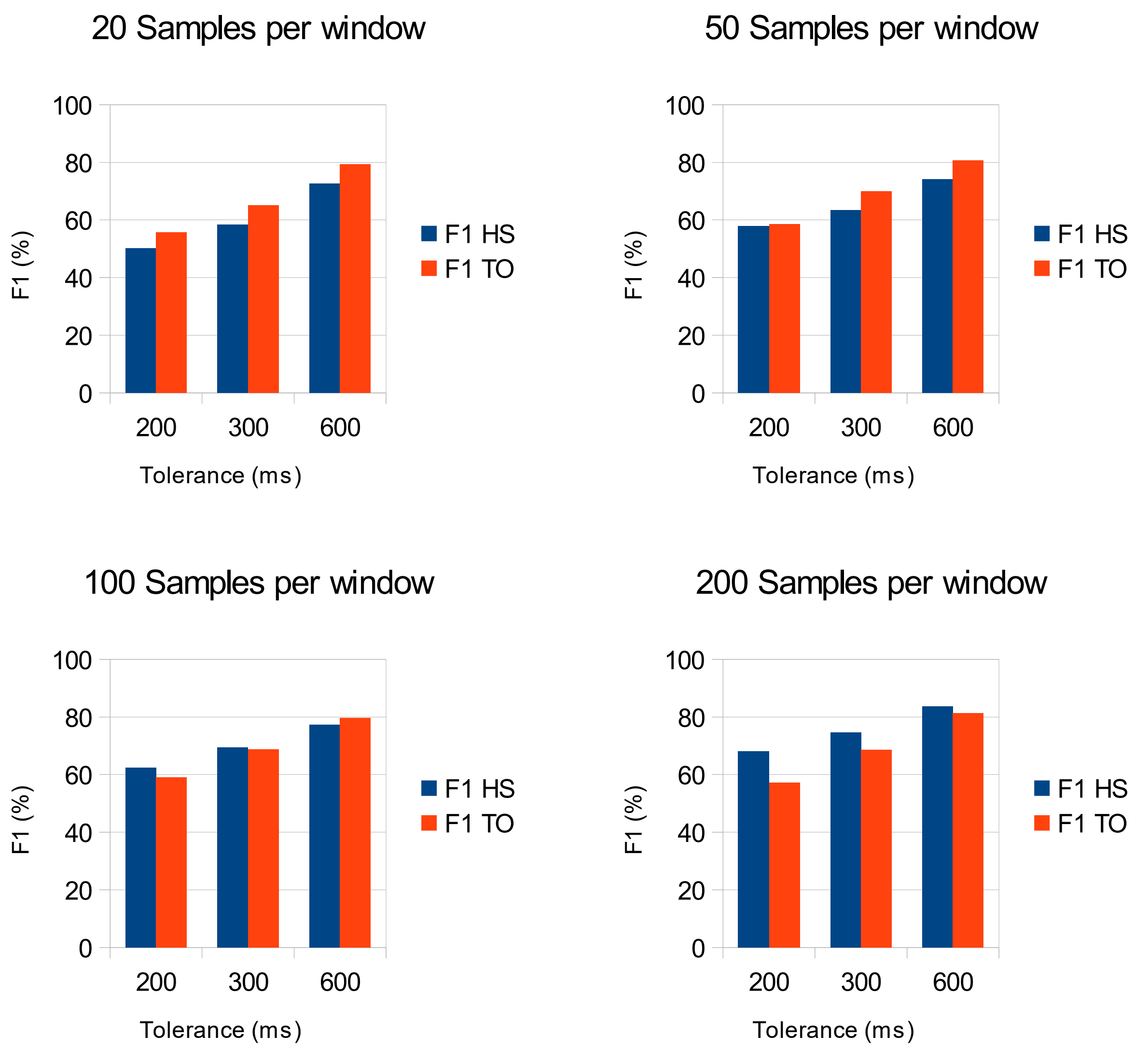

Figure 32: F1 Score values for different window size with threshold of 300ms

MEAN AVERAGE ERROR (MAE)

Here below, graphical representations of MAE values for HS and TO were reported.

All graphs show MAE computed, over the 20 folds, with a tolerance of 600 milliseconds.

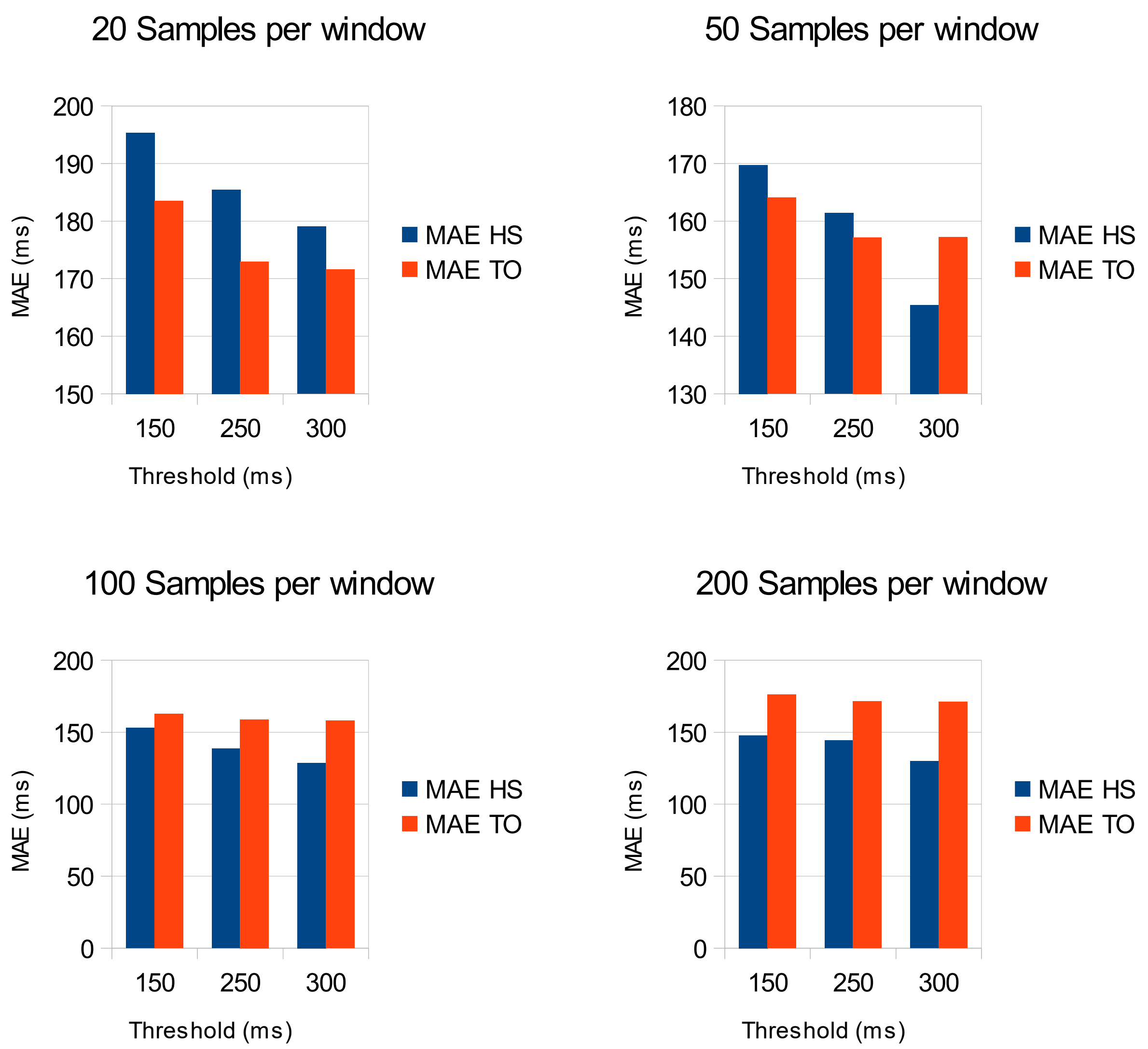

Figure 33: MAE values for different window size with tolerance of 600ms

In the following, there are the graphical representations of MAE values, computed over the 20 folds, varying with tolerance at the fixed threshold of 300 ms.

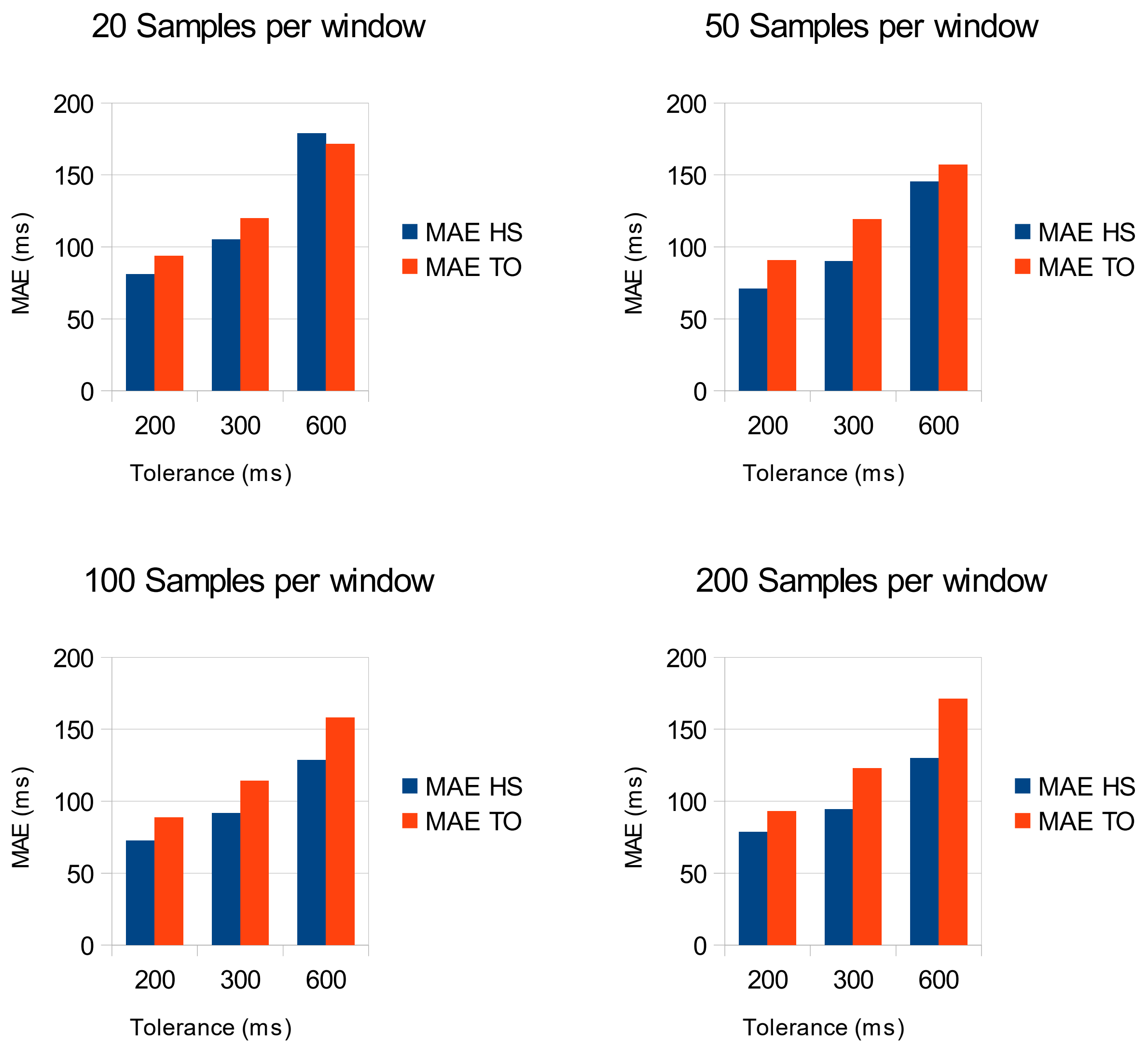

Figure 34: MAE values for different window size with threshold of 300ms

MEAN AVERAGE ERROR AND TOLERANCE

Here below there are a table and a graphical representation showing how mean average errors, calculated over the 20 folds, change with tolerance both for HS and TO. Data were reported considering windows with 200 samples and a threshold of 300.

Table 10: MAE for HS and TO considering windows of 200 samples

Samples per window	Threshold	Tolerance	MAE HS	MAE TO
200	300	100	48,40	51,31
200	300	200	78,46	93,06
200	300	300	94,37	123,01
200	300	600	129,93	171,15

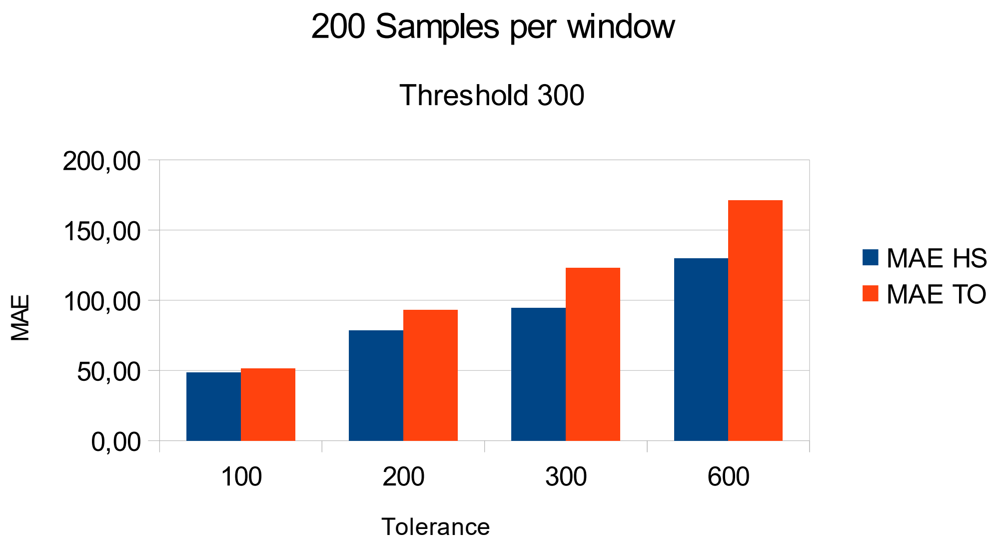

Figure 35: MAE computed for different tolerances

FALSE POSITIVES AND TOLERANCE

In this page there are a table and a graphical representation showing how the number of false positives changes with tolerance both for HS and TO. Data were reported considering windows with 200 samples and a threshold of 300.

Table 11: False positives for HS and TO considering windows of 200 samples

Samples per window	Threshold	Tolerance	FP-HS	FP-TO
200	300	100	52,00	67,29
200	300	200	28,71	40,75
200	300	300	21,25	27,88
200	300	600	10,29	13,33

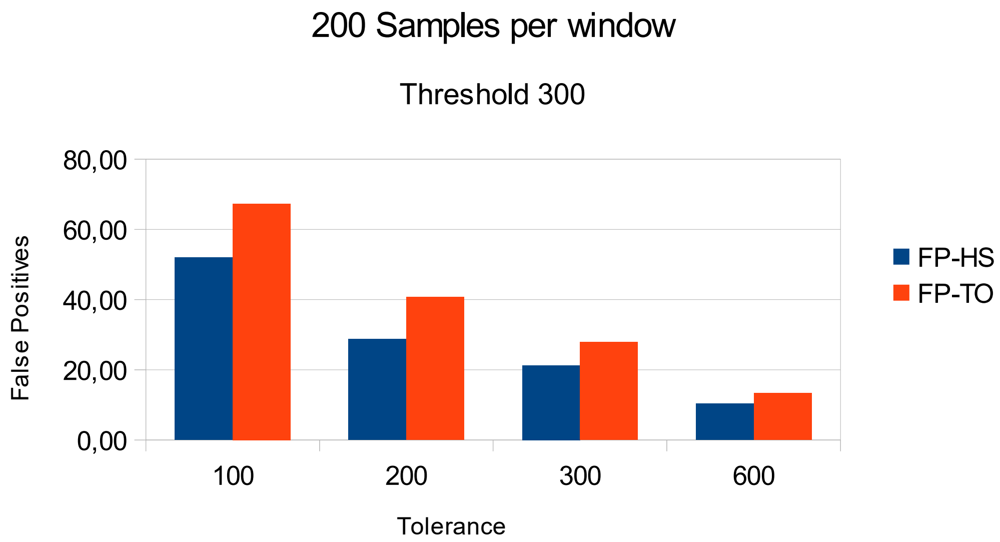

Figure 36: False positives found for different tolerances

7 - DISCUSSION

In the present work, basographic and sEMG signals of 20 hemiplegic children, previously acquired, were used to reach a precise purpose, i.e. classifying gait phases (stance and swing) and predicting with the highest reliability transitions between these phases, i.e. heel strike and toe off, by using the deep learning approach.

In order to get the most accurate gait phases classification and gait events prediction from sEMG signals of hemiplegic children, many experiments have been performed in order to obtain the best performances by the artificial neural network.

Experiments were performed each time considering windows composed by a different number of samples (20, 50, 100, 200) in order to see when the neural network gives the best results. Sensitivity of the performances to the threshold of the procedure for cleaning the predicted basographic signals and to the tolerance to identify true positives were also tested.

After having performed the training and the test of the neural network, results about the accuracy of gait phases classification were obtained both for learned and unlearned subjects. The first thing that it is possible to notice immediately is that classification accuracy in learned subjects is higher than unlearned subjects' one, as expected Table 1). However, there is not a great difference between the two subjects categories (except for the case of windows with 20 samples), and this induces to think that the chosen neural network, a feed-forward multi layer perceptron neural network with 3 hidden layers (FF5), is able to learn signal patterns that generalize well to unlearned subjects. The best accuracy for what concerns unlearned subjects was obtained with 200 samples windows, while on learned subjects the best accuracy was found with 20 samples windows (that gave the lowest accuracy for unlearned subjects). Moreover, it is easily noticeable that on unlearned subjects the standard deviation is higher. This is partly due to the fact that gait patterns can change importantly from subject to subject. Also for what concerns precision, recall and F1 score learned subjects show better results than unlearned ones, as expected, both for stance and swing periods. As in the case of accuracy, unlearned subjects show again a much higher standard deviation, i.e. a greater variability. By looking at table 1, it is possible to notice also that swing phases show better results than stance ones both for learned and unlearned subjects.

The present approach allows also to predict foot-floor-contact signals and thus the transition timing between phases, i.e. HS and TO. Four different tolerances to identify true positives in the predicted foot-floor-contact signal were evaluated. For each of these tolerances, five different increasing thresholds for leaning the predicted foot-floor-contact signals were tested (Tables 2-9). Moreover, by observing these tables, it is possible to see how prediction performance varies considering windows with a different number of samples. First of all, it is easy to notice that precision, recall and F1 score increase, reaching a higher accuracy level, by setting the temporal tolerance to 600 milliseconds: this happens for both gait events, HS and TO (see tables 2-9). Also the mean average error increases for HS and TO but it is simply due to the fact, that with a higher temporal tolerance there are less false positives (see table 11 and figure 36) and more true positives which then will be considered for the prediction evaluation. This is due to the fact that in predicted signals a gait event is considered as a true positive if it is temporally less distant than 600 ms from the corresponding gait event in the ground truth signal.

By considering parameters obtained at each experiment, it is evident that, globally, all parameters improve by increasing the number of samples per window; improvements are visible also by increasing tolerance for all parameters, except the mean average error. For what concerns the threshold by increasing its value, both for HS and TO, precision improves, recall worsens; conversely F1 score and MAE remain more or less constant, except the case in which the tolerance is set to 600 ms (see tables 2-9 and figures 27-35).

At the end, the best performance in classifying gait phases and predicting gait events in hemiplegic children was obtained by creating 200 samples windows to feed in input to the neural network and by post processing predicted signals setting the threshold to 300 ms and the tolerance to 300 ms. Thus, this configuration was proposed by the present work as approach to classify stance and swing and to predict basographic signals with the highest reliability: the classification accuracy was 82.4% for learned subjects and 80.9 for unlearned subjects; for what concerns prediction the mean absolute error was 94.4 ± 40.9 ms for HS and 123.0 ± 59.6 ms for TO.

In order to estimate the goodness of these results it's necessary to compare them with what reported in literature. In [64] gait analysis was performed on healthy adult subjects walking on a treadmill: in this study a classification accuracy of 87.5% for learned subjects and of 77% for unlearned ones was accomplished; mean average errors, computed by means of a neural network, were 35 ± 25 ms for HS and 49 ± 15 ms for TO; in [56] gait analysis was performed on healthy adult subjects walking in natural conditions: classification accuracy was 94.8% for learned subjects and 93.4 for unlearned ones; mean average errors were computed through a neural network and were 21.6 ± 7.0 ms for HS and 38.1 ± 15.2 for TO.

By analyzing results obtained by these two studies, it is possible to notice that they are quite better than results achieved in the present work. This difference could be explained by the fact that in children affected by hemiplegia there is a great variability in gait parameters due to walking difficulties caused by neuromuscular disorder; this variability wasn't found in the other two studies probably because gait analysis was performed on adult healthy subjects.
However the present work can be proposed as an innovative approach used to classify and predict stance and swing phases from sEMG of hemiplegic subjects and in the future it could be quite improved, so that it will become possible to get very good performances in classifying and predicting basographic signals not only for healthy subjects but also for unhealthy ones.

8 - CONCLUSIONS

The present work proposed a gait analysis method based on deep learning approach in order to classify gait phases (stance and swing) and to predict transitions between these phases, i.e. heel strike and toe off, in hemiplegic children; this work has also proposed a good technique for pre-processing sEMG signals that consists in extracting linear envelopes in order to train better the neural network and to improve its performances.

To the best of our knowledge, this is one of the first studies to estimate HS and TO from sEMG signals of hemiplegic subjects. Results about classification and prediction performances are preliminary and thus promising for future: in this work actually by modifying some parameters (number of samples per window, tolerance and threshold) it was possible to get better performances (higher precision, recall, F1 score and lower MAE) for what concerns both classification and prediction. So by changing parameters at each experiment, new better performances can be obtained.

For future works, other experiments can be performed, like trying to use a different type of neural network, creating superimposed windows and increasing the number of subjects recruited for gait analysis; in this way the goodness of classification and prediction can be easily increased.

The approach proposed by the present work is well promising for future also because it allows to predict HS and TO directly from sEMG signals, so if this method will be adequately improved, in future probably it will be possible to perform gait analysis without using foot-switch sensors. This would represent a good advantage for analysis performance because a lower number of sensors will be necessary and thus time-consumption and costs will be reduced.

9 - BIBLIOGRAPHY

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