

Spatiotemporal analysis of cane-assisted gait in post-stroke patients using inertial measurement units

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Abstract

Context Stroke is a worldwide and devastating disease, whose consecutive lesions can result in a constellation of impairment. In some cases, the disability is such that the patient will need a gait assistance for walking. Among the existing walking aids, the four-points cane is the most widely used in post-stroke rehabilitation. However, it has the major disadvantage of having to be lifted at every step, and of preventing the patient from walking smoothly in two phases as in normal gait. To deal with this problem, the physiotherapist G. Dellicour had the idea of creating the Wheeleo © cane, which is a four-legs cane equipped with wheels at each end extremities. Qualitative observations and an initial trial carried on post-stroke subjects have shown that patients walk significantly faster with the Wheeleo©. To quantify precisely the effects of the cane in terms of gait stability, symmetry, and fluidity, a measurement of the gait spatiotemporal parameters is necessary. However, such measurement requires laboratory equipment, such as force platforms, as the current existing wearable systems are not suitable for post-stroke patients walking with cane.

Objective The main objectives of this thesis were articulated around three broad focuses: (1) the implementation of a new quantitative measurement technique suitable for post-stroke individuals walking with cane, (2) the assessment of the performance of this technique, and (3) the application of the implemented tool to measure the effect of the Wheeleo © cane on gait spatiotemporal parameters.

Results The measurement technique was based on unsupervised clustering. Algorithm parameters were dependent to the mean gait velocity of the patient. It demonstrated good performance for detecting the gait events (fail rate of 1.55%), and an acceptable confidence interval of accuracy ($CI = \pm 0.101$ seconds). The effects of the wheeled cane and classic cane were compared in six post-stroke individuals. It appeared that the Wheeleo © cane provides significant positive significant effect on the spatiotemporal parameters, and on the swing-stance symmetry ratio.

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List of abbreviations

IMU	Inertial Measurement Unit
AP	Antero-posterior
CC	Classic cane
FN	False negative
FP	False positive
FP	Force platforms
GRF	Ground reaction forces
HP	High-pass
HS	Heel strike
IMU	Inertial Measurement Unit
LP	Low-pass
ML	Medio-lateral
NP	Non-paretic
P	Paretic
TO	Toe off
Tst	Stance phase duration
Tsw	Swing phase duration
WC	Wheeled cane

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Chapter 1

Introduction

Despite the extensive improvements made in prevention and treatment over the last few years, stroke remains a worldwide serious disease. In this chapter, we will briefly review the definition and medical concepts around stroke. We will also see that lesions consecutive to a stroke attack can result in a constellation of impairments, ranging from minor temporary disabilities to serious permanent infirmities. Post-stroke gait pattern is therefore specific to each patient. In some cases, the disability is such that the patient will need a walking aid to travel.

There are different types of walking aids. Among these, the four-points cane is the most widely used for post-stroke rehabilitation and gait assistance. However, it has the major disadvantage of having to be lifted at every step, and of preventing the patient from walking smoothly in two phases as in normal gait. This chapter will explain how Geoffroy Dellicour, a physiotherapist of the William Lennox neurological rehabilitation center, had the idea of designing a the Wheeleo © cane, a new walking aid to deal with the current problems related to the use of the current four-point cane. Results about the first trial clinical trial conducted on patients walking with the Wheeleo © cane will also be presented.

1.1 Essential medical concepts

1.1.1 Stroke, a worldwide devastating disease

Despite the extensive improvements made in prevention and treatments over the last few years, stroke remains a worldwide serious disease. With an incidence of 6 million events annually in Europe at the beginning of the 21st century (Béjot, Bailly, Durier, & Giroud, 2016), stroke is the leading cause of motor disability in adults, and the third most common cause of death in industrialized countries (WSO, 2012). In addition, given the close link between the age and the stroke occurrence, the ageing of the population in industrialized countries will inevitably lead to a rising number of annual stroke events for years to come (Béjot et al., 2016). Among the millions of people suffering early from stroke, about 30% suffers from permanent residual disabilities. Stroke is therefore a growing global chronic disease. Enable post-stroke patients to improve their autonomy is a current major health challenge.

1.1.2 Definition of stroke

According to the World Health Organization, a stroke, also called cerebrovascular accident (CVA), is characterized by “the sudden death of some brain cells due to lack of oxygen when the blood flow to the brain is lost” (Johnson, Onuma, Owolabi, & Sachdev, 2016). Two main types of stroke can be distinguished. The first and most common is the ischemic attack, characterized by a loss of the cerebral blood flow due to a clot or another blockage source in an artery supplying the brain. The second type, whose consequences are generally less serious, is caused by an intracerebral hemorrhage (hemorrhagic stroke). In both case, the brain is deprived of oxygen and nutrients, causing temporary or permanent damages to the brain tissue (WHO, 2018).

1.1.3 Risk factors of stroke

The main risk factors associated with stroke are similar to those for common vascular diseases: high blood pressure, atrial fibrillation, high blood cholesterol, tobacco use, unhealthy diet, physical inactivity, diabetes, and advancing age (McKay, 2004). Currently, most of these stroke risk factors become more prevalent, which explains partly why stroke is a growing disease (Béjot et al., 2016). Effective prevention strategies include therefore targeting modifiable unhealthy lifestyles.

1.1.4 Stroke stages

Two main stroke stages can be distinguished according to the timing from the onset of stroke (Kornienko & Pronin, 2009). The acute phase is defined as the first 48 hours after symptoms appear. During this period, a rapid and effective medical care is crucial to

minimize brain damages and post-stroke disorders. Comes next the post-stroke chronic phase, during which a shorter or longer period of patient rehabilitation can begin. In some cases, the brain injury is such that, even after a period of rehabilitation, the patient will need a permanent gait assistance such a cane.

1.1.5 Post-stroke condition

The lesion consecutive of a stroke attack can result in a wide range of disorders that can affect the gait pattern. Depending on the extent and the location of the lesion, as well as on the quality and the swiftness of the care, sequels can range from minor temporary disability to serious permanent impairment. Both types of stroke (ischemic and hemorrhagic) can lead to various neurological disorders, which may be divided into two main categories: sensory-motor disorders and cognitive disorders. Some disorders can lead to serious gait abnormalities in post-stroke patients. Therefore, for a better understanding of the impact of stroke on gait pattern, it is important to highlight these disorders. It should be noted that the list of disorders described below is not exhaustive but includes the disorders that are commonly encountered after a stroke.

1.1.5.1 Sensory-motor and motor control disorders

The most common and widely recognized motor impairments caused by stroke are hemiplegia and subsequent loss or limitation of muscle control (Kristensen, Stenager, & Dalgas, 2017). Hemiplegia is defined as a partial or complete paralysis of one side of the body ("Hemiplegia," 2003). Those motor disorders lead to a loss or limitation of the muscle strength, motion control, and can therefore seriously impact the patient mobility.

Spasticity is another common complication of stroke. It is defined as a velocity-dependent increase in tonic stretch reflexes with exaggerated tendon jerks (Francisco & McGuire, 2012). It limits then negatively muscle control and compounds gait abnormalities.

Finally, proprioceptive deficits are also very frequent in post-stroke patients. Proprioceptive sense enables the perception of the position of the body parts during the motion. Therefore, a loss of proprioception can seriously impact the quality of the motion control and impairs the patient's gait (Park, 2013).

According to the level of sensory-motor impairment, the patient's usual activities of daily living can be impeded, and quality of life can therefore be seriously reduced.

1.1.5.2 Cognitive disorders

The prevalence of cognitive impairment is very high in post-stroke patients. In the same way as for the motor control disorder, there exist a large spectrum of cognitive disorders, with a level ranging from minor cognitive decline to dementia, and that can also impact the gait quality. Indeed, walking is a very complex task, involving continuous motor control coordination and cognitive resources (Oliveira et al., 2018). Attention and concentration

deficits, as well as cognitive-motor interference, are very frequent in post-stroke patients and can affect the gait speed and quality (Goh, Tan, Yang, & Ng, 2017) .

1.2 Existing walking aids for post-stroke patients

In order to deal with the residual walking disorders after stroke, different adaptive equipments exist. Determining which technical assistance is the most appropriated for the patient is an important aspect of the rehabilitation. Indeed, it will help stroke patients having greater independence in their daily activities. In addition, patients with greater autonomy tend generally to participate more in activities, to come out of their homes, and thus avoid getting into a vicious circle of sedentary lifestyle.

The choice of the gait technical assistance depends on patient's recovery and abilities. In patient with residual hemiplegia, the one-point, the four-points canes, and the hemi-walker are the most commonly walking assistances used. They are illustrated in Figure 2.4.



Figure 1.1: Typical walking assistance for post-stroke subjects
(Unodis, 2018)

The wheeled walker

The wheeled walker, also called “rollator”, consists of a frame with four large wheels and two handles equipped with brakes. Accessories such as a built-in seat, transport plate or basket are often added on wheeled walkers for patient's comfort. It was proven that, in some case, the use of this gait assistance impacts positively the gait spatiotemporal parameters and the comfort of the patient (Tung, Chee, Zabjek, & McIlroy, 2015). However, as the wheeled walker requires the use of both hands to be guided, it is not intended for use in patients who exhibit significant motors disorders on the arm.

The single-point and the four-points canes

As they do not require the use of both hands, single-point or four-points cane are usually favored in patients with a disabled arm. The effect of both types of cane on the gait symmetry, velocity, patient endurance and balance during stance phase were analyzed

through different studies (Jeong, Jeong, Myong, & Koo, 2015; Kuan, Tsou, & Su, 1999; Laufer, 2002). Those effects are summarized in a qualitative way in Table 1.1.

Table 1.1: Summary of the effects of the single-point and four-points

Gait parameters	Single-point	Four-points
Gait symmetry	Improved	No effect
Gait velocity	Substantially improved in patients with good balance	Slightly improved
Patient endurance during gait	Substantially improved in patients with good balance	Slightly improved
Balance during stance phase	Slightly improved	Substantially improved

Summarized from Laufer, 2002

The single-point cane is very effective for improving the gait symmetry. Slighter and more maneuverable than the four-points cane, it allows increasing gait velocity and endurance if the patient does not exhibit severe balance disorders. Therefore, given the small size of his supporting base, the single-point cane increases only slightly the balance of the patient when compared to walking without stick.

In contrast, the four-points cane, with his larger sustentation base, increases stability of hemiparetic patients during stance, in comparison to the one-point cane. Therefore, in patients exhibiting a very poor balance, the use of this cane is recommended and even required in some cases. But this increased stability happens at the cost of a lower velocity: given that the four-points cane is bulky, patient walk slower with a four-point cane than with a one-point cane. In addition, the gait fluidity is deteriorated when walking with a four-point cane. Indeed, the requirement to lift the object at each step disturbs the normal and fluid gait in two-stages, favoring instead an asymmetrical three-stages gait. Nevertheless, it can be noted that gait velocity with a four-point cane remains higher than with no cane.

In conclusion, the three gait assistances commonly used for post-stroke rehabilitation must be selected in accordance with the patient's residual functions and capabilities. In some cases, for example in patients with low arm motor dysfunction, or in patients with a relatively good balance, the wheeled walker and the single-point cane, respectively, can be suitable. In the majority of cases, the use of the four-point cane is preferable to ensure the patient's safety during the walk, but to the detriment of gait velocity, fluidity and patient's endurance.

1.3 A new walking assistance: the Wheleo ©

In order to deal with the different disadvantages of the standard four-point cane, a new walking assistance was designed by Geoffroy Dellicour, a physiotherapist of the William Lennox neurological rehabilitation center (Ottignies, Belgium). His basic idea was to adapt the original and commonly used four-points cane in a wheeled cane that therefore does not require to be raised at each step. To this end, he removed the four rubber caps at the ends of each leg of a standard cane and placed four wheels instead. The prototype of the cane is illustrated at Figure 1.2.

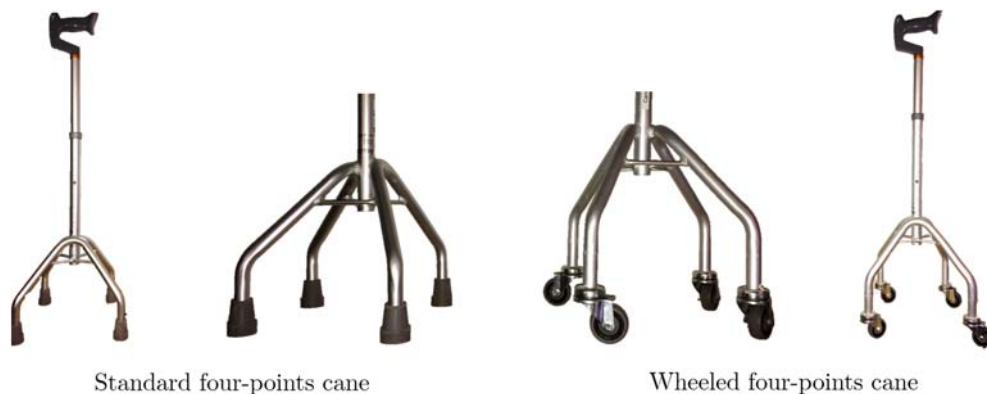


Figure 1.2: Standard four-points cane and wheeled four-points cane prototype

According to many physiotherapists responsible for the rehabilitation of post-stroke patients, this idea of providing wheels on a standard cane in order to allow a permanent contact with the ground seems to be totally out of place. Indeed, as the post-stroke patients present generally high balance disorders, and sometimes even lateropulsion syndrome, there is a tendency to think that, as soon as the patient will rely on the wheeled cane, the cane will simply slide on the ground and bring the patient in its fall. These observations were emitted after realization of a poll carried out on fifteen physiotherapists working in neurological rehabilitation, asking them what they thought the wheeled four-points cane. Three of them disapproved completely the idea, seven were not convinced of it, but were curious to see the effects of the cane, three others approved the concept and the last two physiotherapists noted that a wheeled four-points cane could be a good idea, from the condition to add a blocking system on the wheels to avoid sliding when the patient is relying on the cane.

But, contrary to this first idea, the use of the wheeled four-points cane to assist the hemiparetic gait, without any brake or wheel blocking system, exhibits numerous positive effects. If you wish to preview those effects, a video available online (<https://youtu.be/NAO6x-pvkGw>) represents a given patient walking with both canes consecutively. Screenshot of this video at 0, 10, 20, 30 and 40 seconds are shown in Figure 1.3. The patient was asked to go and return on two square marks that are five meters distant, with the classic cane and then with the wheeled cane. It can clearly be seen that,

for a given time, the patient traveled a longer distance with the wheeled cane than with the other.

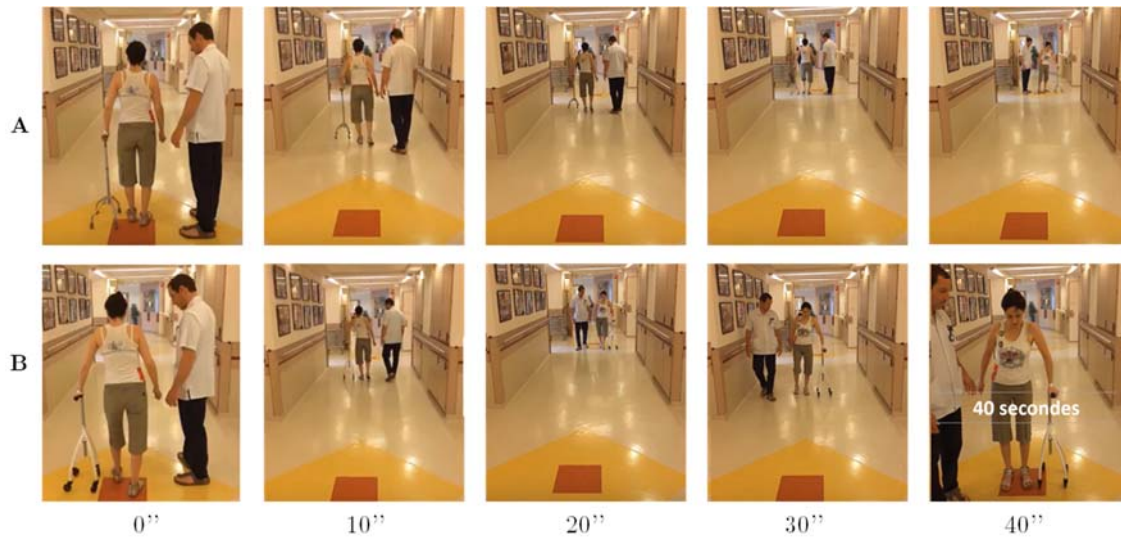


Figure 1.3: Comparison between the effects of classic cane and the wheeled cane

The same patient performed two round trips of same distances with both canes consecutively. **A. Classic cane** at 0, 10, 20, 30 and 40 seconds. **B. Wheeled cane** at the same times. It can be clearly seen that the patient walks almost twice as fast with the wheeled cane than with the classic cane.

This observation was done on several other paretic patients in the neurological rehabilitation center of William Lennox, such as other positive effects. Here is a list of the six qualitative observations done by the physiotherapists that tested the wheeled cane on hemiparetic subjects (Dellicour, 2018):

1. Improvement of the gait velocity and cadence
2. Decrease of the energetic cost
3. Improvement of the patient's comfort and satisfaction
4. Improvement of the step symmetry
5. Transition from a three steps gait to a two steps gait (improvement of the gait fluidity)
6. Improvement of the balance

All those effects were quantitatively studied on 32 patients in a recent study comparing the impacts of both canes on hemiparetic gait (Dellicour, 2017). The study has not yet been published. Details about the tests performed for this study and statistical results are presented in Appendix 1. In summary, the outcomes indicate that five of the six mentioned effects are significative. First of all, when computing the velocity on a ten meters walking test at comfortable speed, at faster velocity, or on a six minutes walking test, the velocity is in each case higher with the wheeled cane than with the classic cane (+ 26.7 %, +27.4%, +30.4 % respectively, $p < 0.001$). In addition, the physiological cost index (representative of the energetic cost) was smaller with the wheeled cane (- 27,3 %, $p < 0.001$ for a ten meters walking test). Also, the satisfaction score measured on a ten points visual analogical scale from the 32 patients was better (+ 1.7, $p < 0.01$).

Finally, the number of supports on the cane during ten minutes walking tests was smaller (-5%, $p < 0.05$), which means that the gait pattern was closer to a two steps gait and the steps were therefore more symmetric. With regards to the balance, that was assessed by the number of contacts with the physiotherapists during the walking test, no significant differences were observed.

In view of the numerous positives outcomes observed, as well as the patient demand for obtaining such a wheeled cane, G. Dellicour decided to design and commercialize the concept. He thus adaptated the prototype of the wheeled cane in an ergonomic medical device, with a modern design, so that it can be industrialized. The new medical device, baptized *Wheeleo* ©, is presented in Figure 1.4, and its technical features in Table 1.2 (TousErgo, 2018).



Figure 1.4: The Wheeleo © cane
(InnoRehab, 2018)

Table 1.2: Technical features of the Wheeleo © cane

Dimensions	
Height	74 to 98 cm
Wheel diameter	7,5 cm
Central tube diameter	3,5 cm
Extremity tube diameter	2,2 cm
Weights	
Cane weight	2,8 kg
Tolerated weight	120 kg
Material	
Structure	Painted steel structure

(TousErgo, 2018)

1.4 The need of quantifying the gait quality with wearable measurement tools

In the above section, we can underline that the effects of a new medical walking assistance, such as the Wheleo © cane, on the patient's gait pattern is mainly evaluated by qualitative observations. Some parameters, for example, the mean gait velocity, energetic cost, the balance, can be assessed in a quantitative way using some standard tests. However, those types of test only provide global and/or indirect information about gait characteristics. Indeed, the ten meters walking test or six minutes walking test give an estimation of the mean gait velocity, but do not measure potential variations of the velocity during the test. The assessment of the patient's stability by counting the number of contacts with the physiotherapist during the walking test is a right way to proceed when no quantitative measures are available but represents an indirect and subjective method. In addition, such qualitative observation, such as the gait symmetry, could have not been assessed during the clinical trial because of the lack of gait parameters quantitative measures.

Those observation leads to the statement that there is an important need of quantifying in an objective way some gait parameters such as the gait fluidity, symmetry, and stability. In addition, the measurement technique must be wearable, given the difficulty of bringing impaired subjects in gait laboratories. The two next points will review in more details the numerous interests of gait spatiotemporal analysis and wearable measurement tool.

The interest of gait spatiotemporal parameters analysis

A very common and well-established way to characterize pathological gait pattern is the spatiotemporal gait analysis. We will see in following sections that the spatiotemporal parameters of post-stroke patients differ from those of healthy subjects. The parameters values, compared to those of the normal population, can therefore give an indication about the level of the gait disorders. Indicators of gait stability and gait symmetry can also be computed from the spatiotemporal parameters, as it will be seen later.

As the spatiotemporal parameters allow to quantify precisely the gait quality, they can be used for different purposes. Main use casse are enumerated in Table 1.3 (Baker, 2006).

Table 1.3: Reasons performing spatiotemporal gait

-
1. *Assessment* of the severity, extent or nature of the post-stroke impairment
 2. *Monitoring* progress in the presence or absence of intervention
 3. *Prediction* of the outcome of intervention (or the absence of intervention)
-

Adapted from Baker (2016)

Firstly, spatiotemporal parameters can be used for assessing quantitatively the severity of the patient's impairment. The data can be, for example, compared to those of healthy

people of the same age to determine how the gait pattern differs from normal one. We will see in Chapter 2 that markers of gait balance and symmetry can be computed on the basis of spatiotemporal parameters. Detection of such markers is important for preventing falls and guiding rehabilitation treatments.

In addition, the potential evolution of the patient over time can be quantitatively assessed with spatiotemporal parameters. This evolution can occur naturally (spontaneous improving or worsening of patient's condition), or after an intervention such as a physiotherapy rehabilitation treatment or a surgical intervention. The use of a new walking assistance such as the Wheeleo © cane is also part of interventions that could directly affect patient's spatiotemporal parameters. In this sense, spatiotemporal parameters can therefore be used to quantify the effect of a gait rehabilitation tool on the patient's gait quality, balance and gait symmetry.

Finally, spatiotemporal parameters can also be used in a prediction purpose. This last spatiotemporal parameter usage, based on patient-specific modeling, is just starting to emerge in literature.

The need for wearable measurement systems

Currently, several systems exist for measuring the spatiotemporal parameters in post-stroke patients. We will see in next section that the force platforms or the optical motion capture system are validated and highly effective for that purpose. However, such systems are costly, imposing, and non-wearable. Their use is generally restricted to gait laboratories. If it is easy to bring healthy subjects in such laboratories, this is not the case for post-stroke subjects with mobility disabilities. All this makes it difficult to perform a continuous and long-term monitoring of patients' impairment levels.

During the past few decades, with the development of micro-electro-mechanical technology, a substitute for force plates and optical motions captures systems were found in the use of Inertial Measurement Unit (IMU). Cost-effective, lightweight, wearable, and reliable, they are now widely used in healthy gait analysis. However, most of the IMU-based algorithms are designed and effective only for healthy gait, which is cyclic, regular and symmetric. In recent years, a limited number of studies focused on IMU-based post-stroke gait analysis. The algorithms proposed so far in the literature are, to my knowledge, not well optimized in the case of patients with a small level of gait impairment, that do not need the use of an assistance for walking.

1.5 Summary and roadmap

In conclusion, the ideas emerging from this first chapter are as follows:

1. Stroke is a worldwide and chronic disease, and the leading cause of permanent disabilities in adults
2. According to the extent and the location of the lesion, disorders caused by a stroke can result in a wide range of sensorimotor and cognitive disorders that affect the patient's waking pattern with varying degrees
3. Given the large spectrum of potential poststroke neurophysiological disorders, each patient will present a unique gait pattern
4. There exist different types of walking aids for post-stroke patients. The Wheeleo © cane is a new wheeled four-points cane that improves the patient's satisfaction and the gait velocity and fluidity.
5. The level of gait quality can be assessed by measuring the spatiotemporal parameters. Some ratio and indexes of gait symmetry and gait quality can be computed on the basis of the spatiotemporal parameters
6. The use of IMU and IMU-based algorithms are effective to evaluate the spatiotemporal parameter of healthy people or post-stroke subjects with a small level of gait impairment, that do not need the use of an assistance for walking

In view of these observations, the main objectives of this study can be stated in three different key targets:

1. Design a gait parameter measurement tool that is wearable and optimized for post-stroke subjects walking with a gait-assistance device such the four-point cane and the Wheeleo © cane. This implementation goes through three main steps:

- i. the choice of a suitable sensor
- ii. the definition of an adapted measurement technique
- iii. the development of an algorithm optimized for data carried out in post-stroke subjects

2. Test and validate the implemented measurement tool by comparing the results it provides to those delivered by a gold-standard measurement tool.

3. Apply the designed measurement tool to a post-stroke subject's sample for answering to the initial clinical question, which is the quantify the effects of the Wheeleo © cane to those of the four-points cane on gait balance and gait fluidity.

In view of those objectives, we decided to organize the next chapters as follows:

Chapter 2: *Theoretical notions about normal and pathological gait*

In this chapter, a theoretic description of the normal gait and clinical analysis of the pathological post-stroke gait will be addressed. Knowledge of these concepts will indeed be useful to understand in detail the challenges related to gait analysis in post-stroke subjects.

Chapter 3: *Review of some gait parameter measurement systems*

This short chapter will give an overview of the existing gait parameters measurement tools, specifying their main principle, advantages, and drawbacks.

Chapter 4: *State of the art in gait analysis with inertial measurement units*

In the continuity of chapter 3, we will propose a state of the art in gait analysis with inertial measurements units. Different measurement methods and algorithms for gait cycle segmentation and spatiotemporal parameters decomposition will be described and discussed.

Chapter 5: *Development and validation of a new algorithm for spatiotemporal gait analysis in post-stroke subjects walking with gait assistance*

In the light of observations made in chapter 4, we will propose the design and the implementation of a new measurement technique and algorithm that are suitable for post-stroke subjects requiring gait assistance for walking. The implemented technique will next be assessed by means of a preliminary validation study.

Chapter 6: *Application of the algorithm for measuring the effect of the classic cane and the Wheeleo © on the temporal parameters in post-stroke subjects*

In this chapter, the results of the measurements on post-stroke subjects carried out and analyzed using the designed technique and algorithm will be presented. More precisely, the effect of the Wheeleo © cane on the gait stability and fluidity will be compared to those of the classic four-point cane.

Chapter 7: *General discussion and conclusion*

Finally, general limitations and prospects of this Master's thesis will be addressed.

Chapter 2

Theoretical notions about normal and pathological gait

Before dealing with the gait spatiotemporal measurement technique suitable for post-stroke subjects, it is important to become familiar with the different theoretical notions related to normal walking, but especially to know how post-stroke gait pattern differs from normal gait pattern.

In this way, this second chapter introduces all relevant conceptual theory addressed in the frame of this thesis. It is divided into two main parts. The first section considers the theoretical background about normal gait and gives the operational definition of the spatiotemporal parameters. The second section explains how the post-stroke gait differs from the normal gait.

2.1 Normal gait description

We have now reviewed the medical terminology and concepts around the stroke, such as the eventual impact of some post-stroke symptoms on gait quality. Before dealing with the spatiotemporal characteristic of gait pattern in post-stroke patients, understanding about normal gait features are required. The next section will therefore briefly synthesize different theoretical notions presented in a review of normal gait state of knowledge (Willems, Schepens, & Detrembleur, 2012).

2.1.1 Gait cycle segmentation

The theoretical segmentation of the gait cycle is presented in Figure 2.1. The start and end, as well as the different phases of the gait cycle, are defined according to two events: the heel contact (HC) and the toe off (TO). By convention, a single complete gait cycle begins and ends with the heel contact of the right foot. Given that the absolute gait phase durations differ according to the gait velocity, normalization according to the complete gait cycle duration is also recommended. A single gait cycle consists then of two steps, a right one followed by a left one. A step begins, by the definition, with the HC and ends with the TO. In the case of a symmetric normal gait, 50 % of the cycle thus corresponds to the left heel contact. The heel off (HO) and toe strike (TS) are also two events relevant to study.

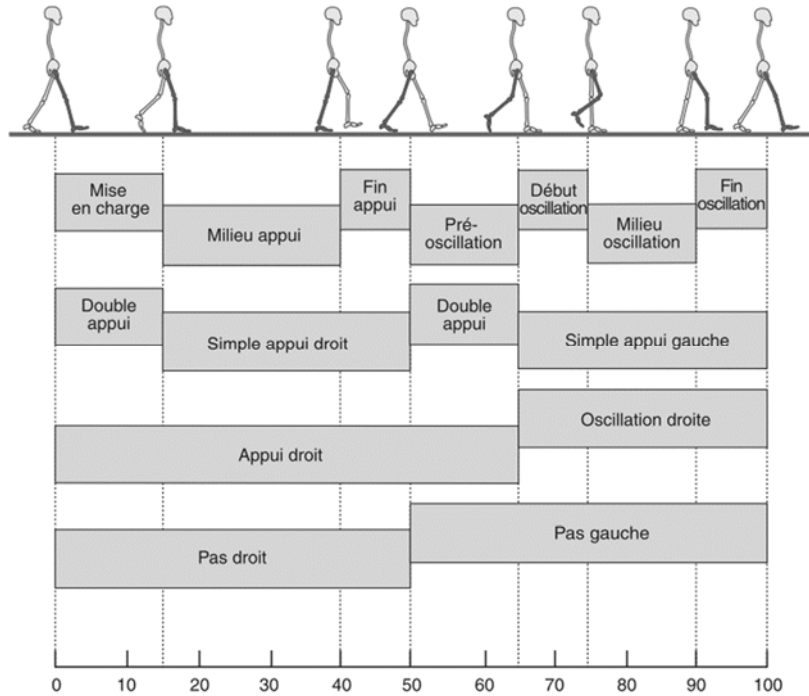


Figure 2.1: Gait cycle segmentation

(Willems et al., 2012)

The gait cycle consists of double stance phases, single stance phases, and swing phase. The first phase of the cycle (from 0 % to 15 %) corresponds to a double stance phase,

ranging between the right heel contact and the left toe off. During this first phase, a weight transfer of the body from the left lower limb to the right lower limb occurs. Next comes the right stance phase, extending from the left toe off (15 %) to the left heel contact (50 %), and during which the left lower limb swings forwards. The right single stance phase thus matches the left swing phase. Then, the same two phases are symmetrically observed on the left side. From the left heel contact (50%) to the right toe off (65 %), the subject is in double stance phase, and the body weight is transferred from the right lower limb to the left lower limb. Next, the cycle is completed by a single stance phase on the left foot, from the right toe off (65 %) to right heel contact (100 %), and during which the right lower limb swings forwards.

2.1.2 Operational definition of spatiotemporal parameters

The precise definition of spatiotemporal parameters may sometimes vary slightly in the literature (according to the chosen anatomical marks, for instance). Therefore, the present section will briefly review the terminology used for each spatial and temporal parameter.

We have seen that a single gait cycle consists of two consecutive steps, one on each leg. In healthy subjects, the right and left step usually present similar descriptors, due to the symmetry. In post-stroke subjects, we do not talk about left or right steps but about “paretic” or “non-paretic” step. The paretic step corresponds to the phase where the paretic foot is oscillating, and the subject relies on his non-paretic foot.

2.1.2.1 Spatial parameters

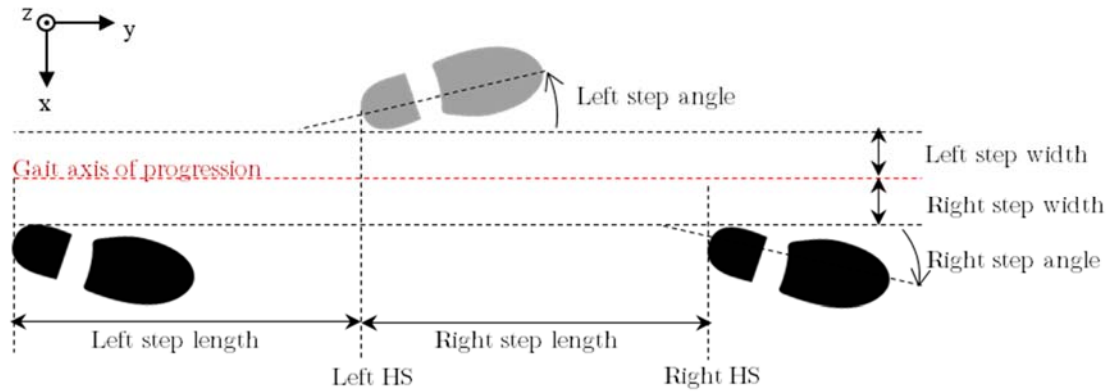


Figure 2.2: Step length, step width, and step angle

Step length

The step length corresponds to the distance, in the direction of the progression axis (y-direction on the figure), traveled by the oscillating foot in comparison to the other foot. In other words, the length of a step (for example, the right one) equals the distance between both heel tips during the double stance phase, just after the opposite (in this case, the left

one) heel strike. In comfort speed and in non-pathological gait, standard step length is comprised between 0.6 and 0.8 m (Fusco, 2008).

Stride (or cycle) length

The stride corresponds to two consecutive steps, one on each side. By definition, the stride length is thus the sum of the left step length and the right step length, usually in centimeters.

Step width

The step width corresponds to the distance, in the direction perpendicular to the progression axis (x-direction on the figure), between the two medial foot borders. Standard values of step width are comprised between 7 and 11 centimeters (Owings & Grabiner, 2004).

Step angle

The step angle is the angle, in degrees, between the foot axis and the progression axis, the latter being the axis passing through the heel tip and the second metatarsal. Step angle is, in normal gait, an outgoing angle and usually ranges from 5° to 13° (Cibulka et al., 2016).

Minimum and maximum foot clearance

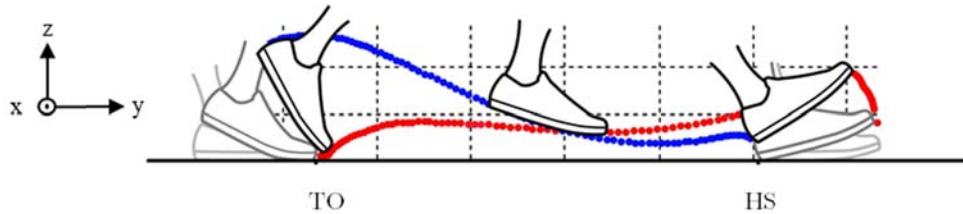


Figure 2.3: Heel clearance and toe clearance
(modified from Mariani et al. , 2009)

The foot clearance is defined as the trajectories in the sagittal plane (plane formed by z and y-axis in Figure 2.3) of the foot during the stance phase of the gait cycle. We distinguish more specifically the heel clearance and the toe clearance. The foot clearance is usually studied in terms of maximum vertical height for the heel (MaxHC), and minimum and maximum vertical heights for toes (MinTC and MaxTC). Values for MaxHC, MaxTC, and MinTC in normal gait range, respectively, from 0.24 to 0.035 m, from 0.05 to 0.09 m, and from 0.01 to 0.03 m (Mariani et al., 2010).

2.1.2.2 Temporal parameters

Gait cycle (or stride) duration (T_{sc})

As already noted, a single complete gait cycle begins with the heel strike of the right foot, and ends with the next heel strike of the same foot. For each leg, the stride cycle is

thus the sum of the stance time (T_{st}) and the swing time (T_{sw}). The normal mean stride ranges usually from 0.75 seconds to 1.45 second (Fusco, 2008).

Swing phase duration (T_{sw})

The swing phase corresponds to the period in which the foot is not in contact with the ground. The swing phase duration of a foot is thus the time between the toe off of this foot and the heel strike of the same foot. Swing phase duration is often expressed in percentage relative to the gait cycle duration. The percentage swing time ($\%T_{sw}$) is therefore calculated as $\%T_{sw} = (\frac{T_{sw}}{T_{sc}}) \times 100$. The standard value is 35 % of the gait cycle duration, as mentioned in the previous section (Willems et al., 2012).

Stance phase duration (T_{st})

The stance phase is the period during which the foot is in contact with the ground. The stance phase duration thus begins when the heel strikes the ground and ends when the toes leave the ground. The stance phase is also often expressed as a percentage of the total stride duration: $\%T_{st} = (\frac{T_{st}}{T_{sc}}) \times 100$. The standard value for a normal stance phase duration is 65 % of the gait cycle duration (Willems et al., 2012).

Double support phase duration (T_{ds})

During a gait cycle, there is a short period during which both feet are in contact with the ground, called the double support phase. This lasts consequently from the heel contact of a foot until the moment just before the toe off of the opposite foot and occurs twice during a single gait cycle. The standard value for double support phase duration is 30 % (2 x 15 %) (Willems et al., 2012).

2.1.2.3 Gait velocity and step frequency

The gait velocity is related to two main parameters: the step length, and the step frequency, which corresponds to the number of steps per unit of time (Fusco, 2008). The step frequency is also called the cadence when it is expressed in number of steps per minute. The velocity (V), the step length (L_{step}), and the step frequency (F_{step}) are linked by the relation $V = L_{step} \times F_{step}$ (Fusco, 2008). The comfort speed corresponds to the speed that the subject chose naturally, optimizing the gait velocity and the energetic cost (Ralston & Lukin, 1969). It varies from one subject to another but also according to subject's status and environment conditions. It was measured that, in non-pathological gait, the comfort speed is generally comprised between 1.10 and 1.60 m/s (step length: 0.6 – 0.8 m, cadence: 110 – 130 steps per minute (Fusco, 2008).

2.1.3 How to use spatiotemporal parameters for quantifying the gait quality in post-stroke subjects?

Now that the terminology around the spatial and temporal parameters has been clarified, the question becomes how quantifying the gait quality, for instance of a pathological subject, on the basis of measures of those parameters.

Comparison to measures in normal population

A first way to evaluate the gait quality is simply to compare the spatiotemporal parameters values of pathological gait to those of a normal population. This will be done for post-stroke patients in the section 2.2.2. It can indeed be assumed that the closer the parameter values are to those of a normal walk, the closer the walking pattern is to a normal walk pattern. However, as the spatiotemporal parameters are themselves highly variable in healthy subjects, the use of other gait quality indicators is usually favored.

Use of symmetry ratios

Another and more interesting way of scoring the quality of the gait, especially in post-stroke subjects, is the use of symmetry ratios. Normal gait is almost fully symmetrical. In post-stroke subjects, half-body sensorimotor disorders cause usually considerable gait asymmetry. Ratios that can be used to quantify the spatial or temporal symmetry are presented in Table 2.1 (Yang et al., 2013).

Table 2.1: Temporal symmetry ratio for post-stroke subject

Temporal ratio	Definition
Temporal swing ratio (R_{sw})	$R_{sw} = \frac{T_{sw}(P)}{T_{sw}(NP)}$
Temporal stance ratio (R_{st})	$R_{st} = \frac{T_{st}(P)}{T_{st}(NP)}$
Temporal swing-stance ratio (SRR)	
Paretic (SSR(P))	$SSR(P) = \frac{T_{st}(P)}{T_{sw}(P)}$
Non-paretic (SSR(NP))	$SSR(NP) = \frac{T_{st}(NP)}{T_{sw}(NP)}$
Overall temporal symmetry ratio	$OSR(NP) = \frac{SSR(P)}{SSR(NP)}$

(Yang et al., 2013)

Temporal swing ratio (R_{sw}) is defined as the ratio between the paretic swing time ($T_{sw}(P)$) and the non-paretic swing time ($T_{sw}(NP)$), the temporal stance ratio as the ratio, and between the paretic stance time ($T_{st}(P)$) and the nonparetic stance time ($T_{st}(NP)$). Temporal swing-stance ratio (SSR) is defined as, for each lower limb (paretic and non-paretic) as the ratio between the stance time and the swing time. Finally, the overall

temporal ration is the ratio between the paretic temporal swing-stance ratio (SSR(P)) and the non-paretic temporal swing-stance ratio (SSR(NP)).

Evaluation of the step-to-step variability

Classical method

Another indicator of the gait quality is the step-to-step variability of those spatiotemporal parameters. Indeed, step-to-step variability was the subject of a large number of studies over recent years and has been proven to be an important index of the integrity of the gait control system and the balance (Chisholm et al., 2014; Moon, Sung, An, Hernandez, & Sosnoff, 2016; Rebula, Ojeda, Adamczyk, & Kuo, 2013; Warlop et al., 2016).

Even when environmental and external conditions are fixed, measures of gait spatiotemporal parameters are not constant but rather fluctuate from one step to the next. In healthy adults, those step-to-step fluctuations are relatively small and the coefficient of variation of many parameters is on the order of just a few percents (Hausdorff, 2005). When the gait control and regulatory systems are disturbed, as it is the case in post-stroke subjects, movement control may be impaired leading to increased the step-to-step parameters changes, thereby increasing variability (Hausdorff, 2005).

Basically, the gait variability can be assessed by using elementary variability estimators, such as the standard deviation, the coefficient of variation, and the mean absolute deviation (Chisholm et al., 2014), of which familiar definitions are given in Table 2.2.

Table 2.2: Variability estimators

<i>Variability estimators</i>	<i>Definition</i>
Standard deviation (SD)	$CV(x) = \sqrt{\sum_{i=1}^n \frac{(x_i - \bar{x})^2}{n}}$
Coefficient of variation (CV)	$CV(x) = (SD(X) / \bar{x}) \times 100$
Mean absolute deviation (MAD)	$MAD(x) = med(x - med(x))$

(Chisholm et al., 2014)

Complex mathematical methods

Step-to-step gait parameters variability can also be investigated in terms of its temporal organization, using non-linear analysis, which provides complementary indications about the evolution of the parameters with time across consecutive steps (Warlop et al., 2016).

Indeed, when analyzing consecutive steps over the long term, we can observe that gait parameters fluctuate in a structured and complex organization over the long term, exhibiting long-range autocorrelations (LRA), that can be assessed by complex mathematical methods (Bollens, Crevecoeur, Detrembleur, Warlop, & Lejeune, 2014).

In their paper, Warlop et al. explain that LRA result from the “memory” of the preceding values in the series, which reflects the existence of a complex temporal structure in human locomotion (Warlop et al., 2016). This structure is maintained across distinct tasks.

As reviewed in another study (Bollens, Crevecoeur, Detrembleur, Guillery, & Lejeune, 2012), studies showed that long-range autocorrelations could be interpreted as a discriminating marker between fallers and non-fallers in the elderly subjects (Herman, Giladi, Gurevich, & Hausdorff, 2005) and are significantly related to other indexes of stability (Jordan & Newell, 2008). In patients with central nervous diseases, such as Huntington’s, Parkinson’s, and amyotrophic lateral sclerosis, long-range autocorrelations present the characteristic of being disrupted (Hausdorff, 2005).

In conclusion, the study of the long-range autocorrelations has shown its effectiveness in terms of instability indicator in some elderly and in patients with specific central nervous diseases, and might be particularly interesting to study the LRA in gait spatiotemporal parameters of post-stroke subjects. However, the LRA analysis requires an important number of successive gait cycles and it is preferable to perform this type of analysis on measures that were carried out with validated sensors tools and measurement techniques. Therefore, such analyses will not be performed in the framework of this Master thesis. The classical method for assessing variability that was described in the previous section will be used instead.

2.2 Gait disturbance in post-stroke patients

As mentioned earlier, disorders caused by a stroke can result in a wide range of sensorimotor disorders that affect the patient's walking pattern with varying degrees. It was reported that 50 % of patients who experienced a stroke are initially unable to walk without gait assistance after the accident, 13 % need an assistive equipment for walking, and 37 % are able to walk autonomously (Balaban & Tok, 2014). In this section, the typical patterns in post-stroke patients will be described, in terms of qualitative clinical observations and quantitative measurements.

2.2.1 Qualitative clinical observations

The post-stroke hemiparetic gait is dependent on the affected brain area, on the residual cerebral functions, and on the presence and severity of the different sensory-motor and cognitive disorders. Given the large spectrum of potential poststroke neurophysiological disorders, each patient will present a unique gait pattern. However, a sample of some typical post-stroke gait disturbances can be described. Knowing and understanding those different disturbances will be helpful in several following sections of this thesis.

Visible spatiotemporal parameters disturbances

After a stroke, step length and cadence are often significantly reduced, which thereby visibly limits the global gait velocity. Foot clearance is also commonly drastically reduced, causing a considerable increase in the risk of falling due to the fact that the foot is more likely to grip the floor. Secondly, given the post-stroke hemiparesis, a step asymmetry, as well as compensatory motions of the non-affected side of the body, are almost systematically observed (Chen, Patten, Kothari, & Zajac, 2005; Sibley, Tang, Patterson, Brooks, & McIlroy, 2009). All those gait disturbances are such that they could be observed qualitatively during a visual clinical exam of the gait, but quantitative measures are obviously more appropriated for measuring them precisely.

Typical gait pattern in post-stroke subjects

Due to neuromotor disorders, uncontrolled muscles contractions can occur with the coactivation of numerous muscles (Hwang et al., 2005), leading to involuntary parasites motions during walking, called "synkinesis". Because of an altered spatial representation of the body position, the lateropulsion, also called the "pushing syndrome" which is an unconscious body incline to one side, is also very common. Finally, the terms "foot drop" is commonly used to describe the hemiparetic gait. Indeed, due to a weakness of the muscles that allow the flexion of the ankle, the patient cannot point the toes upward, causing the foot to drop during the swing phase. In most of the foot drop cases, there is therefore no real heel strike on the paretic side.

Patients with significant foot drop must, for avoiding toes scrapping over the ground during the swing phase of the paretic limb, use compensatory strategies. They are very

often encountered in the post-stroke subject, and we will see later that they could considerably interfere with the measure of spatiotemporal parameters when using sensors.

Compensatory strategies in patients with foot drop

A first type of compensatory strategy is the so-called “waddling gait”: the subject leans slightly forward and bends more the knee for allowing the forward swing of the paretic foot without the foot gripping the ground. Another similar compensatory motion is the “steppage”: subject bends the knee further, and then ejects the lower paretic limb forward, the toes touching the ground before the heel. If the disorder of the patient is such that the patient has difficulties to bend the knee, compensatory strategies will instead be the “swing-out gait” and the “stiff gait”. In the “swing-out gait”, patient flops the paretic limb away of the body at each step for avoiding ground snagging. The “stiff” gait” for its part is characterized by the fact that both knees stays extended during all the oscillatory phase and the forward foot crossing is permitted usually by an exaggerated elevation of the hip. A modeling of the four strategies of foot drop compensation during the stance phase to allow the paretic foot toward passing is represented in Figure 2.4.

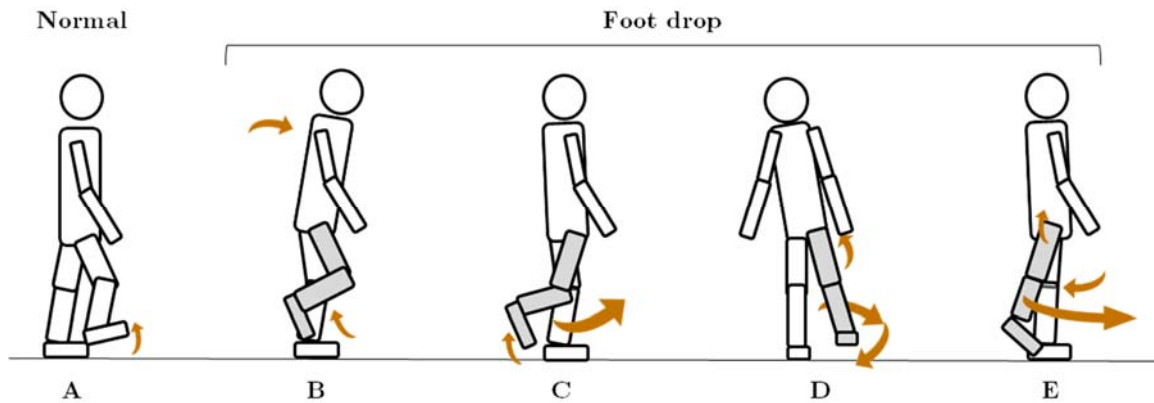


Figure 2.4: Compensatory motions of foot drop during the swing phase

The paretic lower limb is represented in grey. The view is in the sagittal plane except for the C, which is in the frontal plane. **A) Normal swing forward of the foot.** The ankle is in dorsiflexion and the toes are pointing up. **B) “Waddling gait”:** subject leans slightly forward and the flexion of the knee is exaggerated. **C) “Swingout gait”.** The subject raises more the paretic hip and flops the lower limb away from the body. **D) “Steppage gait”.** At the beginning of the oscillatory motion, the subject uplifts the hip, bends more the knee and then ejects the paretic lower limb forward. **E) “Stiff gait”.** Knee at both the healthy and the paretic side remain extended during all the oscillatory phase of the paretic lower limb.

2.2.2 Quantitative spatiotemporal analysis

The different post-stroke gait irregularities described in the above section have also an impact on the quantitative parameters of hemiparetic gait, namely step and stride length, step time, stance phase and swing phase durations. Table 2.3 provides the mean and the standard deviation of spatiotemporal parameters of healthy elderly subjects and those of post-stroke subjects. Choosing a comparison with elderly subjects, and not middle age adult is typically done because the population affected by stroke is usually older.

Table 2.3: Spatiotemporal parameters in elderly and post-stroke subjects

Parameters	Mean $\pm$ Standard Deviation		
	Elderly	Post-stroke (P)	Post-stroke (NP)
Velocity (m/s)	1.17 ± 0.16	0.54 ± 0.26	0.54 ± 0.26
Stride Length (m)	1.23 ± 0.15	0.78 ± 0.28	0.78 ± 0.28
Step Length (cm)	61.5 ± 0.15	41.7 ± 13.0	36.4 ± 16.6
Step Time (s)	0.53 ± 0.05	0.92 ± 0.30	0.64 ± 0.11
Stance time (% cycle)	64.7 ± 0.10	66.2 ± 5.0	76.2 ± 7.6
Double Support time (% cycle)	12.11 ± 0.12	42.4 ± 11.5	42.4 ± 11.5
Swing time (% cycle)	35.3 ± 0.10	33.8 ± 5.0	23.8 ± 7.6

(Kuan et al., 1999; Patterson, Rodgers, Macko, & Forrester, 2008; Trojaniello et al., 2014)

A first observation that can be made on the basis of this table is that, in healthy subjects, as the gait is symmetrical, mean spatiotemporal parameters are the same for both body sides. Conversely, concerning the paretic subjects, the parameters of the paretic sides are quite contrasted to those of the non-paretic sides. Hemiplegic gait is indeed fully asymmetric, as it was mentioned in the previous point.

In addition, this table allows us to perform two different comparisons: the first one between the healthy elderly subject and post-stroke subject parameters, and the other one between the paretic and the non-paretic parameters.

Comparison between healthy elderly and post-stroke subjects

When comparing the global parameters of healthy and post-stroke subjects, it can be noted that mean comfortable speed, as well as mean stride, are higher in healthy elderly people than in hemiparetic subjects. The cadence was not reported in the studies summarized in the present table but it was shown that it is also decreased in post-stroke subjects (von Schroeder, Coutts, Lyden, Billings, & Nickel, 1995)

These data also show that standard deviations of all parameters are greater for the post-stroke subjects than for the healthy subjects. Indeed, due to the wide range of post-stroke disorders, hemiparetic gait pattern exhibits a very high interindividual variability. In addition, as it was already discussed, the step-to-step variability is also higher in post-stroke subjects (Pardo, Knuth, McDermott, Powell, & Goldberg, 2013).

Another key observation is the relative double support time, which is almost four times greater in the post-stroke subject. Data about post-stroke patient do not distinguish here paretic and non-paretic side for the double support time, but it was reported that this increase is mainly due to an increase of the double support time on the non-paretic side (Kuan et al., 1999). Paretic and non-paretic double support phase correspond, respectively, to the double support phase where the paretic foot and the non-paretic are behind. We will see just after that this longer double support time reflects a compensation measure in patients with a lack of balance (Lauzière, Betschart, Rachid Aissaoui, & Nadeau, 2014).

Comparison between the paretic and non-paretic side

In paretic subject, the non-paretic step ($36.4 \text{ cm} \pm 16.6 \text{ cm}$, for the gait parameters without cane) is generally shorter than the paretic step ($41.7 \text{ cm} \pm 13.0 \text{ cm}$), and, in the same way, the non-paretic swing phase duration (23.8 ± 7.6), is shorter than the paretic swing phase duration (33.8 ± 5.0). The same constataions can be emitted for patients who walk with gait assistance. It can be explained by the fact that, because the difficulty and also the patient's fear of bearing the body weight on the paretic limb during the non-paretic swing phase, the subject will tend to rest the healthy foot as early as possible on the ground. This has the effect of lowering the non-paretic swing time and traveled distance by the oscillating non-paretic foot. In some rare cases, the opposite phenomenon is observed: if the patient has great difficulties for raising and moving his paretic limb upward, the paretic step length will be shorter and the patient will spend more time in stance phase on the affected side (Lauzière et al., 2014; Olney & Richards, 1996).

The longer non-paretic double support time in comparison to the paretic one (with the non-paretic foot behind), that is not represented here, can be explained by the fact that, as the paretic leg is weaker, the transition of the weight from the paretic leg to the non-paretic leg is slower, resulting in a longer paretic double support time (Lauzière et al., 2014). In addition, in the same way as for the decreased paretic stance phase explained above, as the patient generally presents a lack of confidence for bearing on his paretic side, he usually rapidly advances the non-paretic leg immediately after the paretic heel strike, contributing also to a shorter non-paretic double support time (Lauzière et al., 2014; Nadeau, Betschart, & Bethoux, 2013)

Other quantitative spatiotemporal analysis

Some spatiotemporal parameters are not represented in the table but exhibit considerable differences between post-stroke subjects and healthy population.

Firstly, post-stroke subjects present generally a larger step width in comparison to healthy subjects. It seems that increasing step width is a strategy to deal with the consequences of the increased sway in the frontal plane (Hak et al., 2013). Next, the hemiparetic foot usually remains in external rotation, leading to a decreased stability and gait speed (Roth, Merbitz, Mroczek, Dugan, & Suh, 1997). Finally, the deficit in the paretic hip and knee flexors muscles, as well as in the muscles responsible for dorsiflexion, lead to a measurable decreased toe clearance (foot drop), that is representative of the risk of tripping (Little, McGuirk, & Patten, 2014).

2.3 Summary

Throughout this second chapter, we made the following key observations:

1. The gait is defined by a succession of gait cycles, which are themselves divided into a succession of phases. The segmentation of the gait cycle is at the origin of the computation of gait spatiotemporal parameters.
2. Post-stroke gait pattern is dependent on the lesion and on a wide range of factors that make him very patient specific. However, typical patterns are commonly observed after a stroke: the pushing syndrome, the “steppage” gait, the “swingout” gait, the “waddling” gait, and the “stiff” gait.
3. In pathological gait, the level of gait impairment can be assessed by measuring the spatiotemporal parameters and computing indicators based on those parameters.
4. In post-stroke subjects, indexes of gait symmetry and gait variability are very informative to assess the risk of fall, to determine the patients’ ability to adapt to changing conditions during gait, and to evaluate the response to therapeutic interventions.

Chapter 3

Review of some gait parameter measurement systems

Technologies for measuring the locomotor function were introduced a few decades ago. There is currently a wide and extended number of measurement systems. With the development of miniaturized technologies, wearable systems of gait motion capture emerged.

This short chapter will briefly describe the most common gait measure instruments, from the robust and validated laboratory material to the miniaturized wearable system, and how to evaluate the quality and efficiency of such systems.

3.1 Quality criteria for gait analysis sensor systems

Technologies for measuring the locomotor function were introduced a few decades ago. There is now a wide and extended number of existing systems. The quality and the performance of such systems can be evaluated according to different criteria that are summarized in Table 3.1.

Table 3.1: Quality criteria for gait analysis systems

Accurate
Reproducible
Appropriately validated
Capable of distinguishing normal and abnormal gait
Must not alter the function it is measuring
Reported in a form analogous to accepted clinical concepts
Cost-effective
Provide measures not observable by the skilled clinician

(From Brand, 1989)

Until about a decade ago, instruments for assessing gait parameters were mostly laboratory-based. They are usually very expensive and their non-wearable status is not practical for processing measures on patients with locomotor difficulties, but they provide precise and validated measurements. Force platforms are, for example, laboratory-based systems which is the gold standard in spatiotemporal gait analysis.

During the last decade, with the development of miniaturized technologies, wearable systems of gait motion capture emerged. In literature, the term “wearable” is used to describe sensors system making it possible to process measurements outside a laboratory, directly on the human subject, and even during the person’s everyday activities (Muro de la Herran, Garcia Zapirain, & Mendez Zorrilla, 2014). Some camera systems are thus “transportable” but not “wearable”. Non-wearable sensors systems require, in contrast to the wearable sensor-systems, the used of fixed and standard locations for the sensors. In addition, subjects must to walk on clear marks to enable data capture. In light of this, the wearable status of the gait analysis systems can be added to the quality criteria cited in Table 3.1.

Next section will briefly describe some type of wearable and non-wearable sensors motion systems designed for gait analysis.

3.2 Overview of available gait analysis technologies

3.2.1 Non-wearable sensor systems

Video-motion capture systems

Gait analysis can be performed with recording obtained by means of digital or analogic video cameras. For two-dimensional analysis, only one camera positioned perpendicular to

the movement plane of interest is required. The reconstruction of three-dimensional motions requires the use of at least two cameras, positioned at fixed standard places (Akhtaruzzaman, Shafie, & Khan, 2016). Data are next analyzed using several image processing techniques, such as binary segmentation and threshold filtering (Muro de la Herran et al., 2014), to gather the measures for gait spatiotemporal parameters. For three-dimensional analysis, additional methods are necessary to measure the depth component of the position. An example of a reconstruction of the subject's kinematic using markerless video motion capture system and appropriated segmentation algorithm is showed at Figure 3.1 (Corazza et al., 2006).

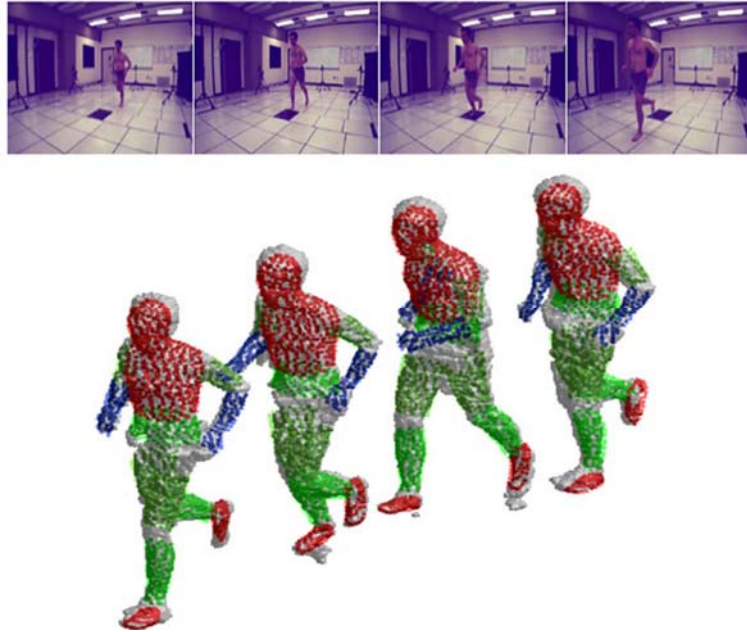


Figure 3.1: Example of a kinematic reconstruction of a running sequence based on video images
(Corazza et al., 2006)

The main disadvantages generally encountered when using video motion capture systems are the need of at least two cameras as well as the high computational cost associated with image post-processing. In addition, as the cameras must be fixed in precise and well-established positions, such systems are generally non-transportable (in addition to being non-wearable). Some transportable solutions exist but provide less accurate results (motion, 2015).

3.2.1.1 Marker-based motion capture system

Marker-based motion capture systems are based on the same principle as video motion capture systems, with the exception that the cameras track reflective markers placed on the body instead of filming body segments. Usually, the cameras emit an infrared light that is reflected by the markers placed at points of interest on the body. This reflection is then captured by the different cameras positioned around the subject and provides information

that can be used for a precise reconstruction of the marker position in three-dimensional space (Akhtaruzzaman et al., 2016). Other systems use instead acoustic, magnetic, or LED markers.

In the same way as video motion capture systems, marker-based systems require specific equipment placed in standardized and fixed positions. However, they allow a reconstruction of the motion with a very good accuracy (to the nearest millimeter) and remains one of the gold-standard in the human motion assessment and gait analysis. Some transportable solutions have been developed.

An example of optoelectronic system (BTS Bioengineering, Smart DX) and its placement is presented in Figure 3.2.

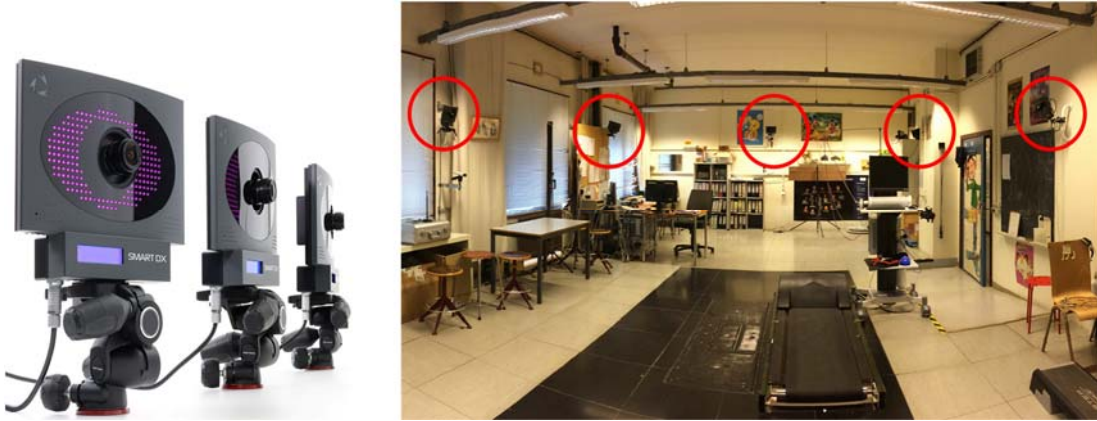


Figure 3.2: Example of optoelectronic infrared cameras

Left: Smart DX cameras (BTS Bioengineering, Quincy (USA) (Corp, 2018). Right: placement of the optoelectronic cameras in the gait laboratory of the Saint-Luc university clinics.

3.2.1.2 Floor sensors

Floor sensors usually consist of steel plates provided with pressure or force sensors and transducers in each corner. When subjects walk on the plates, pressures or forces are detected by the sensors and the resulting signal is converted into an electrical signal by the transducers (Morris & Lawson). Two main types of floor sensors can be distinguished: the pressure measurements systems (equipped with pressure sensors) and the force platforms (equipped with force sensors). Both allow a quantification of the displacement of the pressure center when the subject walks on them, but force platforms measures provide three-dimensional ground reaction forces while pressure systems only quantify the pressure patterns under a foot over time (Muro de la Herran et al., 2014). In other words, pressure systems cannot measure horizontal or shear components of the applied forces.

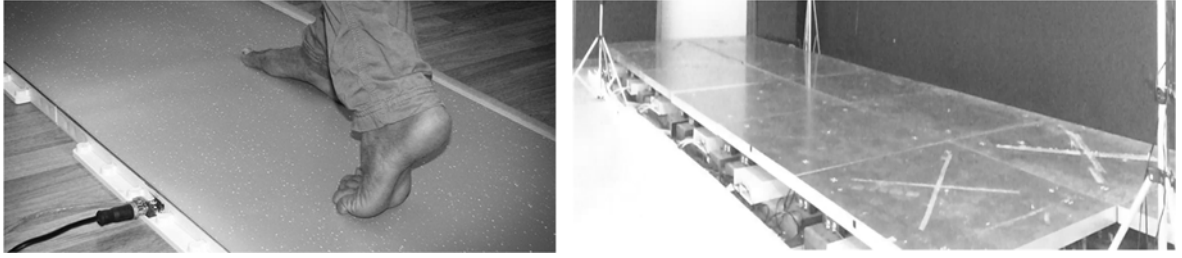


Figure 3.3: Example of floor sensor systems

Left: StepScan © system (Inc., 2018). Right: 12 platforms tray of the Cosy laboratory (Louvain-la-Neuve, Belgium)

3.2.2 Wearable sensor systems

3.2.2.1 Shoe-Integrated Sensor System

The different types of in-shoe sensor systems are usually flexible so that they can be integrated in the shoe. They provide measurements of the distributed pressure or force, during the entire foot stance phase (Akhtaruzzaman et al., 2016; Razak, Zayegh, Begg, & Wahab, 2012). There are several devices available on the market, based on different types of sensor technologies. In the same way as floor sensors, in-shoes sensor systems can consist of force sensors or pressure sensors. Most of these systems offer the advantage of being miniaturized and low-cost but they present the risk of slipping in the shoes (Razak et al., 2012). To prevent slipping, a suitable system to secure the sensor in the shoes is required, which can alter the position of the foot and therefore lead to biased measures. Another limitation of such sensors is the lower spatial resolution when comparing to platform sensors, due to the fewer number of sensors (Razak et al., 2012). As an example of shoe-integrated sensor system, the F-scan © system is presented in Figure 3.4.



Figure 3.4: F-scan © system (Tekscan)
(Tekscan, 2018)

3.2.2.2 Electromyography

During the walk, muscle contraction produces an electrical signal that can be measured by means of electromyography (EMG). The measure of the electrical signal can be done by using non-invasive surface electrodes positioned on the skin, or invasive needle electrodes that need to be inserted in the deep muscles (Akhtaruzzaman et al., 2016). The second method provides more accurate signals but its invasiveness represents a major inconvenient. Recording and analysis of EMG signals are complex subjects given the very small value of the measured signals (Muro de la Herran et al., 2014). It has been shown that EMG are useful for measuring gait characteristics pathophysiological mechanisms such as spasticity, paresis, and passive changes in muscle and tendon properties (Muro de la Herran et al., 2014). The temporal pattern of the different muscles group activity during the normal gait has also been thoroughly studied (Willems et al., 2012) and can be used as a reference for analyzing pathological gait patterns. In practice, EMG is usually combined with other techniques such as kinematic plots of joint angular motion. EMG signals have also a lot of applications in the field of prosthetic limbs, as muscle electric activity measure could be used for prediction of gait initiation (Muro de la Herran et al., 2014). If the data coming from the EMG are very informative, it is however impossible to reconstitute the gait spatiotemporal parameters on the basis of these signals. In addition, the EMG signal amplitude fluctuates according to the electrode positions, the subject's morphology, and the contraction type and velocity, which makes inter- and intra-individual comparisons difficult to achieve (Willems et al., 2012).



Figure 3.5: Example of an EMG system: the Brainquiry © Wireless system

(Muro de la Herran et al., 2014)

3.2.2.3 Inertial measurement system

An Inertial Measurement Unit (IMU) is a self-contained system combining one or several accelerometers and gyroscopes (Galinski, 2016). The operational principles of IMU will be explained in the next chapter (section 4.1.). They present many key advantages: miniaturizable, low powered, durable, inexpensive, highly mobile, and readily available (Taborri, Palermo, Rossi, & Cappa, 2016). In addition, unlike the in-shoe sensor systems, IMU does not only provide information on events occurring during the stance phase, but also during the swing phase. The combination of one or several gyroscopes or accelerometers allows efficiently recognize the different gait phases and to compute the spatiotemporal parameters.

During the last decades, the use of IMUs in gait analysis for sportive or medical applications became the focus of a wide range of studies. We will see in the next chapter

that gait analysis with IMUs can be approached in many different ways. In non-laboratory gait assessment, IMUs tends to be the most used solution (Taborri et al., 2016).

3.3 Summary

The two key ideas of this brief chapter are as follows:

1. Non-wearable sensor systems, such as force platforms and video motion capture systems, have been shown to be valid and efficient for measuring gait parameters in pathological subjects. They fulfill most of the cited quality criteria, but their non-wearable status is very constraining when studying pathological gait.
2. Among the existing wearable systems, the use of IMU has been expanding in gait parameters analysis. It has the major advantages of being wearable, inexpensive, and has been proven to be valid when analyzing the normal gait.

Chapter 4

State of the art in gait analysis with inertial measurement units

During the past decade, the use of inertial measurement units in gait analysis for athletic or medical applications became the focus of a wide range of studies. But how exactly does an IMU work? And how can the provided signal be interpreted as spatiotemporal parameters for gait analysis?

In the present chapter, there will first be given more details about the components and the functioning of typical inertial measurement units that are used in biomedical applications. A description of the errors and noise that could result from IMU measure as well as a clarification of the AHRS algorithm and Kalman's filter will also be given. Finally, the steps required for transforming an IMU signal to spatiotemporal parameters will be described and illustrated by some examples.

4.1 IMU: operational principle

An Inertial Measurement Unit (IMU) is a self-contained system integrating one or several accelerometers and gyroscopes whose value of measurement is obtained on the basis of their own inertia (Galinski, 2016).

Description of the IMU components

Accelerometers are usually composed of a spring linked to a seismic mass. During a linear acceleration, the inertia of the seismic mass causes a deformation of the spring, which is proportional to the applied acceleration. IMUs used in biomedical application usually comprise a triad of accelerometers, one for each of the 3D direction (Galinski, 2016). Calibrated accelerometers can also measure the gravity vector in three directions, and can therefore be used as inclinators when the acceleration is small compared to the gravity (Luinge, 2002).

Gyroscopes are commonly composed of a vibrating body of which the rotation will cause, via the appearance of a coupling related to the Coriolis effect, another vibration mode. The amplitude measurement of these variations provides the angular velocities. Just as for the accelerometer, IMU-integrated gyroscopes are generally triaxial, in order to measure 3-D angular velocities (Galinski, 2016).

It is important to keep in mind that raw data provided by IMUs are therefore angular velocities and accelerations relative to an IMU-attached reference system of coordinate, and not a terrestrial reference.

The other common constitutive elements of IMU are digital signal processing hardware and software, optimized for measuring the acceleration analog signal and converting it to digital, as well as a battery and a power conditioner, and communication hardware and software. A magnetometer is sometimes also integrated (Novatel, 2014).

IMUs used in the framework of this thesis

The x-IMU (X-IO Technologies limited, Inc., USA) is an IMU sensor that includes a triaxial accelerometer (with a selectable range up to ± 8 g), a triaxial gyroscope (with a selectable range up to ± 2000 °/s), and a magnetometer (selectable range up to ± 8.1 G). A real-time communication via Bluetooth is used to collect and log the data. A picture of the x-IMU with and without housing, as well as the dimensions of the x-IMU in its housing are presented in Figure 4.1.

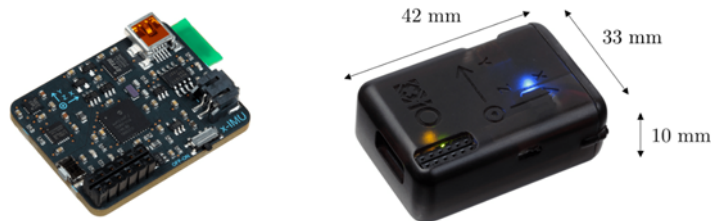


Figure 4.1: X-IMU without and with housing and dimensions

Picture from X-IO technologies website (X-IOTechnologies)

4.2 Examples and interpretation of raw signals derived from IMUs

Typical raw signals acquired via IMUs placed on the right forefoot of a healthy subject walking on a straight line are presented in Figure 4.2. The IMU was placed on the forefoot, with the x-axis corresponding to the gait progression axis, the z-axis aligned with the vertical and pointing upward, and the y-axis pointing horizontally from right to left.

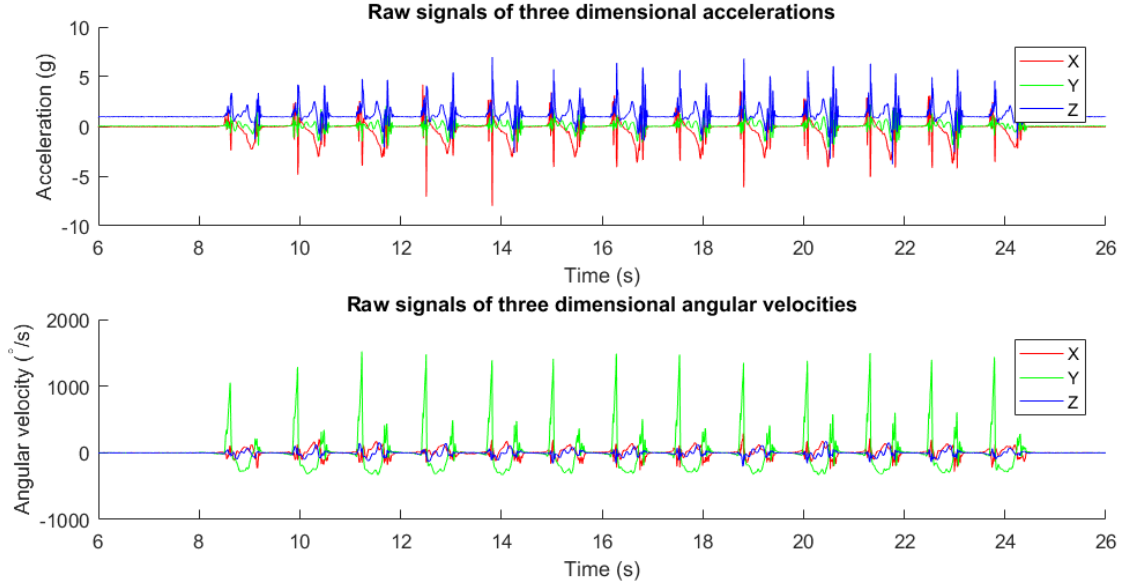


Figure 4.2: Examples of raw IMU signals

Data and source code to obtain this figure are available online (X-IOTechnologies).

The subject was standing without moving until the eighth second, and then started to walk a number of 13 steps until the twenty-fifth second.

If we look at the acceleration signal, we can observe that the z-component acceleration (the blue signal) is equal to 1 g, namely the constant gravity vector, while the subject is standing still. The x and y-components of the accelerations during this period are null. After the eighth second, we can identify successive phases where the foot is in acceleration and stationary. We will later see that is broadly corresponds to the swing and stance phase. At the beginning and at the end of each of the stationary phases, the x and z-component are characterized by positive and negative peaks, respectively. The y-component of the acceleration is less informative than the two others.

However, when looking at the angular velocity measures provided by the gyroscope, the y-component is characterized by a succession of positive and negative peaks, and then again slightly positive, occurring during the swing phase that is broadly detected in the accelerations signals. Those peaks correspond, respectively, to the foot pre-swing phase (namely, the phase during which the heel leaves the ground just before the toe off), followed by the dorsiflexion of the ankle before the heel strike, and then by the toe pose after the heel strike.

4.3 Errors in raw IMU-received signals

The raw data described in the section just above are generally not exploited as such, because of the presence of noise. Noise in raw IMU-received signals can have two main sources: inherent to the sensors themselves or related to the source itself (external errors or noise). Next sections describe some possible external sources of noise and the noise inherent to each of the sensors.

4.3.1 Errors related to the source

Misalignment error

In many clinical applications, motions or positions of interest are related to a terrestrial reference frame, which is to be distinguished from the IMU coordinate frame. We denote the Cartesian coordinate systems as the Unit Local Frame (ULF) and the Global-Earth-fixed Frame (GGF). For example, the spatiotemporal parameters of foot clearance and step length are defined as distances in directions relative to GGF axes. Ideally, ULF axes are aligned to the GGF axes, so that any motion of the IMU in the GGF generates a response in the corresponding axis of the IMU. However, in practice, after the IMU has been placed on a part of the subject's body, anatomical and mechanical imperfections inevitably cause misalignment errors (Abyarjoo, Barreto, Cofino, & Ortega, 2015). Each misalignment error will have two components, as it is shown in Figure 4.3. Algorithm processing data from IMU will always have to take the misalignment error of the IMU in the terrestrial reference frame into account.

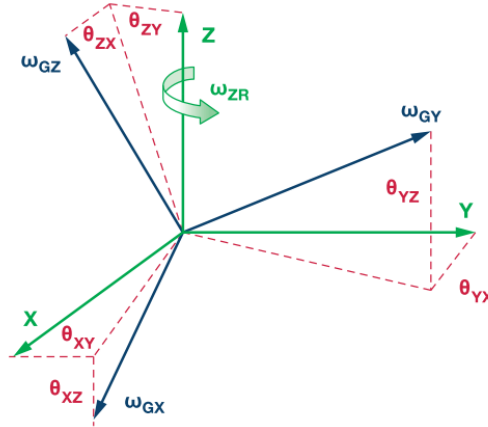


Figure 4.3: Example of misalignment error

Green: Global-Earth-fixed Frame (GGF). Blue: Global-Earth-fixed Frame (GGF). Red: two components of misalignment error of each axis (Looney).

If the two components of the misalignment error of the IMU relative to the GGF is known, the data can be corrected by using trigonometric functions.

Other potential external errors

When taking measurements with IMU, many other errors related to the conditions or the source can occur. Undesirable motions or slipping of the IMU can, for example, make data noisy if the IMU is placed above clothing, or placed where it is difficult to firmly fix it. As regarding the magnetometer, it should be noted that any environmental electromagnetic modification is also likely to make the magnetic field data noised.

4.3.2 Errors inherent to sensors

As many sensors, the accelerometer, gyroscope, and magnetometer suffer from fluctuating offsets, due to temperature changes (thermal noise) or small alterations in the component structure (mechanical noise). Even if the IMU is paced under null inertial conditions, fluctuations are recorded. In the module specification of the X-IMU, it is mentioned that the noise density of the accelerometer is $218 \mu\text{g}/\sqrt{\text{Hz}}$, and this of the gyroscope $0.01^\circ/\text{s}/\sqrt{\text{Hz}}$. When a time-integration is performed on the accelerations or angular velocity data, a drift due to the accumulation of the noise by the time-integration will be observed on the velocity and rotation data, respectively (Abyarjoo et al., 2015). The noise derived from the accelerometer can usually be neglected but the gyroscope bias drift over time is too important to be neglected. Any algorithm implementation for IMU data analysis must account for the gyroscope bias drift. In addition, the gyroscope presents an erroneous response to linear motion, that is equivalent to $0.1^\circ/\text{s}/\text{g}$ for the X-IMU.

4.4 Orientation estimation algorithms

As it was already mentioned, IMUs enable the tracking of rotational and translational movements relative to their own coordinates system. This coordinates system is moving in relation to the fixed terrestrial reference frame. Additional algorithms are required to estimate the orientation of the IMU in space. Once the orientation of the IMU is known, misalignment errors can be corrected by using rotations matrix products.

Most orientation filters consist in the fusion of Kalman-based approaches and gyroscope drift compensation techniques. Kalman's filter, that is widely applied in time series analysis consists in an iterative process based on a most-likely estimate of the behavior of the system under consideration and an update of this estimation using the noise measurements.

Another approach can be used to estimate the orientation of the IMU in space, for instance, the Madgwick's algorithm that is based on a quaternion orientation representation and uses a gradient descent algorithm to compute the measurement error of the gyroscope (O H Madgwick, J L Harrison, & Vaidyanathan, 2011).

We will see later that, according to the desired measure, the use of the gyroscope data and of an orientation estimation algorithm is not always required.

4.5 Typical steps of algorithms designed for spatiotemporal gait analysis with IMU

In order to gather information that is useful for gait analysis, namely for the spatiotemporal parameters, raw signals provided by IMUs must be post-processed via adapted algorithms. Currently, there exist a wide range of algorithms providing a decomposition of spatiotemporal parameters, each of them presenting their own approach and post-processing techniques. Some of them have proven to be robust, reliable and valid in healthy subjects, as is the case for Khandelwal and Wickström's algorithm, for example, that will be described later.

Despite the large spectrum of their proposed post-processing techniques, gait analysis algorithms available in the literature usually presents six common steps. They are illustrated with a non-exhaustive list of examples for each step in Figure 4.4.

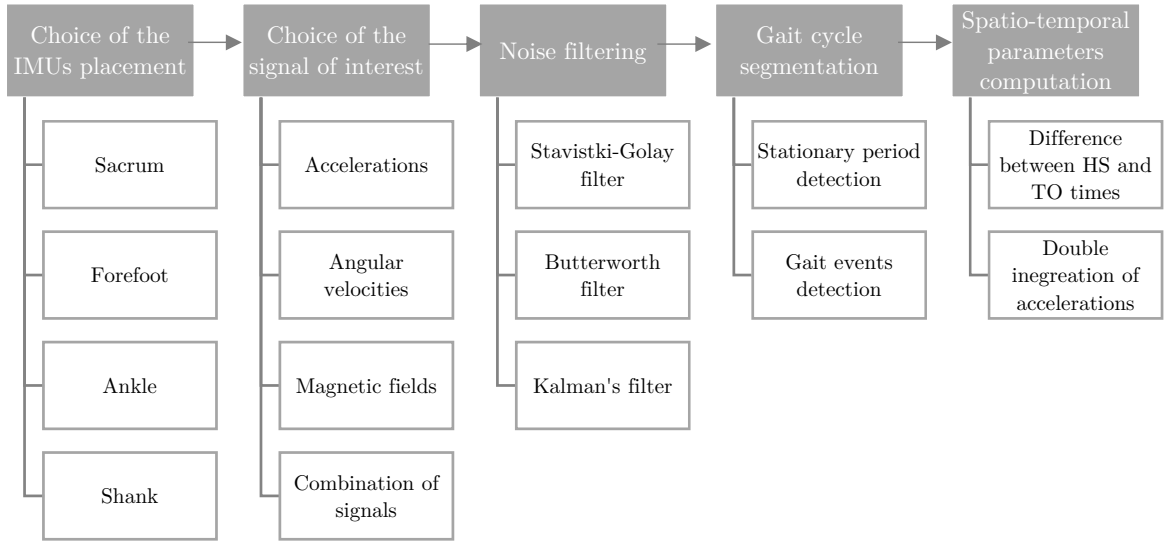


Figure 4.4: Common steps of IMUs signals-based gait analysis methodology

IMU positioning

The choice of the IMUs placement on the body is the first, and a critical step, in the implementation of the gait analysis methodology. Indeed, it is obvious that signals gathered by IMUs will present drastically different profiles depending on the body areas where sensors are attached. The accordingly implemented algorithms will have to be adapted to the considered signal profiles. Figure 4.5 presents different possibilities of IMU positioning for gait tracking.

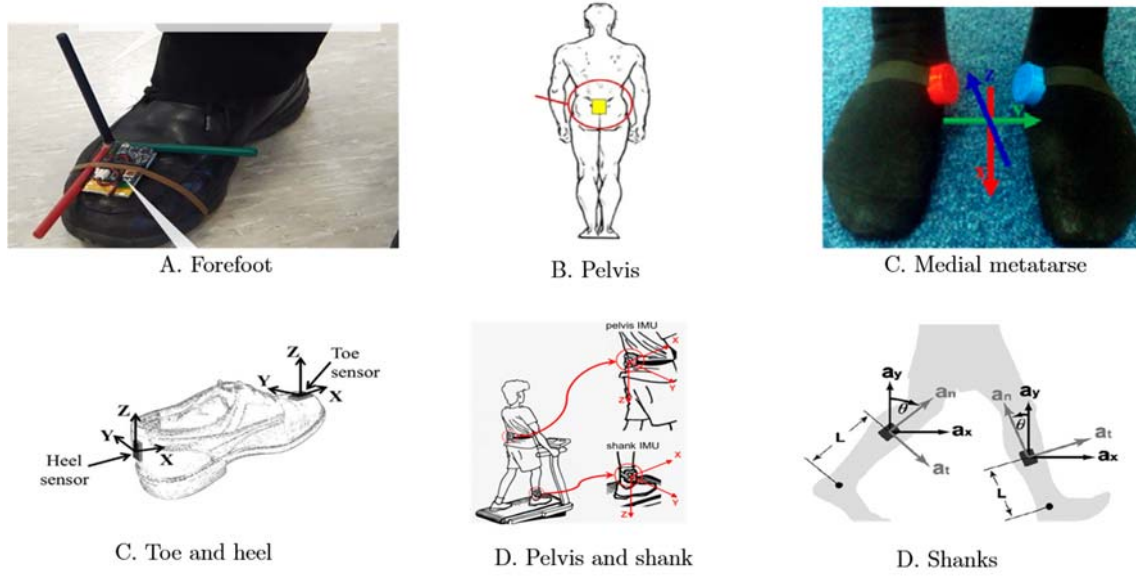


Figure 4.5: Example of different IMU positionings (Anwary, Yu, & Vassallo, 2018)

Choice of the signal to analyze

As it was mentioned in section 4.1, IMUs provide three-dimensional accelerations, angular velocities, and sometimes magnetic field signals. Even if a few existing computational algorithms for the detection of spatiotemporal parameters are based only on one type of signal (acceleration or gyroscope), most of them process on a combination of two or even three of these output signals.

Noise filtering

The third step is usually the choice of an adapted filter to smooth the raw data. A wide range of filters is used in the literature in IMU signals post-processing techniques. In biomedical application, the most common are the Statviski-Golay's filter and the bandpass Butterworth's filters. The challenge with the use of noise filters to smooth data is the same as in a lot of applications: finding a compromise between the noise reduction and the relevant data preservation. In some instances, the difference between the noised and the relevant data can be clearly identified but is often rarer when analyzing pathological gait signals. To make sure they exploit any kind of information, authors sometimes choose not to apply any filter and directly analyze the noised data.

Gait cycle segmentation

The step of the gait cycle segmentation is a very critical step of the algorithm and is the subject of a wide range of studies. As a reminder of what was explained in section 2.1.1, the gait cycle can be divided into stance phase, swing phase, and double support phase. The events of heel strike (HS) and toe off (TO) allow the definition of the start and end of those phases. The gait cycle segmentation thus consists in identifying the exact moment of the occurrence of the HS and TO events. Different techniques are used in the literature, the two most common being the stationary period and peaks detection routines. Roughly

speaking, the first method considers that, if the signals provided by the IMU are below a certain threshold, the IMU is static and therefore the current phase is the stance one. The HS is then identified at the beginning of the stationary period, and the TO at the end. The second technique, based on the model of the HS and TO signals, aims to identify some peaks or pieces of signal corresponding to HS and TO events. Such routines will be explained in section 4.6 with examples of algorithms. Illustration of gait segmentation routines results is presented in Figure 2.1Figure 4.6.

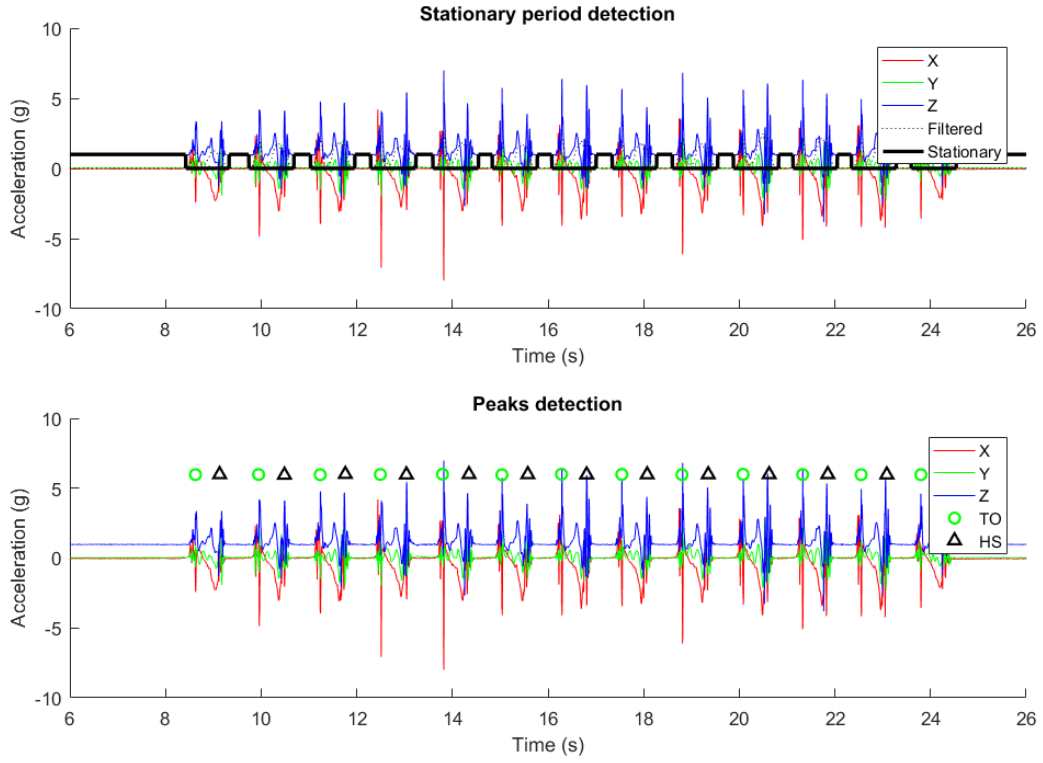


Figure 4.6: Example of gait cycle segmentation routine results

Spatiotemporal parameters computation

Once the gait cycle segmentation has been performed, the computation of the temporal parameters is trivial: the stance phase is defined as the duration between the HS and the TO, the swing phase as the duration between the TO and the HS, and the double support phase as the duration where both feet are in stance phase. However, computation of spatial parameters requires additional processing techniques, such as orientation estimation algorithm and compensation of the drift due to time-integration.

4.6 Review of some existing algorithms for spatiotemporal gait analysis

4.6.1 X-IO Technologies Algorithm

X-IO Technologies is a UK based company specialized in embedded sensing solutions and that commercialized, among other, the inertial measurement units that were used in the framework of this thesis, namely the X-IMU. Different algorithms useful for post-processing signals obtained via the IMUs were implemented inside the company. The source code of these algorithms are available on the company's GitHub page (X-IOTechnologies). Among these, the "Gait-Tracking-With-x-IMU" code allows foot position tracking from signals obtained via one IMU attached to the foot. One of my first reflexes was thus to analyze and understand the functioning of this proposed algorithm. The algorithm source code is available in Appendix 2.

Choice of the IMU positioning

Authors chose to place IMUs on the forefoot, with the x-axis and y-axis in the horizontal plane, the positive x-axis pointing toward the gait direction axis as presented in Figure 4.7.

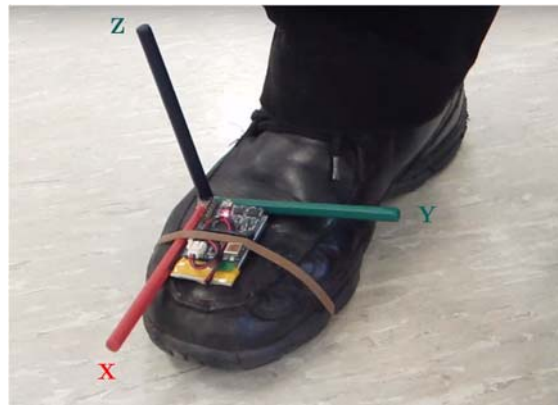


Figure 4.7: Placement of the IMU for the X-IO algorithm
(X-IOTechnologies)

Choice of the signals of interest

The algorithm used the magnitude of three acceleration signals to perform the gait cycle segmentation and a combination of the accelerations and angular velocities signals to perform the spatiotemporal parameters decomposition. The magnetometer signal was also used to obtain the quaternion evolution over time. The signal acquisition frequency was set at 256 Hz.

Noise filtering

At the start of the signal processing, a high-pass (HP) one-order Butterworth filter, followed by a low-pass (LP) one-order Butterworth filter, with a cut-off frequency of 0.002

Hz and 5 Hz, respectively, are applied on the acceleration magnitude signal for noise smoothing. The high-pass filter has the effect of correcting the amplitude and phase of the signal near the HP cut-off frequency, and attenuates signal with lower frequency. Such high-pass filter is included to prevent drift in the accelerometer signal. The low-pass filter was to here to remove the gravity component of the signal.

Gait cycle segmentation

The gait cycle segmentation was performed directly after the application of HP and LP filters, by using a stationary method detection. The principle is simple: if the filtered magnitude acceleration signal is below a threshold of 0.05, the signal is considered as stationary. Figure 4.6. that was used previously to illustrate instance for gait cycle segmentation shows the results of gait stationary period detection of the present algorithm.

Computation of the position evolution over time

The present algorithm does not provide detailed spatiotemporal parameters but computes the analysis of the position evolution over time, which ultimately to obtain the same type of information. Between the gait cycle segmentation and the acquirement of the position evolution, many processing steps were applied.

First, an orientation estimation algorithm was applied to compute a complete measurement of the orientation of the IMU relative to the earth. As mentioned in section 4.4, orientation estimation algorithms are designed to compensate the gyroscope bias drift. Here, Madgwick's algorithm was applied to the accelerations and angular velocity data. This algorithm provides the quaternion representation of the IMU orientation in space.

The quaternions data provided by the orientation estimation algorithm are next used to construct a rotation matrix, and to rotate the acceleration data, which are initially expressed according to an IMU-attached moving reference frame, relative to the fixed earth's reference frame.

Once these steps have been completed, the position evolution is calculated by using a double integration of the acceleration signal. Again, to avoid drift due to integration, this step is performed in three stages. First, the instantaneous velocity is computed by using the classic motion equation, with the additional constraint that, if the signal is considered in a stationary phase, the instantaneous velocity is fixed to 0.

$$v(t) = \begin{cases} v(t-1) + a(t) \times T, & \text{if non-stationary} \\ 0, & \text{otherwise} \end{cases}$$

Next, the integral drift of the velocity is computed and removed from the velocity signal. The drift rate is defined for each of the detected stationary periods, as the difference between the velocity at the end of the considered stationary period and the velocity at the start of the stationary period.

The position evolution over time can be next deducted from the traditional motion equation.

$$x(t) = x(t - 1) + v(t) \times T$$

Resulting signals and interpretation

Obtained three-dimensional accelerations, velocities, and positions relative to earth frame are presented in Figure 4.8. It should be noted that the data that were used as input of the algorithm were the data provided by the X-IO technologies company with the code source.

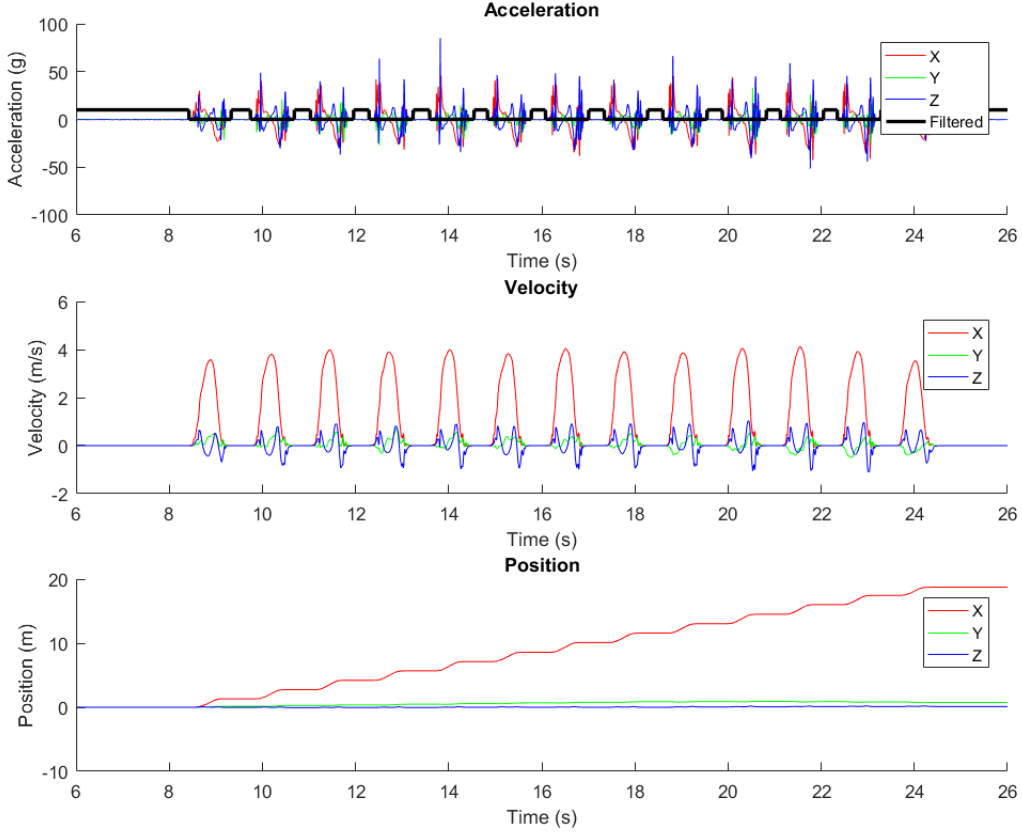


Figure 4.8: Signals resulting from the X-IO Technologies company's algorithm

While observing the acceleration signal, the algorithm seems to provide a clean segmentation of gait cycle. Oscillation and stance phases of each step present a regular duration, and the 13 steps performed by the subject were well detected. The velocity signal is also very consistent with what is expected in normal gait. Indeed, the velocity in the x-direction (the red signal) presents positive peaks at the beginning of each step, which corresponds to the forward acceleration of the foot. Those positive peaks are also a very regular step-to-step gait and are followed by a decrease of the signal to zero, corresponding to the phase in which the foot is slowing down before the heel strike event. The velocity in the z-direction (the blue signal) is also informative and is represented, in each oscillatory phase, by four small peaks that are consistent with the reality. Indeed, each beginning of oscillatory phase is characterized by a small velocity raise-up in the z-direction, explained by the upwards toe off. Then the velocity becomes slightly negative for a short time, during which the foot goes down to the ground. A third peak, small and positive, represents the

toe upswing before the heel strike, and the last small negative peak corresponds to the slowing down before and during the foot pose. Finally, the position signal shows very well that the subject is walking in the x-direction, being stationary during each stance phase and rising slightly during each oscillatory phase, reaching a traveled distance of 20 meters at the end of the 13 steps.

Personal remarks and test of this algorithm

A first observation that can be emitted is that the authors, in the view of the way the algorithm is implemented, consider that the stationary phase of the IMU is equivalent to the stance phase. In practice, as it was mentioned before, the foot stance phase begins with the heel strike. After the heel strike, the IMU placed on the forefoot continues to move, the signal does therefore not meet a value below the threshold of 0.05 g and is not considered as “stationary”. In the same way, the end of the stationary phase is detected before the end of the real foot stance phase, as the IMU placed on the forefoot will start to move before the toe off events. The IMU stationary period is, therefore, smaller than the foot stance phase. Moreover, as it was mentioned in the section 2.1.1 describing a typical gait cycle segmentation, the stance phase represents, in normal conditions, 65 % of the total gait cycle. Here, we can see that the stationary phase represents only 40 % of the gait cycle.

Another key issue that I noted with this algorithm is the presence of predefined thresholds to segment the gait cycle into oscillatory or stance phases, namely the cut-off frequencies for the two filters and the threshold below which the signal is considered as stationary. In biomedical signal analysis, the use of predefining thresholding is highly inappropriate because of the presence of important interindividual and intraindividual signal differences.

However, as the source codes of this algorithm were already available, and as it was specifically designed for the IMU that I used in the framework of this thesis, I decided to test the algorithm with, as an input, data acquired by my own using the same placement method as the one suggested by the company, on healthy subjects, and on post-stroke subjects. Results provided by the algorithm, that are presented in Figure 4.9 show that the algorithm of gait cycle segmentation failed. In conclusion, this algorithm seems to be effective when considering the data provided by the company, but needs adaptations to be optimized on larger samples of data and on post-stroke subjects.

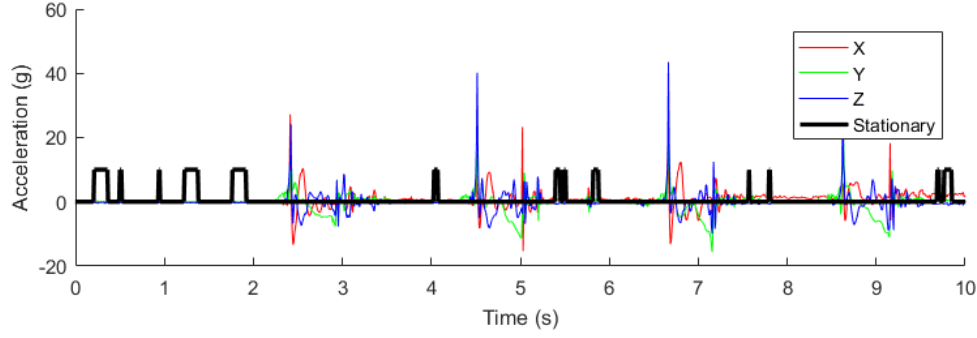


Figure 4.9: Test of the algorithm on a post-stroke subject

The IMU was positioned on the paretic forefoot. The subject was standing still for two seconds and then started to walk. Three steps were performed between second two and second 10. We can see that the algorithm was unable to correctly detect the stationary and the swing phases.

Similar algorithms

After reviewing the literature, it appears that several algorithms broadly use a similar series of steps. This is, for instance, the case of Kitagawa and Ogihara's algorithm (Kitagawa & Ogihara, 2016), and Mariani et al. algorithm. (Mariani et al., 2010).

4.6.2 Yang et al. algorithm

Another type of algorithm that caught my attention is the one proposed by Yang et al. (Yang, Zhang, Novak, Brouwer, & Li, 2013). According to the authors, they developed an algorithm that allows estimating walking speed and simultaneously evaluating gait spatiotemporal parameters, for stroke survivors without the need of pre-calibration. Next points describe the implementation of the algorithmic gait spatiotemporal parameters decomposition.

Choice of the IMU positioning

In this study, two IMUs were attached to the midpoint of each shank on the lateral side, using athletic tape, as presented in Figure 4.10.

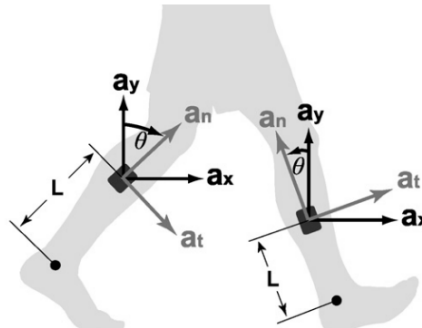


Figure 4.10: IMUs positioning in Yang et al. study
(Yang et al., 2013)

Choice of signals of interest and noise filtering

Only the signal of angular velocities was used to perform the gait cycle segmentation estimation. The acceleration signal was needed to compute the velocity. The IMU sensors which have been used in this study did not integrate any magnetometer.

For the noise reduction, a second-order Butterworth low-pass filter with a cut-off frequency of 10 Hz was use for both signals. For the gait segmentation, a second-order Butterworth low-pass filter with a cut-off frequency of 2.3 Hz was applied to the gyroscope signals.

Gait cycle segmentation

According to the authors, measurements obtained via shank mounted gyroscope allows the detection of the toe off and heel strike events. Figure 4.11 shows that the toe off and the heel strike events of the non-paretic and the paretic limb are identified by the negative peaks in the angular velocities data. Here, the stride cycle of each lower limb was defined as commencing at the time at which the lower limb is vertical and ending at the next moment at which the same lower limb leg is vertical again.

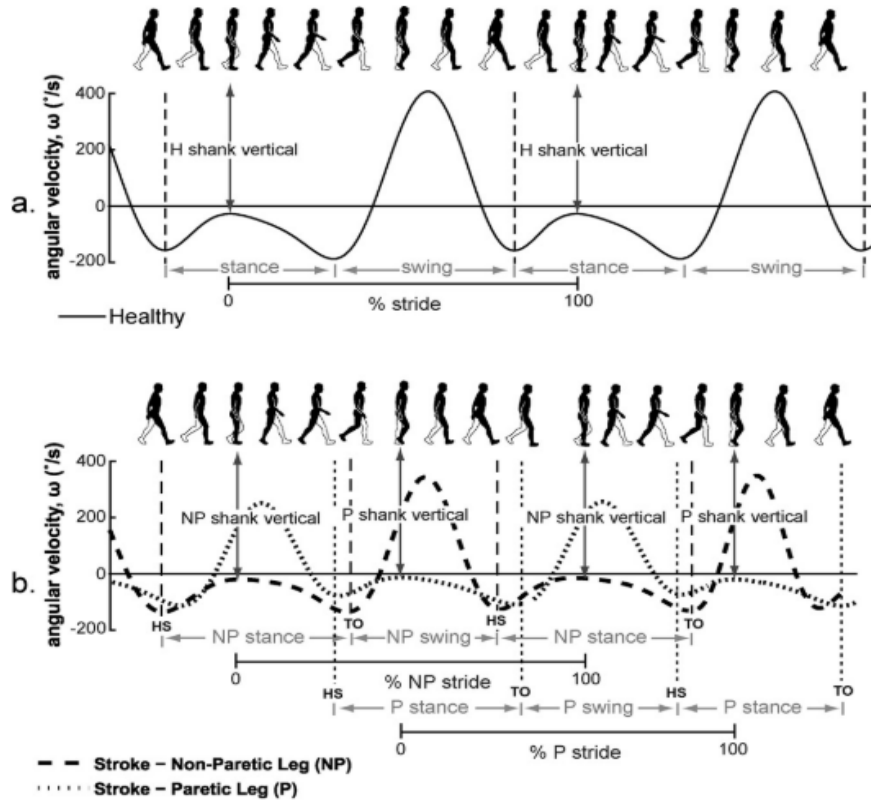


Figure 4.11: Characteristic of shank angular velocity during two consecutive strides

a. Healthy subject and b. Post-stroke subject. The angular velocity of the non-paretic leg (NP) is indicated by the thick dashed curve, and the paretic leg (P) is indicated by the thin dashed curve. The stride cycles of the NP leg and the P leg were determined by the mid-stance shank vertical event, at which point the magnitude of the angular velocity approached a local maximum close to zero. The swing phase and the stance phase of each leg were determined by the heel-strike (HS) and toe off (TO) gait events, which were identified by the negative peaks of the shank angular velocity. (Yang et al., 2013)

Spatiotemporal parameters analysis

The swing phase and the stance phase of each lower limb were determined by using the definition already mentioned in section 2.1.2 (Operational definition of spatiotemporal parameters, page 15). The symmetry ratio was defined as the difference between the paretic swing-stance ratio and the non-paretic swing-stance ratio.

Author's algorithm test and discussion

To test the efficiency of their algorithm, the authors processed angular velocity measures on 13 post-stroke subjects. Inclusion criteria were defined such as subjects: (1) reported residual unilateral lower limb weakness, (2) were able to walk independently, and (3) could follow instructions. Without going in all the details of the method and the statistical considerations of the paper, it basically says that the findings support the validity of the shank-attached gyroscope algorithm that they developed for quantifying temporal gait symmetry. However, most of the subjects tested (12 of 13), presented patterns of shank angular velocity similar to the healthy population. Authors stipulate that when the shank angular velocity differed from the healthy group profile, as it was the case for one patient (Figure 4.12), gait segmentation algorithm failed, suggesting that new gait segmentation methods need to be developed.

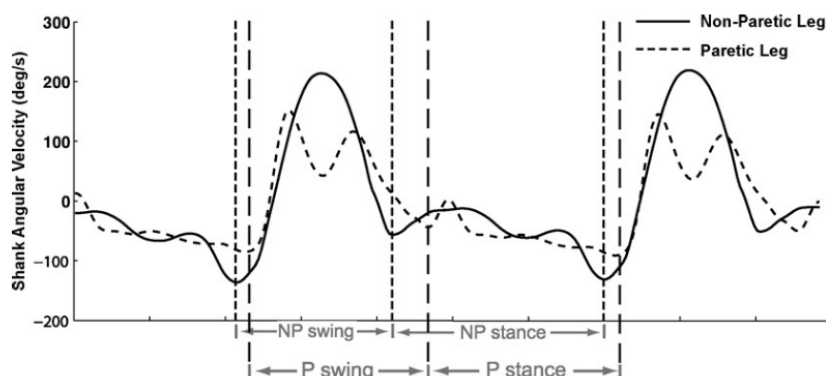


Figure 4.12: Shank angular velocity profile of a subject for who the algorithm did not correctly identify key gait events

(Yang et al., 2013)

Critic and personal remarks

In the section 2.2.1 (Qualitative clinical observations, page 21), we explained some typical gait patterns that can be observed by means of a visual exam of the patients. Among those, the “steppage” gait and the “stiff” gait are very often present in post-stroke gait patterns. As a reminder, they are characterized by the fact that the paretic lower limb remains extended during the whole oscillatory motion, instead of bending the knee. In “steppage” gait, to compensate this lack of knee flexion and send the foot forward, the hip on the paretic side is elevated higher and the paretic lower limb is flopped away from the body. In the “stiff gait”, the knee of the non-paretic limb is also held in extension throughout the stance phase, allowing an elevation of the paretic foot and his passage

towards the heel strike. In both cases, the push-off and the hip flexion of the paretic side are reduced. We can, therefore, stipulate the angular velocities measured at the level of the shank by the gyroscope will present smaller fluctuation.

To check the present statement, I performed measuring of angular velocities on my own shank and imitated the “steppage gait” and the “stiff gait”. As expected, the angular velocity signal did not allow the identification of the toe off and heel strike events.

A reason which may explain that Yang et al. algorithm worked on 12 post-stroke subjects is the inclusion criteria. Subjects that were recruited were required to walk independently, without any assistance device. Such criterion selects patients who have a gait pattern closer to the healthy gait pattern. The aim of the present thesis is to analyze the effect of a gait assistive device on the spatiotemporal parameters and on in patients walking with gait assistive device, and therefore with gait patterns far from the healthy gait pattern (indeed, if the gait pattern is close to the normal gait pattern, patients would not need, a priori, a walking assistance). Other methods of gait cycle segmentation are therefore required for patients with gait patterns far from healthy gait patterns.

Finally, another big issue related to this algorithm is the dependency of the IMU orientation in space. Indeed, authors speculated that the t and n -axis of the IMU positioned on the shank like in Figure 4.10 were oriented in the sagittal plane, namely, the plane formed by the vertical and the gait axis of progression. In practice, the plane formed by the t and n -axis of the IMU usually do not match with the sagittal plane, because of potential inaccuracy IMU positioning and anatomic shape of the shank. Robust gait parameters measurement technique should instead require an independence of the results with the absolute orientation of the IMU in space. This is the case of the next algorithm that will be described below.

Similar algorithm

A series of other algorithms are based on the same idea as the one of Yang et al. (Catalfamo, Ghoussayni, & Ewins, 2010; Formento, Acevedo, Ghoussayni, & Ewins, 2014; Lau & Tong, 2008; Lee & Park, 2011)

4.6.3 Algorithms based on time-frequency analysis

Several algorithms are based on time-frequency analysis to detect gait events from accelerometer and gyroscope signals or to compute spatiotemporal parameters after detecting gait events.

In Sabatini et al. algorithm, for instance, Fourier analyses were performed on signals provided by an IMU positioned on the shank. The gait was first segmented by using the mediolateral component of the gyroscope, and then the three stride-by-stride components of accelerations were integrated analytically over time by means of Fourier series coefficients. The three-dimensional shank displacement of each stride was then reconstructed by means of the reverse Fourier series. Without going into experimental and

statistical details, the algorithm was tested on healthy subjects walking on a treadmill and was proven to be performant, according to the authors. However, for the same reasons as the one specified for Yang et al. algorithm in section 4.6.2, the gait cycle segmentation is likely to fail when considering post-stroke subjects with foot drop, “waddling” or “stiff” gait. Fourier analysis could be a possible means for the reconstruction of three-dimensional displacement while avoiding time integration drifting, but present the major disadvantage of a loss of control on the temporal spread. Signals must therefore be analysed stride by stride as it was done in the Sabatini et al. study.

4.7 Summary

The main points arising from this chapter are as follows:

1. IMUs used in gait analysis consist in a triaxial accelerometer, triaxial gyroscope, and triaxial magnetometer
2. The main issues of designing a measurement technique based on IMU signals are the choice of the IMU positioning on the subjects and the implementation of an algorithm.
3. Related to the above, there is a tremendous amount of possibilities for processing IMU signals and deducing the spatiotemporal parameters.
4. Some existing IMU measurement techniques and algorithms are performant to evaluate the spatiotemporal parameters of healthy people or post-stroke subjects with a small level of gait impairment, but they are not optimized for subjects presenting an impairment such that they require walking devices for traveling

Chapter 5

Development and validation of a new algorithm for spatiotemporal gait analysis in post-stroke subjects walking with gait assistance

As mentioned in the last section, the performance of gait cycle segmentation and spatiotemporal computation algorithms shown to be efficient in healthy subjects. However, most of those algorithms are not optimized when considering post-stroke patients and, more specifically, disable patients that are used need a walking assistance.

In this chapter, we will propose the implementation of a new adaptative algorithm for gait cycle segmentation that could be efficient in post-stroke patients, taking into account the characteristic specific to post-stroke gait mentioned in Chapter 2. The process of algorithm parameter optimization will also be described.

In a second stage, the performance analysis of the implemented algorithm will be carried out, in two different ways. Firstly, the ability of correctly detect the occurrence of a step in a sample of post-stroke subjects will be assessed. Secondly, the validity of the quantity provided by the algorithm, namely the phases duration, will be investigated in a validation study carried out in healthy subjects.

5.1 Design of the measurement technique

5.1.1 Measure systems requirements

In chapter 3, we reviewed some of the quality criteria of spatiotemporal measurement tools, such as the reliability, repeatability, and the sensitiveness to detect abnormal and normal gait. It was mentioned in the same chapter that validated measurement tools such as force platforms and optical motion capture system are very efficient for measuring the spatiotemporal parameters, but their non-wearable status is particularly restrictive, especially if the patient suffers from mobility issues.

We have also seen that the use of predefined fixed thresholds is non-recommended in signals which are likely to present variability in the noise and amplitude, as it is the case for data collected in post-stroke subjects.

We also noted that an accurate positioning of the IMU in the space, with one or two IMU axis corresponding exactly to one or two axis of the terrestrial referential frame, is rarely feasible, due to external constraints or potential displacement of the IMU during the trial. In contrast, IMU positioning that are stable over time, easy and quick to install should be preferred in non-laboratory conditions.

Knowing all of this, we are able to enumerate the different requirements and specifications that should fulfill an algorithm designed for the gait cycle segmentation in post-stroke subjects, added to the quality criteria that were already mentioned in Table 3.1.

Table 5.1: Measurements tool requirements and specifications

Requirements related to the measurement technique

1. Wearable and feasible in non-laboratory environments
2. Efficient for post-stroke gait pattern
3. Easy and stable IMU positioning

Requirements related to the gait cycle segmentation algorithm

4. Capable of managing misalignment errors
 5. Auto-adaptative algorithm (not based on thresholds)
 6. Unsupervised algorithm (unknow mapping function)
-

5.1.2 Design of the measurement technique

In light of those previous facts and required specifications, as well as after having performed a succession of little experimentations to confirm, or infirm, each of my hypothesis, we chose to design the measurement technique and implement the algorithm as described in the following points.

IMUs positioning

IMUs were firmly attached at the forefoot, by means of large rubbers, as presented in Figure 5.1. Pieces of adhesive tape were added above the IMUs and the rubbers to avoid potential anteroposterior motion. On the paretic side (the right foot on the picture), a larger adhesive strip was sticked above the rubber, on the sole, to prevent rolling of the rubber in case of foot sna. This IMU installation offers series of major advantages: it is fast and easy to apply and to remove, it does not require to take off any piece of clothing, is suitable to all types of shoes, and it is sufficiently stable to avoid movement of the IMU during the measurement process. Therefore, we comply with the requirement number 4, namely the easy and stable IMU positioning.

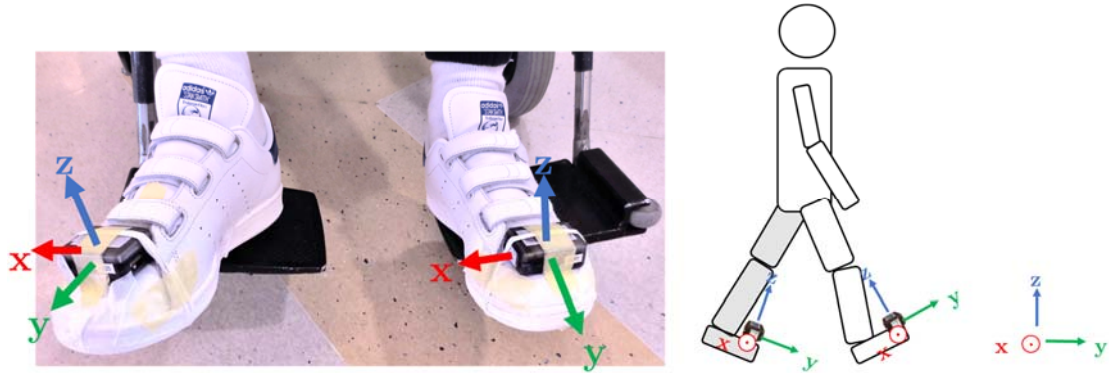


Figure 5.1: Positioning and orientation in space of the IMUs

Signal of interest

Given that the system must be efficient in non-laboratory conditions, the use of the magnetometer data is not recommended. Indeed, as mentioned in previous sections, the magnetometer is very sensitive to external magnetic disruptions. In hospital or rehabilitation center environment, having a control on the potential magnetic disruptions is infeasible. In addition, the four-point cane itself generates variation in the magnetic signal.

Regarding the gyroscope data, after several question and investigation, it was decided to not include them in the algorithm. The main reason for this choice is illustrated in Figure 5.2, which schematizes the position of the foot during a gait cycle in normal and in foot drop gait, and in Figure 5.3 which represents how the gait events can be detected on a medio-lateral gyroscope signal.

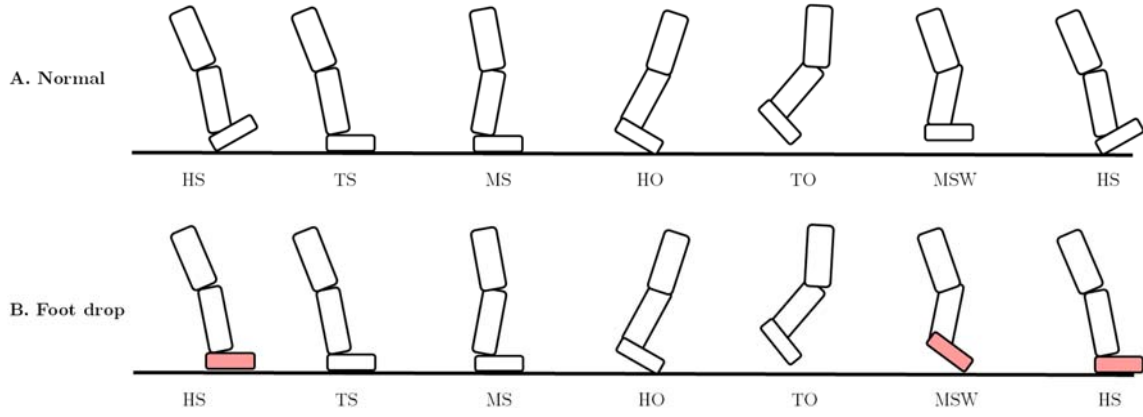


Figure 5.2: Trajectories of the foot in normal gait and foot drop gait

HS : heel strike, TS: toe strike, MS: midstance, HO: heel off, TO: toe off, MSW: midswing

A.Normal gait. During the midswing phase, toes are raised up due to the dorsiflexion of the ankle. **B.Foot drop.** Lack of motor control causes an incapacity to raise the toes up during the midswing phase.

In normal gait analysis, when the IMU is positioned at the forefoot, data given by the axis perpendicular to the sagittal plane (namely, the mediolateral axis (ML), or the x-axis if the IMU is oriented like in Figure 5.1) are very informative for detecting gait events. During the heel off, a first negative peak is clearly visible on data. The sign of the peaks is dependent of the orientation of the IMU: if the x-axis points to the right, as it was the case here, the heel off leads to a rotation of the IMU around his x-axis in the anti-clockwise sense and the measured angular velocity will, therefore, be negative. After the heel off, the toe off is characterized on the gyroscope data by a rapid rise of the signal. The swing phase, during which the toes are raised up for the foot crossing, is seen as a larger positive wave on the signal. Finally, a second smaller negative peak indicates the event of the toes strike, just after the heel strike.

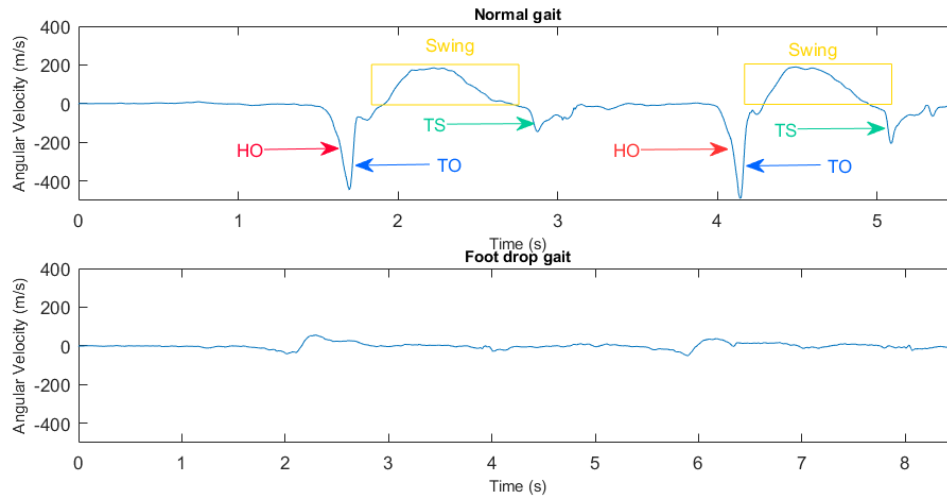


Figure 5.3: ML gyroscope signal from an IMU positioned at the right forefoot for two consecutive steps.

A. Normal gait signal. Different gait events, such as the heel of (HO), toe off (TO), the swing phase and the toes strike (TS) are clearly visible on the signal. B. Foot drop gait. None of those events can be identified.

The gyroscope signal is therefore very informative and useful for gait cycle segmentation in normal gait. However, as a reminder, we have seen that post-stroke patients often present a “foot drop”: due to sensorimotor and motor control disorder in the paretic lower limb, the subject is not able to raise up the toe anymore. Because of this, the foot trajectory does not present a roll of the foot like in normal gait, and the different events for the gait cycle segmentation will be not detected on the gyroscope signal, as it can be clearly seen in Figure 5.3. This problem is acuter if the subject presents also a “stiff gait”. Foot drop and stiff gait are not present in all post-stroke subjects, but they are more common in post-stroke subjects that need a walking aid for traveling.

Based on these findings, we chose to perform the gait cycle segmentation and the spatiotemporal parameters decomposition by using exclusively the three-dimensional acceleration signal, and more precisely, the magnitude of the three signals. The key advantage of such a choice is the independence of the results according to the IMU orientation on the foot, or the foot orientation in the space. In other words, misalignment problems are totally avoided: if the IMU axes are not oriented in a specific direction, or if the patient walks with a foot positioned in an unexpected way (for instance, in external rotation, which is often the case of the paretic foot), there will be no impact on the results. The fourth requirement (managing of the misalignment error) is therefore fulfilled.

An overview of raw data measured in post-stroke subjects

Before dealing with the description of the step of the implemented algorithm, an overview of signals acquired from accelerometers positioned on the forefoot of post-stroke patients seems useful. As a reminder, the keyword describing the gait pattern in post-stroke patients is “patient-specific”. After a stroke, according to the size, the location and the severity of the lesion, each patient will present a unique range of sensorimotor disorders.

In Figure 5.4, we can see, as an example, acceleration signal measured in two different post-stroke patients with the IMUs positioned on the forefoot on the paretic side, each patient performing six consecutive steps. Patients feet were filmed during the measuring process allowing us to manually the gait cycle segmentation in swing and stance phases.

We can see that the characteristics of swing phases differ from patient-to-patient but also step-to-step. In the patient A, the signals corresponding to swing phase at step 1 (at 2 seconds, approximately) and step four (at 8.5 seconds) present both a small positive peak at the beginning of the swing phase and a bigger peak at the end. The two peaks are separated by a small phase where the signal is close to zero, while the foot is not in stance phase. Regarding the fifth swing phase, it corresponded to a very slow and small step of the subject, and the corresponding signal presents smaller peaks. Between each swing phase, there is a small oscillation of the signal, relevant to the small motion of the toes even when the foot is in stance phase.

Regarding the acceleration measured from patient B, it can be observed that signal oscillation at the step number 4 and 6 are smaller than in the other signal, but they still correspond to swing phases. Furthermore, between the seventh and eighth second, small peaks can be observed, with one peak with an intensity of more than 1 g. One might think that this

part of signal coincides to a swing phase, but the foot was still standing on the ground. Those small variations in the signal are corresponding to parasite motion of the toes during the stance phase.

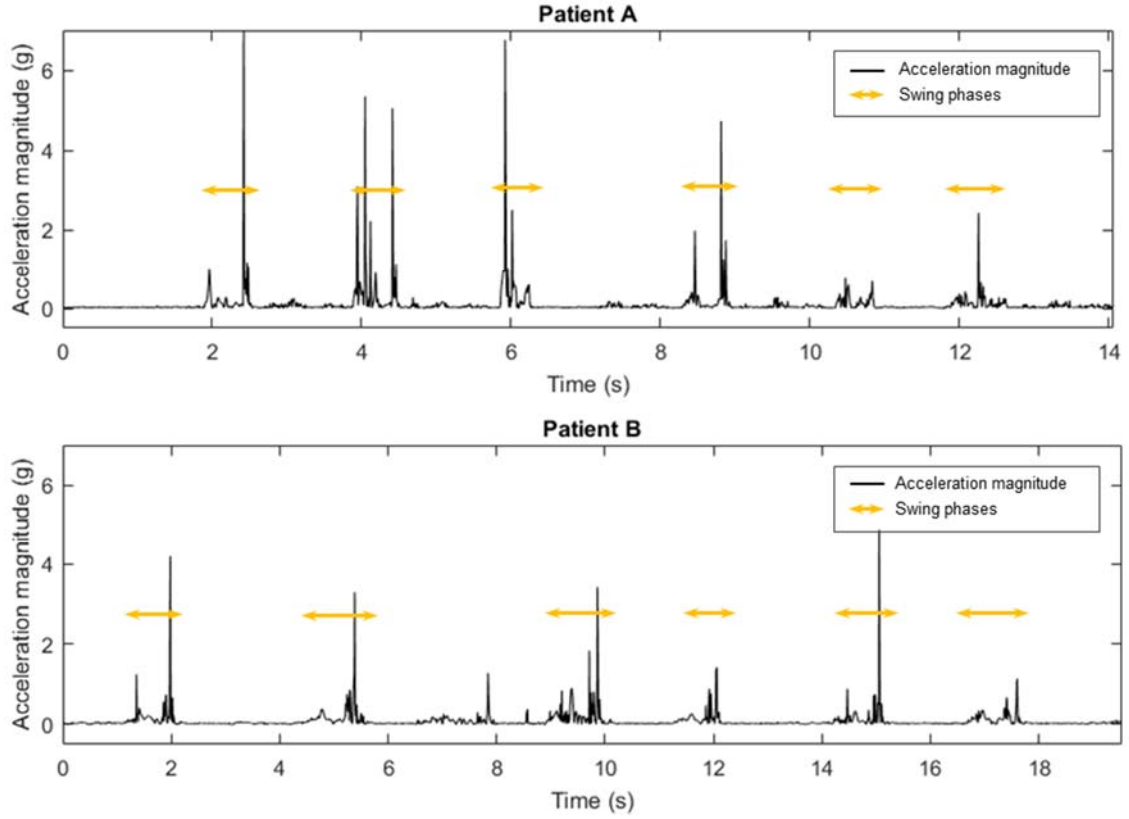


Figure 5.4: Non-filtered acceleration magnitude of six paretic steps in two different post-stroke subjects

The big challenge of the gait segmentation algorithm is, therefore, to clearly identify the part of the signal corresponding to real swing phases, and those corresponding to real stance phases, without interpreting the signal coinciding with parasite motions.

In such situation, the direct application of a filter on the raw and noised data as a first step seemed, in own opinion, irrelevant. Indeed, choosing an appropriate filter and finding the filter parameters (cut-off frequencies, frames, orders...) allowing a noise reduction while keeping relevant information is very tricky and not always possible, especially when considering signal presenting high variation in the relevant information. Besides, choosing those filter parameters is equivalent to use fixed and predefined threshold.

5.1.3 Design of the gait cycle segmentation algorithm

In light of the above findings and considerations, I chose to perform the gait cycle segmentation by combining a basic method of stationary period detection with well known unsupervised machine learning techniques. It should be noted that the proposed algorithm serves only for the gait cycle segmentation, and not for the spatiotemporal parameters computation. The output of the algorithm is a binary signal representing the stance phase (1)

and swing phase (0). The different steps of the algorithm are described as follows, and the methodology for the choice of parameters values will be described in the section 5.2.

Step 1: Peaks detection

The first step of the algorithm consists in the detection of all peaks present in the signal. This was simply done by using the `findpeaks` Matlab function. If we considered that each peak could contain useful information, no input parameters in terms of minimal or maximal height, prominence, width, or distance between peaks were defined, but the height and the prominence of each peak have been stored in a $n \times 2$ matrix, where n was the number of detected peaks.

Step 2: Application of the K-means algorithm

Next, I decided to use the K-means algorithm in order to discriminate the identified peaks in different groups, some of which would be representative of stance phase and other of swing phase. The K-means algorithm is an unsupervised clustering technique that allows a partition of a set of points into k clusters so that points within each group are as close as possible to each other in terms of a certain defined distance. The general principle of the K-means algorithm is detailed mathematically in Table 5.2 (Segers, 2017).

I performed this clustering technique by using the `Kmeans` Matlab function. On the computed peaks height and peaks prominence. Therefore, the data dimension p was equal to 2. The squared Euclidean distance metric was defined as the distance between the data. The number of groups k was set to 9 and the centroid positions were initialized uniformly on the data diagonal. After application of the algorithm, each of the detected peaks was attributed by the algorithm to one of the 9 groups. This is the present step of the algorithm that makes the algorithm “adaptive”. Indeed, the K-means algorithm is a type of unsupervised machine learning technique, which means that the algorithm learns and makes determinations about the group partition from the data without being explicitly programmed.

Table 5.2: General principle of the K-means algorithm

<i>Inputs</i>
- $n \times p$ data matrix X of quantitative variables - q, the number of clusters

<i>Initialization step</i>
1. Select initial cluster centroids:
$c_1^0, \dots, c_q^0 \in R^p$
2. Assign each point x_i to the closest centroid:
$I_k^0 = \{i = 1, \dots, n : \ x_i - c_k^0\ < \ x_i - c_\ell^0\ , \ell \neq k\}$
<i>Iterative main loop</i>
3. Repeat until no more change:
3.a. Calculate the centroids of clusters obtained at previous step:
$c_k^{m+1} = \frac{1}{ I_k^m } \sum_{i \in I_k^m} x_i$
3.b. Reassign each point to closest center:
$I_k^{m+1} = \{i = 1, \dots, n : \ x_i - c_k^{m+1}\ < \ x_i - c_\ell^{m+1}\ , \ell \neq k\}$

<i>Outputs</i>
- A final partition - The positions of the centroids

(Segers, 2017)

Step 3: Assignment of penalty values on groups

In the next step, the groups were sorted in ascending order according to their centroid value. After analysis of several signals provided from both healthy and hemiplegic subjects data, we were able to make the assumption that each peak attributed to the group with the smallest centroid position, namely the group 1, was corresponding to noised fluctuations present during stance phases, and that each peak attributed to group equal or greater than the group 3 was belonging to swing phase signal. This assumption was used to discriminate the detected peaks: a null value was attributed to the peaks belonging to the group 1, and a value of the maximal peak height detected was attributed to the acceleration peaks included in group 3 or more. This assignment of a “penalty” value of zero can be seen as a first step of noise filtering.

Step 4: Application of the sliding window algorithm

Basic stationary period detection routines, such as the one described in 4.6.1, check the value of each signal record one by one and define it as stationary if it is below a certain predefined threshold. Here, it was decided to use the same type of strategy with the added use

of an iterative sliding window that scans the signal from left to right. The window size (WS) was defined as a function proportional to the record acquisition, and inversely proportional to the mean gait velocity, as the following equation:

$$WS = 0.35 \times F_a \times \frac{1}{V_m}$$

Where V_m is the known gait mean velocity (in m/s), F_a is the data acquisition frequency, and WS is expressed in a number of records. The choice of the value of 0.35, that will be designated as the window size factor (WS_f) will be explained in section 5.2. The size of the displacement, or increment (WI) at each iteration, is defined as the multiplication of the window size by a certain factor WI_f . We will see later that the WI_f was set to 11%.

At each iteration, the average of elements contained in the frame was computed. Therefore, instead of considering the value of each record one by one, as it was the case in the algorithm implemented by the company providing the x-IMUs (section 4.6.1), we consider here the value of each record as well as the neighbouring value. This technique, of which the principle is similar to a moving average filter, provides a second step of noise filtering for the stationary period detection.

Step 5: Stationary period detection

Each average value computed during the iterative process of sliding window were retained in a matrix form. The signal was considered as stationary if at least two consecutive frames contained elements of which the computed average was inferior to a threshold of 0.1 g-units.

It may be noted here that an absolute threshold is integrated into the process, while it was mentioned that it was preferable that the algorithm should not include any threshold. However, the step of the attribution of penalty values to signal peaks according to the group to which they belong provides justifies here the use of a threshold here. Indeed, if the peaks were successfully partitioned in stationary or non-stationary group by the K-means algorithm, signals from different subjects or different trials will present a priori the same behavior during the stationary phase, thanks to the attribution of a null value to peaks group 1.

Overviews of the different assumptions made behind the implementation of this algorithms and of the successive process steps are presented in Table 5.3 and Figure 5.5, respectively.

Table 5.3: Assumptions made behind the algorithm implementation

-
- | |
|--|
| <ol style="list-style-type: none"> 1. The real change rate in acceleration is smaller than the sample frequency 2. The peaks contained in the first group reflect noise in stationary phase 3. The peaks contained in the group 3 or greater reflect non-stationary phase 4. There is no swing or stance phase durations smaller than the duration covered by the sliding window size. |
|--|
-

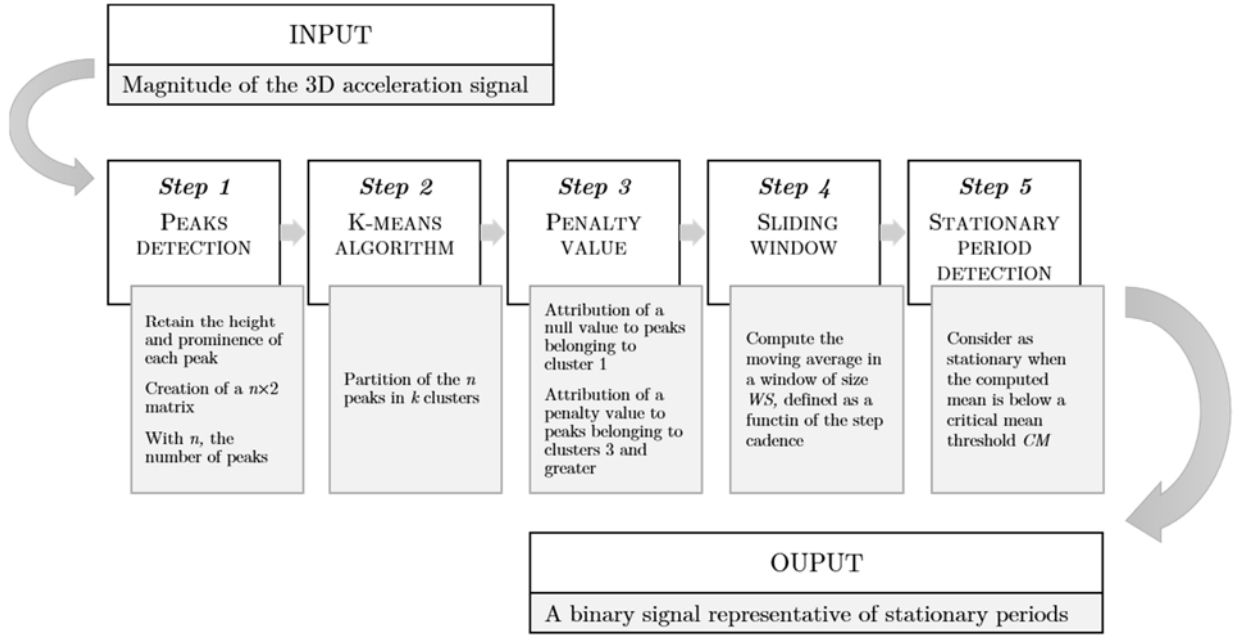


Figure 5.5: Algorithm design

5.1.4 Note about the bias when detecting stationary phase

As it was already mentioned in section 4.6.1 that describes the algorithm provided by the X-IO company, the detection of stationary phase for gait cycle segmentation is not exactly equivalent to the detection of the stance phase. In theory, the stance phase starts with the heel strike and ends with the toe off. However, when the IMU is positioned on the forefoot, the IMU stationary phase starts with the toes strikes (which occurs after the heel strike) and ends with the heel off (which occurs before the toe off). In other words, the stationary phase duration is always underestimated in comparison to the real stance phase.

However, we can speculate that this underestimation of the stance phase when computing the stationary phase is a constant step-to-step shift, namely a measurement systematic bias, as it will be further checked.

5.1.5 Algorithm optimization process

It is important to note that, at the beginning of this Master thesis, absolutely no data in post-stroke subjects, or even in healthy subjects were available. Therefore, the algorithm was not implemented in one session, but was improved and updated in several stages, as represented in Figure 5.6.

Different possibilities were first investigated on the basis of the state of the art and subjective intuitions made by observing and describing typical gait pattern of post-stroke subjects walking with four-point cane and wheeled cane. The first versions of the implemented algorithm took into account both the signals from the accelerometers and those from the gyroscopes. They were not based on machine learning techniques and were thus not adaptive.

Algorithm trials including orientation estimation algorithm were also implemented. Step by step, some of the possibilities of implementation were excluded to finally choose the proposed algorithm.

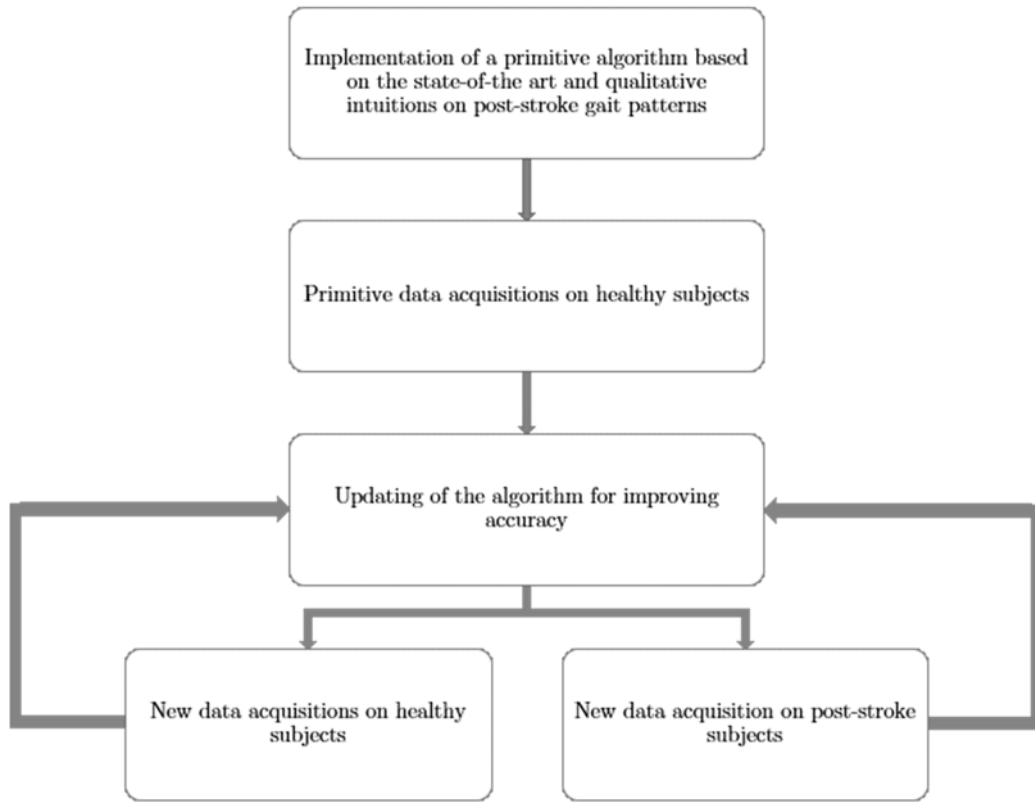


Figure 5.6: Algorithm optimization process

Once the choice of a particular way for the algorithm implementation was made, the parameters of the algorithm, namely the length of the window size (WS) and its increment (WI), the number of clusters performed by the K-means (k), the critical mean (CM), the penalty values for peaks belonging to group greater than 2 (PV), were optimized in an iterative process. The performed simulation and the optimization criterion are described in the next section. In the same way as for the algorithm implementation, the algorithm parameters were updated at each new data acquisition for optimizing the results.

5.2 Choice of the algorithm parameters

Overall method

At first, the choice of the algorithm parameters has also been made on the basis of subjective intuition about the post-stroke gait, and observations of the different signals obtained from measure on healthy subjects.

Next, as data became available, a part of each data set, namely a “training data set” was used to tune the algorithm parameters. The part that was not used for tuning the algorithm, namely the “test data set” was used in a second stage to test the algorithm performance in post-stroke subjects. The methodology associated with the measurement processing on post-stroke subject, as well as the results of the algorithm performance test, will be described in the Chapter 6 that considers in further details the clinical study performed in post-stroke subjects.

For the moment, let's just say that acceleration data were acquired by means of two IMUs positioned on the paretic and the non-paretic feet (on the forefoot) in eight post-stroke patients, that walked consecutively with both types of cane. There were therefore four sets of data per patient (one for each foot and one for each type of cane), except for one patient who didn't walk with the classic cane. Another patient walked only with wheeled walker, and not with four-point cane, but data carried out in this patient was also included in the training data. The design of the data collection and the segmentation of each data set in training and test data set is presented in Table 5.8. In total, 30 data sets were thus available for tuning the algorithm.

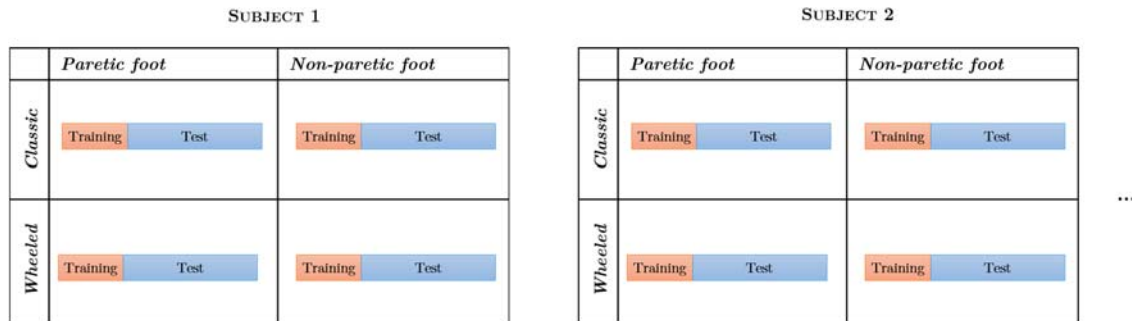


Figure 5.7: Measurements process design and dataset splitting

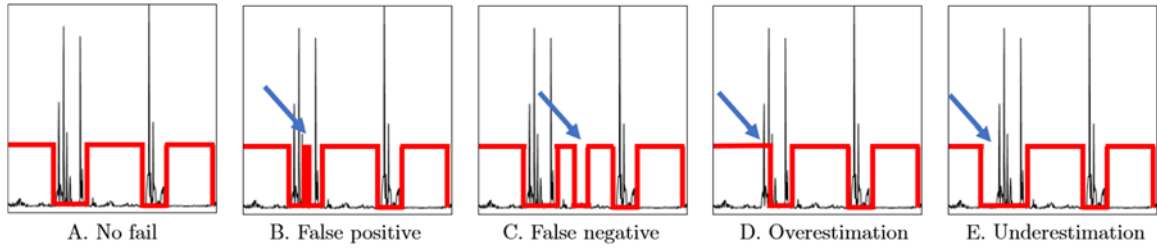
The optimization criterion that was used for quantifying the algorithm performance was based on the occurrence of algorithm fails. Before going any further, a clarification about the different types of potential fails of the algorithm is therefore required.

Potential fails of the algorithm

We can distinguish four types of errors that can result from fails of the algorithm. Throughout this Master thesis, they will be designated by the terms: “false positive” (FP), “false negative” (FN), “stance phase underestimation” (UE), and “stance phase overestimation” (OE). They are described and in Table 5.4 and illustrated in Figure 5.8.

Table 5.4: Type of algorithm fails

<i>Error types</i>	<i>Definition</i>
1. False positive (FP)	A stationary period is detected during a swing phase. The binary signal goes from zero to one while it should stay at zero
2. False negative (FN)	A swing phase is detected during a stance phase. The binary signal goes from one to zero while it should stay at 1.
3. Stance phase overestimation (OE)	The duration of the stance phase is overestimated. This is equivalent to underestimate the swing phase
4. Stance phase underestimation (UE)	The duration of the stance phase is underestimated. This is equivalent to overestimate the swing phase

**Figure 5.8: Example of algorithm fails**

It should be noted that the overestimation and the underestimation errors must be differentiated from bias due to the fact that the algorithm detects the stationary period instead of the real stance phase. Indeed, if this bias is step-to-step constant, it could be considered as a systematic bias and not as an error, as it was explained previously.

Optimization criterion of the algorithm performance

As the exact value of the stance phase and swing phase could not have been estimated in post-stroke subjects in the framework of this thesis (because measurements were carried out in out-laboratory conditions) the optimization criterion was based on the real number of performed steps by the patients.

For each training data set, the real number of steps performed by the subject during the time covered by the data training set was counted by observing the videos of the patient's feet. Let's denominate by $Step_{eff}$ the number of steps effectively performed by the patient. As the algorithm provides a binary signal of stationary and non-stationary phases, representative of the stance phase and swing phases, the number of steps detected by the algorithm, which will be referred to $Step_{count}$, is computed by counting the number of transitions from stationary to non-stationary phase. The optimization criterion was defined as the sum of the absolute value of the difference, for each patient and for each test, between the number of steps detected by the algorithm, and the number of steps that were really performed by the patient.

$$Optimization\ criterion = \sum_s^S \sum_t^T |Step_{eff} - Step_{count}|$$

with S , the number of patients and T the number of tests performed per patient

Therefore, the closer the optimization criterion is to zero, the better is the algorithm performance for effectively detecting steps. Of course, a perfect match of the number steps does not necessarily reflect the absence of FP or FN errors: the occurrences of a FP and a FN error in the same test lead also to a match between the $Step_{eff}$ and $Step_{count}$. However, such a situation is usually rare, because a same patient gait pattern will tend to generate only false positive or only false negative algorithm fails. In addition, a detailed observation of the signal and the video makes it possible to identify such a situation. Potential annulation of the error due to the occurrence of FP and FN in the same test was therefore checked by attentive observation of acceleration magnitude, stationary signal, and patient's feet videos.

It could be pointed out that such an optimization criterion is not fully objective, as it is based on a manual counting, but presents an acceptable way to process when considering out-laboratory conditions.

The number of steps that were already performed by the patients for each trial and for each foot, during the period covering by the training set, is presented in Table 5.5.

Table 5.5: Effective number of steps performed by each patient (training set)

	Classic cane		Wheeled cane	
	Affected	Non-affected	Affected	Non-affected
Patient 1	45	45	39	39
Patient 2	20	20	27	27
Patient 3	/	/	22	22
Patient 4	17	16	20	21
Patient 5	16	16	13	13
Patient 6	28	28	32	31
Patient 7	26	25	32	31
Patient 8	42	43	52	52
<i>Total number of steps: 746</i>				

Algorithm optimization process

Each of the 30 training data sets was submitted to the algorithm to be decomposed in a series of stationary and non-stationary phases. The number of steps detected by the algorithm was evaluated on the basis of the transition stationary/non-stationary in the binary signal and compared to the effective number of steps performed by the patients (Table 5.5). This process was performed a very large number of times, by changing one by one the value of the algorithm parameters. As the effect of each change in a parameter on the result is not independent of the values of the other parameters, it was necessary to evaluate the results of each *combination* of parameter values. The ranges of the tested values are represented in vector form in Table 5.6.

Table 5.6: Range of values tested for each algorithm parameter

<i>Parameter</i>	<i>Range of tested values</i>	<i>Optimal value</i>
Number of clusters partitioned by the K-means algorithm	$k = [7 \ 8 \ 9 \ 10]$	$k = 9$
Cluster number from which a penalty value is assigned	$k_{sw} = [2 \ 3 \ 4]$	$k_{sw} = 2$
Sliding window width factor	$WS_f = ([10 : 40] / 100)$	$WS_f = 0.33$
Sliding window increment factor	$WI_f = [5 : 25] / 100$	$WI_f = 0.11$
Critical mean	$CM = [1 : 3] / 10$	$CM = 0.2$
Number of window	$CN = [1 : 3]$	$CN = 2$

In total, a number of 140616 simulations, with different combinations of parameters, were performed on the training data set. For each simulation, the optimization criterion $Step_{eff} - Step_{count}$ was computed and compared with the one obtained by the other simulations in order to identify the best combination of algorithm parameters. The parameters resulting from this optimization process are also presented in Table 5.6.

5.3 Estimation of the algorithm performance in post-stroke subjects

Now that we have obtained the final algorithm with the combinations of parameters that seems to be the best performing, we can test the algorithm by means of the test data set that was not used for tuning the algorithm. If we compile all data set (from each patient, for each foot and cane type), 2775 steps were performed in total. For each data set, the difference between $Step_{count}$ and $Step_{eff}$, relative to the $Step_{eff}$ are presented in Table 5.7.

Table 5.7: Algorithm fail in step detection

	Classic cane		Wheeled cane	
	Affected	Non-affected	Affected	Non-affected
Patient 1	0 / 145	2/145	1/135	4/134
Patient 2	-1/135	1/136	-1/147	1/147
Patient 3	/	/	-10/74	-1/64
Patient 4	-1/54	0/54	0/35	1/34
Patient 5	1/40	0/36	2/53	2/55
Patient 6	-5/75	0/77	-6/54	0/56
Patient 7	0/133	2/135	1/151	0/152
Patient 8	0/65	0/67	0/30	0/31
Total number of $Step_{eff}$: 2775, optimization criterion: 43, fail rate: $43/746 = 1.55\%$				

Positive and negative value of difference are therefore representative of the occurrence of one or more false positive and false negative type errors, respectively. As we can see, when the algorithm is applied on the training dataset with the optimized combination provided by the simulations, some fails persist for the step detections in three patients. The difference, in absolute value, smaller than 2 can be neglected because they were usually corresponding to a step performed by the patient at the beginning or the end of the trial that was not manually counted

We can see that the step detection in patient 3 (paretic foot) showed very bad performance. Actually, the patient 3 presented a gait pattern highly particular: he walked with a very small velocity (mean velocity of 0.084 m/s which is twice smaller than the mean of others patients), and each of the swing phases was characterized by a stop of the foot, approximately 3 cm above the ground level, before the heel strike. Figure 5.9 illustrates the fails of the algorithm for step detection in the signal obtained from the paretic foot of this patient. The performance for the step detection for the non-paretic foot was solid.

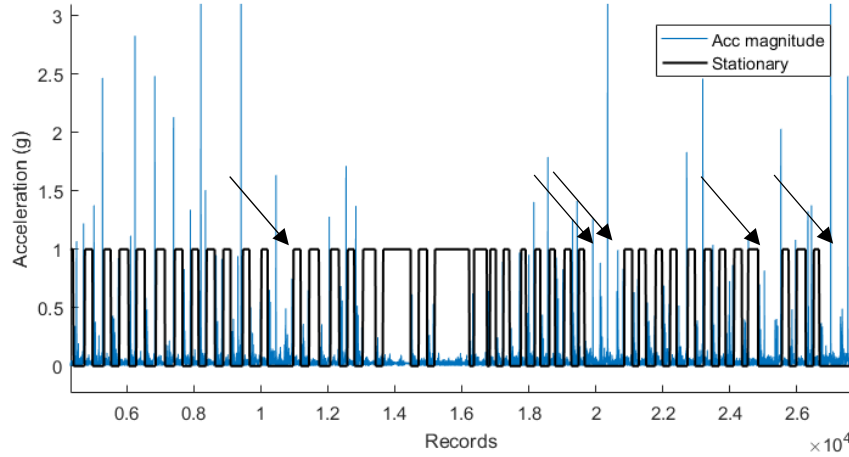


Figure 5.9: Fails of step detection in acceleration signal from patient 3 (Paretic foot)

False negatives are represented by an arrow. Larger between the record 1.4 and 1.6×10^4 represent phases during which the patient stopped walking.

The fails in the step detection performed by the algorithm could be explained by the fact that, in this case, the chose function for expressing the window size according to the step frequency is no longer suitable. Indeed, as it was mentioned before, the window size for the sliding window algorithm is a function of the step frequency (which is usually related to the step frequency). Here, the step frequency was 0.2 steps per second, which leads to a window size of 187 records (or 0.69 seconds). In other words, all phase durations smaller than 0.69 seconds were not detected by the algorithm, which explains the presence of false negative in the binary signal.

False negative also occurred in an important number for the signal provided by the IMU positioned on the paretic foot of the patient 6 (-5 and -6 step detection, for the classic and the wheeled cane, respectively). Those fails could be explained by the fact that the patient was presented an important spastic equinus deformity of the foot, which led to a greater instability of the paretic foot during the paretic stance phase. This instability was reflected in the signal provided by the IMU as parasite motion during the stance phase, resulting in a failure of the algorithm.

Such occurrence of false negative could be managed by decreasing the window size for the concerned patients, but the price is an increased risk of false positive occurrence.

However, when considering the results for all patients combined, the global fail rate of the algorithm is only 1.55% (43 fails on 2775 steps effectively performed). We can therefore conclude that, regarding the errors of FP and FN types, the implemented method and algorithm are performant as they provide a very small error rate.

Both methods used for assessing algorithm performance

At this stage, it may be necessary to distinguish and overview the two different ways that were used for assessing the algorithm performance. They are schematized in Figure 5.10.

We just have seen that the performance of the optimized algorithm could be assessed in terms FP and FN errors, by counting the number of steps effectively performed. However, we

didn't check the algorithm performance in term of underestimation or overestimation types of error. Such a process corresponds to evaluate the validity of the measurement tool, i.e. its ability to measure correctly the quantity to be measured, by means of a validation study.

The availability of an already validated measurement tool, such as force platforms or marker-based motion capture system, is therefore required to estimate the effective value of the phase duration. In the framework of this Master thesis, it was not possible to bring post-stroke individuals to laboratory. However, measurements in laboratory condition were carried out on healthy subjects in order to have an estimate of the validity of the implemented tool. The next main section of the present chapter explains in details the method and the results of this validation process.

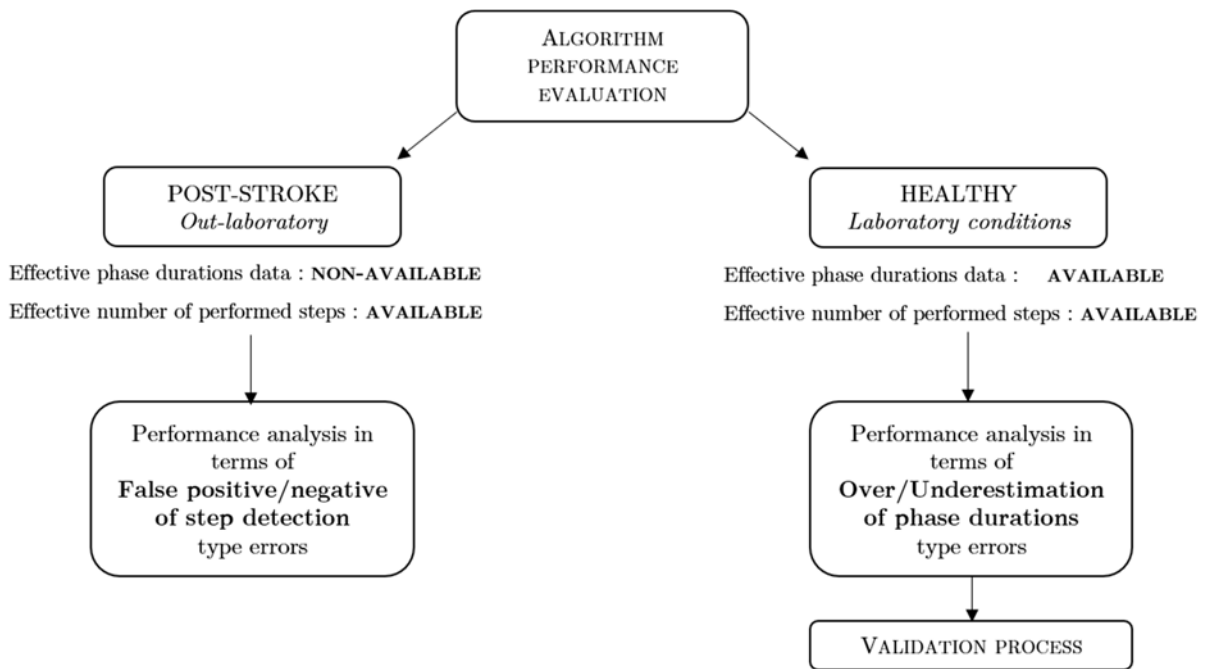


Figure 5.10: Two ways for algorithm performance analysis

5.4 Validation of the measurement technique

The process of validation of the implemented measurement technique consisted in a comparison of the results obtained IMUs combined to the implemented algorithm, to those provided by force platforms (FP), that are the one of the gold-standard in gait parameters assessing. This is therefore a way to quantify potential errors of overestimation and underestimation of the parameters.

5.4.1 Material

A set of 12 strain gauge-based force platforms (Arsalis) of 1 x 1 meter were used to record the ground reaction forces at 1000 Hz. The platforms were arranged in a 2×6 grid as in Figure 5.11. The force platforms acquisition duration was limiting at a maximal time of 16 seconds, due to software constraints.

1	2	3	4	5	6
7	8	9	10	11	12

Figure 5.11: Platforms configuration

Two X-IMUs (X-IO Technologies) were used to acquire the acceleration signal, at a sample frequency of 128 Hz.

5.4.2 Method

Task to be performed by the subjects

A set of videos showing 9 different patients walking with a four-point cane and wheeled cane, provided by Geoffroy Dellicour, were analyzed to identify precisely some gait pattern and foot positioning during the patient's walk. From those nine videos, five main pathological gait characteristics were distinguished:

1. Foot elevator muscles deficiency (foot drop)
2. External foot rotation
3. Steppage
4. Swing-out gait
5. Stiff gait

Measurements were processed on two healthy subjects (one male, 23 years old, and one female, 25 years old). For each trial, they were asked to observe attentively the video showing patient with a specific pathological gait characteristic, and then to imitate as much detail as possible the pathological gait pattern. In addition, they were asked to walk one foot on each side of the line separating the force platforms number 1 to 6 from force platforms number 7 to

12, like represented in Figure 5.12. Four series of walking with a normal gait pattern were also performed.

Obviously, a method based on the imitation of pathological gait instead of direct measure on pathological subjects cannot be considered as scientifically valid in the framework of a clinical trial. However, in the absence of quantitative validated measure in post-stroke subjects, it seemed to be a convenient strategy for providing a first-order approximation of the measurement technique validity.



Figure 5.12: Example of a measurements processing on force platforms

Subjects were asked to imitate a pathological gait pattern and to walk with one foot on each side of the middle line. The length of the force platform row allows approximately 3 to 5 consecutive steps per trial, depending on the imitated post-stroke gait pattern.

Data acquisition for each test

The data acquisition for each test was performed as follows:

- T_0 : the subject is standing on the ground; with right and left foot in front of the FP 7 and 1, respectively
- T_1 : the data recording is triggered both for IMU and FP
- T_2 : the subject starts to walk and performs 3 to 5 consecutive steps
- T_3 : at the end of the force platform, the subject stops walking
- T_4 : the data recording is stopped both for IMU and FP

Another test was then repeated, by imitating another type of post-stroke gait pattern.

Data processing

Walking with feet on each middle line presents the key advantage of a very easy and precise identification of the heel strike and toe off on the vertical ground reaction force (GRF) signals provided by force platforms. Indeed, the GRF signal is null during the swing phase. As soon as the heel strikes the ground, a net and rapid increase of the vertical GRF is observed, reaching a value greater than that of the subject's weight. A threshold of 0.05% of the vertical GRF relative to the body weight was defined as the beginning of the stance phase (namely the HS event). This detection method is illustrated in Figure 5.13.

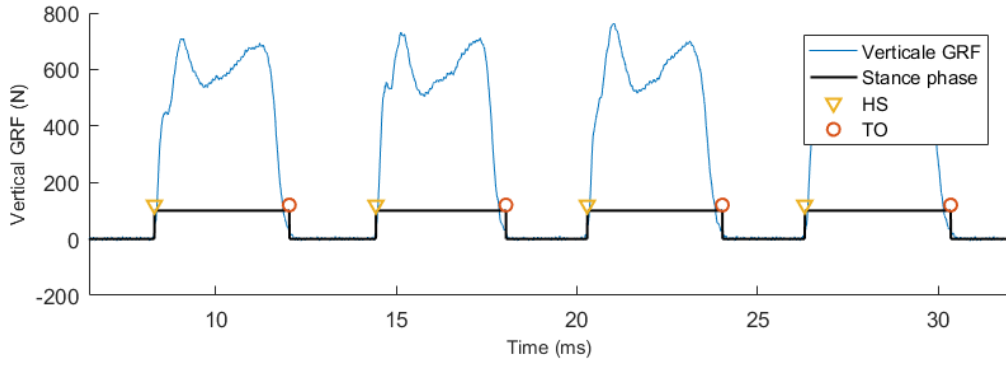


Figure 5.13: HO and TO detection method for the vertical GRF signal

Regarding the data resulting from IMU, the gait cycle segmentation was performed by using the measurement technique and the implemented gait cycle segmentation algorithm described in section 5.1.2, with the parameters listed in Table 5.6.

An example of results provided both by the IMU and force platforms is showed in Figure 5.14. For this test, the subject was imitating a post-stroke gait pattern in which the stance phase duration for the non-affected foot is larger than those for the affected foot, as it can clearly be seen. As a reminder, the gait cycle segmentation performed on the *GRF data* provides a binary signal representative of the *stance phase*, while the gait cycle segmentation of the *acceleration data* provides a binary signal representative of the *stationary phase*. Here, the binary signal for the stance phase was multiplied by a factor of 200 only for visibility reasons.

For each trial, the heel strike and the toe off were defined, respectively, as the start and the end of the stationary or stance phase. The durations of the stance of each step were computed by subtracting the time of the heel strike from the time of the toe off of the same step. The swing phase durations of each step were computed by subtracting the time of the toe off from the time of the heel strike of the next step.

Such a method avoids possible problems related to the difference in the trigger between the IMU data and the FP data. Indeed, the beginning of the data recording was manually initiated from two different computers for both measurement tools, which inevitably led to a time shift between the two measures, of a different value for each test. Therefore, comparing the absolute time of the occurrence of each gait events wasn't a good option. On the other hand, as the time shift between the two measures is constant over time, comparing the stance phase and swing phase durations is insensitive to this time shift.

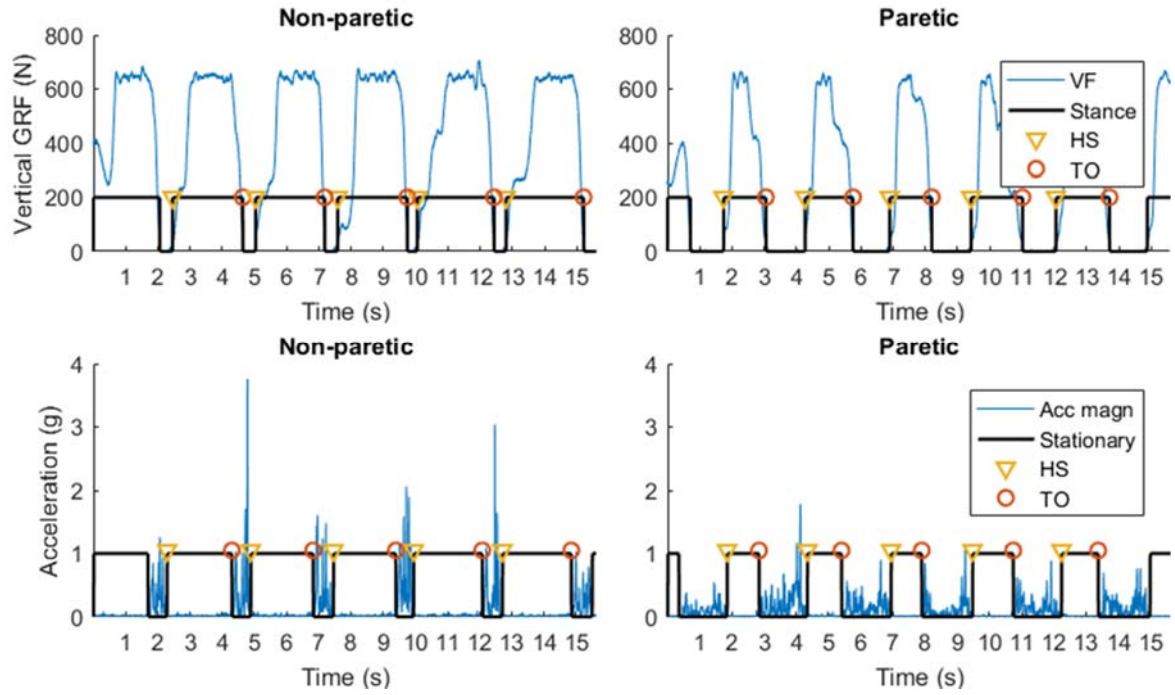


Figure 5.14: Example of gait cycle segmentation results

Upwards: vertical ground reaction force (VF) provided by the force platforms, and the binary signal of stance phase, for the *simulated* paretic and non-paretic foot. Below: acceleration magnitude provided by IMUs and binary signal of stationary phase resulting of the gait cycle segmentation algorithm. Left: simulated non-paretic foot, and right: simulated paretic foot. Subject's weight was 65 kg. The durations of the stance phase were computed as the difference between the TO and the HS of the same foot, the swing duration as the difference between the HS of the next step and the TO. The step durations were computed as the sum of the stance and swing phases.

Statistical analysis

In total, 236 steps, namely, 236 successions of stance-swing phases, were recorded. From those 236 steps, 6 were removed from the analyses, because they were corresponding phases that have not been fully measured by both measurement instruments (the first or last step of each trial, or step that were not performed correctly on both sides of the middle line). As the aim of this analysis was to evaluate the performance of the algorithm for the different walking pattern together, statistical analyses were carried out on all the data combined. Correlation analysis and Bland-Altman analysis, two complementary techniques that can be used to study the relationship between two quantitative values series, were achieved on all data set, by using Matlab version 2016a.

5.4.3 Results

The results of the linear regression and the Bland-Altman analysis are presented in Figure 5.15. These two techniques are complementary and designed to meet different objectives. The regression linear technique looks for the existence of a proportionality relationship between the two series of measures, while the Bland-Altman analysis studies the difference within two value pairs (Grenier, Dubreuil, & Journois, 2000). This last method is appropriated and widely used in the literature to assess the validity of a new measurement technique (here, the IMU +

algorithm measurement technique) against a Gold-Standard technique (here, the force platforms measurement technique) (Giavarina, 2015).

Correlation analysis

Squared Pearson's correlation coefficients show that there is a high correlation between the measures of temporal parameters given by the IMU techniques, and those given by the force platforms (PF) techniques (0.99, 0.99 and 0.94 for, respectively, step durations, stance phase durations, and swing durations, $p < 0.001$ for all tests). In other words, when the measures provided by the force platforms increase, those provided by the IMU measurement techniques also increases, which is always a good sign.

It can also be noted that the regression line of the stance and swing phase durations are vertically shifter of 0.24 seconds up and 0.26 seconds down, respectively. This shift is representative of the underestimation of the stance phase (which is equivalent of the overestimation of the swing phase) that was expected, as mentioned in section 5.1.4. Indeed, as a matter of fact, the vertical GRF provides a direct estimation of the stance phase, while the IMU algorithm segmentation provides an estimation of the stationary period, which is which is a priori shorter than the real stance phase.

Bland-Altman analysis

Correlation analysis showed an obvious linear relationship between the two series of measures but are not sufficient for assessing the “concordance” between the two measurement techniques. The principle of concordance analysis is to appreciate the difference between the two value measures for the same step (or stance phase, or swing phase), and to infer, for all the set of measures, the bias and the confidence interval limits at 95 %. The difference between pairs of values (PF measure – IMU measure) is shown on the y-axis and the mean of the pairs of values is represented on the x-axis.

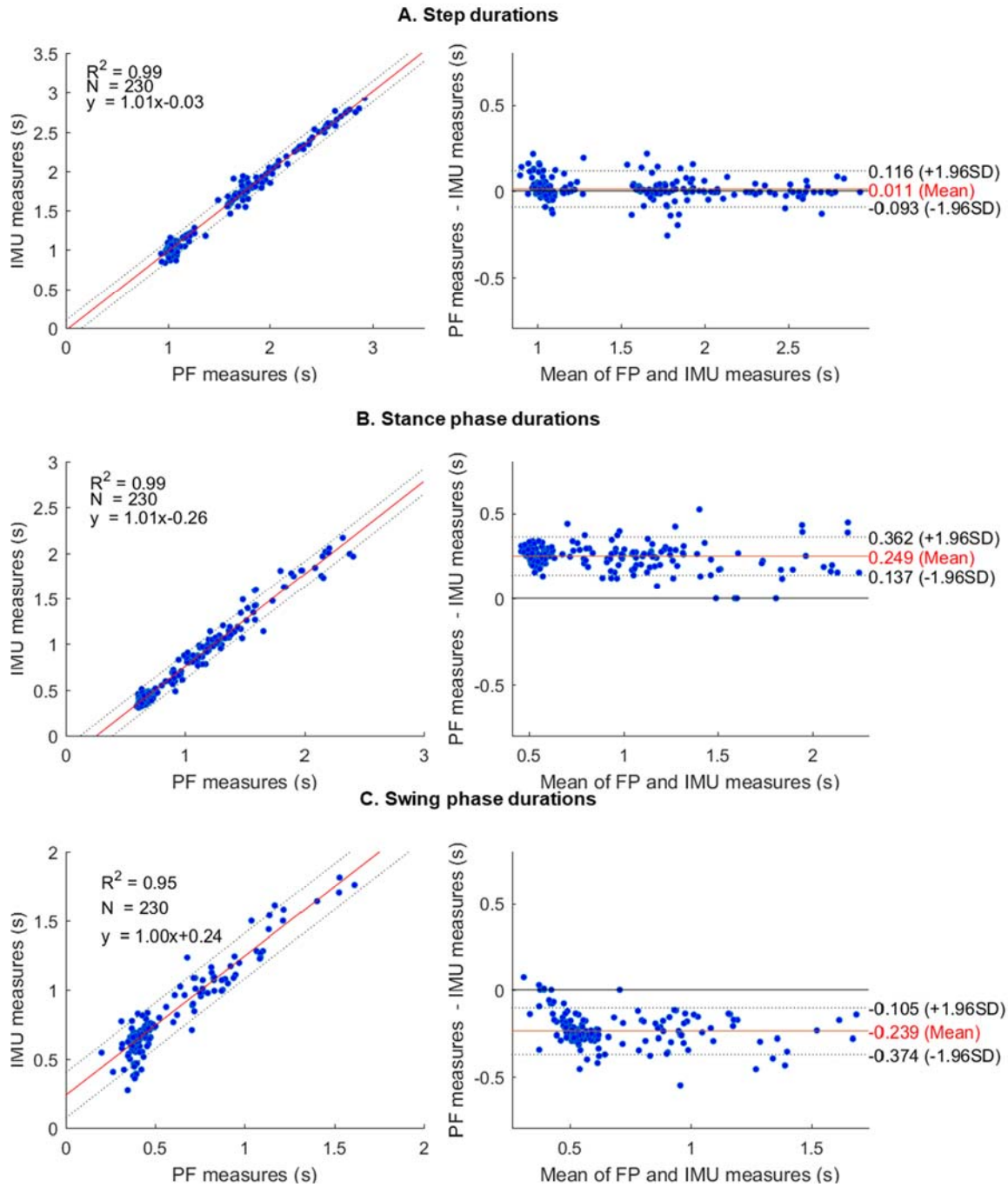


Figure 5.15: Correlation and Bland-Altman analysis

Left: correlation analysis between the force platforms (PF) measures, and the IMU measures. The fitted linear regression line is represented in red. Right: Bland-Altman analysis, with the difference between the platforms and the IMU-measures in the y-axis, and the mean of platforms and IMU measures in the y-axis. Mean difference is represented by the red line and corresponds to the shift due to the underestimation of stance phase duration when detecting IMU stationary phase. Dotted lines represent the upper and lower concordance limits.

A. Step duration measures. B. Stance phase durations measures. C. Swing phase durations

The bias (θ), showed in the red line on the figure, represents the mean of the systematic difference between the value measure pair. It is related to the already mentioned expected underestimation and overestimation of the stance phase and swing phase, respectively. As the

bias is mostly exactly the same, in absolute value, for both stance phase and swing phases (+0.249 and -0.249 seconds, respectively) it makes sense that the bias for the stride durations measures is mostly null (+0.011 seconds).

The variability of the difference between each pair of values allows assessing if the measurement series provide reproducible values. This variability is quantified by using the standard deviation. In Figure 5.15, the dot lines represent the limits of concordance calculated by $\bar{d} \pm 1.96$ SD. We can observe that, for the steps duration, 95% of the differences in measured values are comprised in an interval of 0.093 and 0.116 seconds. Regarding the stance phase and swing phase durations, the differences were comprised, respectively, between 0.137 and 0.362 seconds, and between -0.105 and -0.374 seconds. However, as the mean bias $\bar{d}$ is expected and known, it is more appropriated to look at the deviations from this bias. The same Bland-Altman analyses for stance phase and swing phase durations, after removing the systematic bias $\bar{d}$ are shown in Figure 5.16.

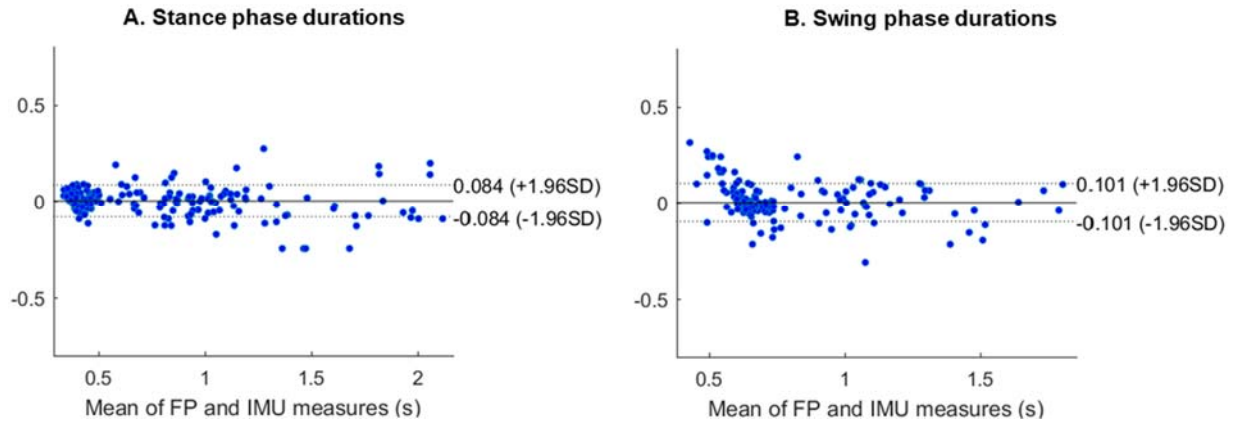


Figure 5.16: Bland-Altman analysis after removing the systematic bias δ

We can see that the 95 % of the difference of measure pair are included in -0.084 seconds to 0.084 seconds for the stance durations, and -0.101 seconds to 0.101 seconds for the swing phase durations. Obviously, narrower concordance boundaries are representative of higher concordance between the two measurements, but it is primarily the clinical context that allows estimating if those limits are acceptable. When considering pathological post-stroke gait, error in the order of one-tenth of a second could be considered as acceptable, given that mean step times are in the order of 1.3 seconds in patients who need a stick for walking (Polese et al., 2012). In addition, after reviewing the literature, a confidence interval of one-tenth of a second for measure the spatiotemporal parameters in post-stroke subjects seems to be a threshold acceptable (Yang et al., 2013).

5.5 Discussion

5.5.1 Discussion about the implemented algorithm

Note about the loss of information when performing gait cycle segmentation

As a first comment, it should be reminded that the gait cycle segmentation is used to divide the gait cycle in stance and swing phase, in a view of computing the spatiotemporal parameters. Therefore, some events such as parasite feet trembling, toes motions during a stance phase, or foot gripping on the ground during a swing phase, are filtered during the gait cycle segmentation to only retain in fine a binary signal representative of the IMU stationary phase (1) and swing phase (0). However, those parasite motions could also provide information about the pathological such as the lack of gait smoothness, the risk of fall, and other indicators. Nevertheless, as the aim of this Master thesis was to provide a way for quantifying the gait variability and symmetry of gait spatiotemporal parameters, we will limit the analysis of the segmented gait cycle. Further studies could be conducted on these parasite motions.

Other ways for the implementation of the gait cycle segmentation algorithm

Secondly, the algorithm that was proposed for the gait cycle segmentation is based on a well-known machine learning technique, namely the K-means algorithm. This algorithm presents the major advantage of being self-adaptive: without being explicitly programmed, the algorithm learns from the data and provides a partition into different groups with similar characteristics. This partition allowed to discriminate the signal fluctuations corresponding to noise or parasite motions during a phase that is supposed to be stationary from that corresponding to real swing phases. A sliding window was then used to detect the stationary period.

This algorithm is only one proposed solution among a wide range of other possibilities. I described in Chapter 4 different algorithm implementation ways that were, in my opinion, unoptimized for post-stroke gait pattern, for the reasons that were highlighted. However, other types of algorithms are worth investigating for post-stroke gait analysis purposes. For instance, an algorithm based on Wavelet transform could also be a way of identifying the HS and TO event. The method proposed by Khandelwal and Wickström (Khandelwal & Wickström, 2016), based on Wavelet transform, has been roughly investigated and tested with post-stroke data and did not provide convincing results being applied as it is. However, it might be interesting to adapt, in further investigation, the Khandelwal and Wickström's method in order to optimize it for signals acquired in post-stroke subjects.

Why do not use an algorithm already validated in healthy gait for the non-affected side?

Another important consideration to be made about the algorithm is its non-specificity to the side (paretic or non-paretic) that is considered. The gait cycle segmentation method is indeed exactly the same for both sides. One could also ask the question: given that they are already existing validated and robust algorithms for gait cycle segmentation in healthy gait,

why not use such an algorithm for the non-affected foot and create a novel one for the paretic foot? I decided not to choose such a solution for two main reasons.

Firstly, even if the hemiplegia usually affects only half of the body, the non-affected side of the body doesn't necessarily follow a healthy gait pattern. For example, as it was explained in section 2.2.2, the post-stroke subject presents generally a fear and difficulties of bearing on the affected side. Therefore, as soon as the healthy foot leaves the ground, the subject will tend to redeposit as quickly as possible its non-affected foot on the ground to bears again on both limbs. The pattern of the healthy limb thus differs from a normal one.

The second reason I decided to perform the same method and algorithm for both the normal and the paretic foot lies in the fact that “implementing an algorithm optimized in post-stroke subjects” does not mean “implementing an algorithm that will only perform in post-stroke subjects”. Indeed, we have seen that there is a wide range of gait pattern that can be observed in post-stroke subjects. Even if this situation is rather rare in patients who need a cane for walking, it may happen that the patient’s gait pattern will be relatively close to a normal one. It must be borne in mind that the boundary between pathological and normal is not always very defined. It decided to not differentiate the algorithm for the affected and the non-affected side but to implement a measurement technique that could be performant for both normal and hemiplegic gait.

Quality criteria and requirements verification

In Chapter 3 about the existing gait parameters measurement tools, we have drawn up the list of quality criteria of such tools. We have also established, at the beginning of Chapter 5, the specifications and requirements that an IMU-based gait parameter measurement tool should meet. We will now check if those quality criteria and requirement were fulfilled (Table 5.8 and Table 5.8).

Table 5.8: Verification of the respect of the quality criteria

<i>Quality criteria (Table 3.1)</i>	<i>Verification</i>
1. Accurate	☒ CI of + 0.1 s and - 0.1 s In healthy subjects
2. Reproducible	☐ Not verified
3. Appropriately validated	☐ Pre-validated in healthy subjects
4. Capable of distinguishing between normal and abnormal gait	☒ Verified
5. Must not alter the function it is measuring	☒ A priori verified
6. Reported in a form analogous to accepted clinical concepts	☒ Phase durations
7. Cost-effective	☒ 2 × £249.00
8. Provide measures not observable by the skilled clinician	☒ Phase durations

The accuracy of the measurement technique was evaluated, in normal subjects, at two-tenths of a second (CI of +0.1 and -0.1 seconds). We have seen that such a value appears to

be acceptable when considering pathological hemiplegic gait. A more in-depth validation study is required before concluding about the validity of the implemented tool.

The capability of distinguishing between normal and abnormal gait was also assessed and was proven to be efficient.

Quality criteria number 5, namely the non-alteration of the measured function by the tool, could not be verified quantitatively. However, from my observations of the subject gait with the IMUs fixed on the forefoot, and on the feeling reported by the subjects, it seemed that the IMUs did not disturb the walk at all.

The quality criteria number 6 and 8 are also verified, as the measures reported, namely the phases durations, could be used for providing accepted clinical concepts such as symmetry ratio and gait variability, and their exact value cannot be quantitatively observable by the clinician.

Table 5.9: Measurement tool requirements verification

<i>Requirements and specification (Table 5.1)</i>	<i>Verification</i>
<i>Related to the measurement technique</i>	
1. Wearable and feasible in non-laboratory environments	☒ Two IMU and one computer required In terms of FP and FN
2. Efficient for post-stroke gait pattern	☒ errors, and efficient in imitated gait pattern
3. Easy and stable IMU positioning	☒ Only one rubber and two pieces of tape
<i>Related to the gait cycle segmentation algorithm</i>	
4. Capable of managing of misalignment errors	☒ Acceleration magnitude signal
5. Adaptive algorithm (not based on thresholds)	☐ Discutable
6. Unsupervised algorithm (unknown mapping function)	☒

Regarding the requirements and specifications of the measurement tool that were listed in Table 5.1, we can say that they are practically all filled.

Obviously, the tool is wearable and easily operable in non-laboratory conditions, as it requires only two x-IMUs and one computer for data acquisition. In addition, the use of a computer could be avoided since sensor data can be stored on an SD card.

With regard to the chosen IMU positioning proved, it proved to be particularly quick and easy to set up, and did not require adjustments during testing.

As mentioned before, the efficiency in post-stroke gait pattern should be measured using a rigorous validation study. However, it was assessed with the limited means available, namely by comparing the number of steps detected by the tool and the one effectively performed by patients. The number of fails in step detection was relatively weak (1.55 % of fail rate).

Regarding the requirement related to the gait cycle segmentation algorithm, the capacity of managing the misalignment errors is undeniable as the algorithm is based on magnitude

acceleration signal. The verification of the adaptive character is more debatable. Indeed, the algorithm is in a way adaptative thanks to the partition of the signal by the K-means process, that adapts the gait partition according to information available in each signal, without being preprogrammed with labeled information. However, the other steps of the algorithm are based on threshold, namely the chosen sliding window size and sliding window increment. Those parameters are nevertheless not absolute, since they are expressed in a function of the effective gait mean velocity, which provides adaptability to the algorithm.

The unsupervised requirement is fulfilled. In other words, we might consider that the optimization process of the algorithm has been correctly performed, with a sufficient number of training set and different gait pattern. The optimized algorithm could be therefore applied on new datasets, measured in new patients, that were not included in the training datasets.

5.5.2 Discussion about the validation study

A first point to be discussed about the validation procedure is the fact that the data were collected on healthy subjects, and not on post-stroke subjects. The subjects were asked to walk “like post-stroke subject”, on the basis on video showing G. Dellicour’s patients walking with cane, but such a methodology is not sufficient to form conclusions about the validity of the implemented measurement tools in post-stroke subjects. However, the algorithm performance was evaluated in term of its capacity to detect correctly each transition from stance to swing phase.

The ideal methodology to perform a validation in a proper and scientific way would be to carry out the same type of analyses, namely a comparison of the results provided by the algorithm to those provided by a Gold-Standard, but directly on post-stroke subjects walking with a cane. This type of analysis could be the issues of further investigations.

Finally, the fact that the subjects were asked to walk with both feet on each side of a line in the gait axis of progression could also represent a disputable point. Indeed, the subject’s is forced to walk in a way that is not his natural walking, which could lead to a bias of measurement. However, in the present validation process, the subjects were already asked to imitate post-stroke gait pattern, and not to walk in a spontaneous way, so the question about potential bias of measurement is not applicable here.

5.6 Summary

1. Perform a gait cycle segmentation on the basis of IMU data carried in post-stroke subjects whose walking is so impaired that they need a gait assistance for traveling represents a challenging work, due to the inability to exploit the gyroscope data and the high inter and intraindividual variability in the acceleration signal.
2. An algorithm based on machine learning techniques was implemented and showed satisfactory outcomes, in the sense that it correctly detects the heel strike and the toe off. An optimization of the algorithm parameters was performed by applying the algorithm on 30 training sets in order to identify the most suitable combination of parameters.
3. Correlation analysis and Bland-Altman analysis revealed that the implemented algorithm present a constant bias of + 0.2 seconds and -0.2 seconds for the evaluation of the stance and swing phases, respectively. This bias was expected. If the bias is removed from measures, the confidence intervals are in the order of one tenth of a second, which seems acceptable when considering post-stroke patients.

Chapter 6

Application of the algorithm for measuring the effect of the classic cane and the Wheeleo © on the temporal parameters in post-stroke subjects

In the first Chapter of this Master thesis, we have seen that the use of the Wheeleo © cane, a new four-wheeled cane designed by Geoffroy Dellicour, improves walking quality among post-stroke patients. This improvement has been measured through qualitative observations, as well as by a measurement of the global gait parameters, such as the average velocity. However, Geoffroy Dellicour was interested in an objective and quantitative analysis of the improvement in terms of gait stability and symmetry provided by the use of the Wheeleo © cane. In the literature, the quantification of the gait stability and symmetry usually involves indicators based on spatiotemporal gait parameters, namely the temporal or spatial symmetry indicators, and the variability estimators.

In addition, we have reviewed the design of a new measurement technique and gait cycle segmentation algorithm, as well as performed an initial validation of the technique on healthy subjects. This algorithm provides direct estimation of temporal parameters.

The current issue is then: can the results of the implemented algorithm be used to answer a biomedical question such the effect of the Wheeleo © on the gait parameters, and more precisely, on gait parameters variability and symmetry ratios? And if it is, what are those effects compared to those of the classic cane?

6.1 Material and method

Subjects

Data acquisition was performed on post-stroke subjects staying at the William Lennox Neurological Rehabilitation Center, during their daily physiotherapy session. Inclusion criteria were (1) stroke (hemorrhagic or ischemic), (2) need a four-point cane for walking, (2) capability of walking with a four-point cane without the assistance of the physiotherapist, or if necessary, with a slight physiotherapist's support for safety reasons. Exclusion criterion was the presence of significant cognitive disorder that may prevent the proper understanding of the research instructions. In total, six post-stroke subjects entered the criteria and agreed to participate in the study. Descriptive characteristics are presented in Table 6.1.

Table 6.1 : Subjects characteristics

Patient	Age (years)	Sexe	Time elapsed since stroke (days)	Type of stroke	Affected side
A	46	M	204	Hemorrhagic	Right
B	69	M	272	Hemorrhagic hypothalamic	Right
C	55	F	184	Hemorrhagic temporal	Left
D	74	F	99	Hemorrhagic Sylvian	Right
E	77	F	82	Ischemic Sylvian	Right
F	70	M	173	Hemorrhagic	Left
G	64	M	129	Ischemic	Left

Task

Data acquisition was processed during the patient's daily physiotherapist session. One session lasts exactly 30 minutes. Ten minutes before the start of the physiotherapy session, the testing procedure was explained to the patients, and IMU were positioned on the patient's feet like in Figure 5.1. Next, the patient was asked to walk the same as he would have done during a conventional session, with the four-points cane and the Wheeleo© cane, consecutively. The order of canes was randomly assigned. To avoid any effect related to fatigue, the distance to travel was dependent on the patient's capacities. The task was performed in a 30 meters long corridor of the establishment. The length of the corridors was graduated by means of marks on the floor, every three meters, so that the distance travelled by the patient can be assessed.

Material

Two X-IMUs were used to collect three-dimensional acceleration data. A classic four-point cane and the prototype of the Wheeleo © cane (Figure 1.2) were used for the tests. IMUs were firmly fixed on the forefoot, by using wide elastics. Pieces of tapes have also been stuck over the IMUs to avoid potential anteroposterior sliding. On the side of the paretic foot, which may rub on the ground during the swing phase, as large piece of tape was stuck over the elastic from preventing it to roll. The positioning was already showed in Figure 5.1.

Data acquisition

Data were acquired directly on a computer via a Bluetooth connection, at a frequency of 128 Hz. During the task, the patient's feet were filmed using a video camera. The computer and video camera system that were used to maintain an optimal distance between the IMU and the computer, and to track the patient's feet with a fluid sliding, are shown in Figure 6.1.



Figure 6.1: IMU and patient's feet camera tracking system

Data processing and temporal parameter computation

Data were processed by using Matlab version 2016a. The acceleration magnitude was first calculated. Then, the gait cycle segmentation algorithm has been applied to magnitude data, in order to obtain a segmentation of the signal in stationary and non-stationary phases. The durations of stationary and non-stationary phases were computed for each step. The stance phase durations were estimated by adding, to the stationary phase durations, the value of the systematic bias of 0.239 seconds. Similarly, the swing phase durations were estimated by subtracting this systematic bias to the non-stationary phase durations. The double support stance phase was also computed for each step. The average gait velocity and frequency for each condition were estimated by using the data of traveled distances, step count, and trial duration. The average stride length was also estimated on the basis of those data. Before each trial, patients were asked for their preference in terms of cane type.

Effect of cane: statistical analysis

The effect of the Wheeleo ©, compared to that of the classic four-point cane, on the temporal parameters was measured by means of repeated measure Student test. Data from both limbs were included in the calculation. The normality of the data was beforehand checked by means of t Kolmogorov-Smirnov test. Temporal symmetry ratio that were presented in Table 2.1 (page 19) were computed for all condition, as well as the variability estimators presented in Table 2.2. An analysis of covariance (ANCOVA) was performed with the gait velocity as a covariate. All the analyses were carried out with Matlab version 2016a.

6.2 Results

The comparison of spatiotemporal means and their standard deviation are shown in Table 6.2. The gait velocity, the estimated stride length, and the relative swing phase duration were significantly increased ($p < 0.05$) when the Wheeleo © cane was used instead of the classic cane. Gait frequency do not show significant difference. The relative stance phase was significantly decreased with the use of a Wheeleo cane ($p < 0.001$), and the decrease in term of double support was significative at a threshold of 1 % ($p < 0.01$).

Table 6.2: Mean $\pm$ SD for the spatiotemporal parameters for each cane

Parameters	Classic cane	Wheeleo cane	P-value
Gait velocity (cm/s)	0.29 ± 0.07	0.40 ± 0.06	.009 **
Gait frequency (step/s)	0.48 ± 0.07	0.51 ± 0.8	.106
Stride Length (cm)	1.28 ± 0.31	1.65 ± 0.37	.002 **
Stance phase (% of the cycle)	0.64 ± 0.03	0.53 ± 0.03	<.001 ***
Swing phase (% of the cycle)	0.36 ± 0.03	0.47 ± 0.03	<.001 ***
Double support times (s)	0.25 ± 0.28	0.21 ± 0.37	.006 **

It should be noted that the value of stance phase, swing phase, and double support phases durations should not be considered in term of absolute value, but in term of difference between both type of cane. Indeed, in the event of the systematic bias computed at 0.239 seconds was not exactly suitable here, an underestimation or overestimation of the phase durations could occur. However, if we assume that, for a same patient, the systematic bias is the same depending on whether he walks with the wheeled or normal cane, it will then have no effect in terms of difference between both canes.

The analysis of the symmetry ratio is presented in Table 6.3. For the reader convenience, the definitions of those ratios that are presented in Table 2.1 are reminded in the same table. We have seen in Chapter 2 that the closer to one are the symmetry ratios, the more symmetrical is the gait. The results show that all ratios decreased slightly to get closer to one. However, this decrease was significant only for the paretic and non-paretic temporal swing-stance ratio ($p < 0.05$ and $p < 0.001$, respectively).

Table 6.3: Mean $\pm$ SD for the symmetry ratio for each cane

Ratio	Definition	Classic	Wheeleo	P-value
Temporal swing ratio	$R_{sw} = \frac{T_{sw}(P)}{T_{sw}(NP)}$	0.97 ± 0.31	0.96 ± 0.27	.236
Temporal stance ratio	$R_{st} = \frac{T_{st}(P)}{T_{st}(NP)}$	1.15 ± 0.36	1.13 ± 0.34	.053
Temporal swing-stance ratio				
Paretic	$SSR(P) = \frac{T_{st}(P)}{T_{sw}(P)}$	1.17 ± 0.48	1.10 ± 0.48	.012 *
Non-paretic	$SSR(NP) = \frac{T_{st}(NP)}{T_{sw}(NP)}$	1.36 ± 0.49	1.24 ± 0.49	<.001 ***
Overall temporal ratio	$OSR = \frac{SSR(P)}{SSR(NP)}$	1.04 ± 0.7	1.01 ± 0.65	.505

In the same way as that for the estimation of stance phase and swing phase duration, the value have to be considered in terms of their differences between both canes, due to the potential inadequacy of the computed systematic bias that were used for correcting the measures.

Ultimately, the results concerning the variability estimators are displayed in Table 6.4. For the effect comparing the classic cane use to the Wheeleo © cane, there wasn't any significant difference in the temporal parameters for all variability estimators. The gait velocity was a significant covariate for all SD and MAD of the stance phase and swing phase, but not for the coefficient of variation. In this ANCOVA model, there was no significant main effect of the cane on the temporal parameters.

Table 6.4: Variability estimators $\pm$ mean SD and P-value for the main effects of cane and velocity

	Cane		ANCOVA	
	Classic	Wheleo ©	Cane	Velocity
Stance time				
SD (cm)	19.00 $\pm$ 4.66	15.53 $\pm$ 4.10	.172	.001 *
MAD(cm)	15.95 $\pm$ 4.32	12.41 $\pm$ 3.59	.481	.001 *
CV(%)	13.26 $\pm$ 5.49	10.00 $\pm$ 3.57	.831	.352
Swing time				
SD (cm)	17.78 $\pm$ 2.46	14.41 $\pm$ 3.56	.481	.001 *
MAD(cm)	15.3 $\pm$ 3.21	12.17 $\pm$ 3.46	.221	<.001 *
CV(%)	10.13 $\pm$ 3.14	10.11 $\pm$ 2.8	.591	.43

6.3 Discussion

Spatiotemporal parameters

This study investigated the direct effect of the cane on spatiotemporal parameters, symmetry ratio and variability estimators. The response of the spatiotemporal parameters showed that patient walked significantly faster with the wheeled cane than with the classic four-point cane. In addition, the stance phase and the double stance phase duration presented a significant decrease, reflected in a corresponding significant increase of the swing phase. Clinically speaking, such changes in temporal parameters coincide with a better control challenge of the paretic limb, and an improvement in single-limb balance control (Yang et al., 2013).

The fact that the difference in gait frequency did not show significant results is not surprising. Indeed, the step frequency is equivalent of the product of the step velocity by the inverse of the length of each step, as follows:

$$\text{Step frequency (number of step/s)} = \text{velocity (m/s)} \times \frac{1 \text{ (step)}}{\text{Length (m)}}$$

Therefore, if the velocity and the length step increase together, as it was the case here, no effect are measured in term of gait frequency.

It is also worth noting that the systematic bias added and subtracted to stationary and non-stationary phases to estimate the real stance and swing phase was maybe not suitable for each patient included in this study. Indeed, the value of 0.239 seconds was computed through a comparison between the IMUs measure to the platforms measures, in non-pathological subject, and was used to estimate the stance phase and swing phase from the stationary and non-stationary phase, respectively. However, if this fixed value of bias does not correspond to the real difference between the stationary and stance phase, and the non-

stationary and swing phase, the phase durations will be overestimated or underestimated. It would appear that the stance phase is indeed underestimated here, it was estimated at 64% and 53 % of the gait cycle durations for, respectively, the classic and wheeled cane. Standard value of relative stance phase in normal gait is 60%, suggesting that the stance phase was underestimated.

However, the presence of such a bias, if it is constant step-to-step, and from one cane to another, will not impact the results, in term of mean comparison and variability estimators, which makes it unobtrusive for concluding about the spatiotemporal parameter results.

Symmetry ratio

Regarding the symmetry ratio, no significant difference was observed in term of temporal stance and swing ratio. On the other hand, the temporal swing-stance ratio were decreased for both feet with the use of the wheeled cane, to get closer to one. In other words, the wheeled cane provides a better balance between the paretic and non-paretic phases durations, compared to the classic four point-canes.

Variability estimators

The response in term of variability estimators of the use of the wheeled cane compared to classic cane did show any significant results. As the gait velocity is suspected to covariate with the variability estimators and to affect the relationship between those effect and the type of cane, an ANCOVA model was used with the gait velocity as covariate variable. This test permitted to evaluate the effect of the cane type on the variability estimators, after removing the gait velocity effect. The effect of the velocity on the MAD and the SD was significative. The effect of canes on variability estimators have remained not significant.

Two different sources could explain the non-significance of the results on the gait variability estimators. Either there is actually no cane effect, either there is actually an effect but it is not measured by the tool because of step-to-step errors generates by the algorithm. Further investigations, for example an in-depth validation of the measurement tool in post-stroke individuals, are required in order to assess the algorithm ability of providing accurate measures.

Study limitations

Varying impairment level

This study of the effect of both canes on spatiotemporal parameters is potentially limited by the fact that the individuals presented a varying impairment level. Indeed, the level of impaired ability could be an additional factor explaining the dependent variables and was not taken into account here. It might be interesting, in further study, assess the level of impairment by means of clinical score validated in stroke patients, such as the CMSA, the BBS, or the COVS scores (Arora, Oates, Lynd, & Musselman, 2018), and to treat them as covariates. On the other hand, a high varying level in patient gait impairment

has been, in my opinion, particularly beneficial for the algorithm optimization process that was described in section 5.1.5. In addition, the subject sample tested is likely representative of a large portion of the stroke patient population.

Another limitation that could be mentioned is the fact that, because of a low level of walking ability, some patient performed a poor number of steps for each cane. In the literature, a number of at least 100 consecutive steps per patient is recommended for analyzing spatiotemporal variability estimators (Yang et al., 2013). This referral was not fulfilled for the wheeled cane trial in three patients, which could be an additional explanation for the non-significance of the difference in variability estimators means.

Finally, it is also important to note that, for several reasons, the experimental conditions were not optimal for processing nice and proper data acquisitions. Indeed, measurement process had to be carried out during the interval of a physiotherapy session of thirteen minutes, which represents a rather short duration when taking into account the fact that a part of the session should be ideally dedicated to the daily rehabilitation treatment. In addition, the 30 meters long corridor in which the measurements were carried out was, at certain times of day, overly crowded. Given the limited time available for the measurement, we were not able to wait until an absolute passage clearance. Therefore, patients were sometimes forced to deviate slightly from their trajectory, which probably also impacted on the significance of the variability estimators.

6.4 Summary

1. A measurement process was carried out in eight post-stroke individuals, by using the tools that were developed in the framework of this thesis
2. Among those eight subjects, six walked with both the classic and the Wheeleo © canes. The collected measures allowed to evaluate the effect of both cane on the spatiotemporal parameters, on the gait symmetry, and on the variability estimators.
3. If we stipulate that the measurement technique and the algorithm are well-performing, the finding showed that the Wheeleo © provides a better walking quality in terms of spatiotemporal parameters and stance-swing symmetry ratio.
4. In addition, if we stipulate that the effect of the cane is real, we can conclude that the algorithm is sensitive to change.
5. The mean difference in stability estimators was not significant, but this may be due to the impact of external factors and constraints, such as the crowd in the hallway where the measurements were carried out. The effect of the cane on gait variability is therefore not excluded.

Chapter 7

General discussion and conclusion

The present Master thesis has been articulated around three broad focuses. Firstly, a novel gait segmentation algorithm, based on unsupervised clustering, was implemented. The main challenge for the design of this algorithm was to optimize and parametrize it in such a way that is effective in post-stroke subjects who need a cane for walking. In a second stage, this algorithm was validated by performing a comparison between the measure provided by the implemented algorithm, and those provided by force platforms, which are considered as a gold standard in gait event detection. Finally, the designed measurement tool was used to answer a biomedical question in the field of post-stroke rehabilitation, namely the effect of the new Wheeleo © cane in comparison to the traditional four-point cane.

At the end of Chapter 5 and 6, we already discussed about the implemented algorithm and the study of its validity, and about the study carried to measure the effect of cane in post-stroke subject. This final chapter will describe, in a synthetic way, the unifying idea of this project, placing emphasize on the achieved and on the prospects for the continuation of the work undertaken.

7.1 Main thread and overviews

The chapter 1 presented the worldwide and serious stroke disease. It was seen that post-stroke condition could lead to a wide range of sensorimotor and cognitive disorders, both of which are likely to impact the individual's gait quality.

In Chapter 2, the normal gait pattern as well as the specificities that are distinctive of the hemiplegic gait were extensively analyzed. We have seen that post-stroke gait is usually characterized by a slower gait pattern, with a reduced step of length, and an increase of the time spend leaning on the non-affected limb. The foot drop, stiff gait, swingout gait, and waddling gait are typically observed gait disturbances in hemiplegic individuals. It was also explained that the variability could be assessed for quantifying the gait fluidity and stability, by means of long-range autocorrelation analyses or simple application of the variability estimator.

This in-depth description of the post-stroke gait characteristics allowed us to better understand the challenges related to the development of measurements tools for detecting the gait events and computing the spatiotemporal parameters by means of IMUs. Some of type of existing algorithm were described in Chapter 4, and it was demonstrated that most of them are based on threshold or assumptions that are not suitable when considering post-stroke patient with level of impairment that is such that they need a cane for walking.

In view of these findings, a novel adaptive algorithm was implemented, optimized, and parametrized in a way that makes it suitable for detecting gait events and computing temporal parameters in post-stroke subjects, as presented in Chapter 5. The designed measurement technique presents some major advantages, such its facility to set up, its partially auto-adaptive character and its independence of the IMUs orientation.

The algorithm performance was evaluated in two different and complementary ways. First, the capacity of the algorithm of detecting the heel strike and toe off events was assessed among post-stroke individuals. Secondly, the validity of the measure provided was measured by means of a comparison with the measure provided by force platforms.

The algorithm showed reasonable performances, but further technical improvements could be planned in order to optimize and upgrade its precision. In addition, the implemented method was a proposition among a wide range of possibilities, and other methods are worth exploring for gait analysis in post-stroke subjects. The use of adapted Wavelet transform, for instance, could be another solution for identifying heel strike and toe off gait events.

In its current state, the algorithm does not provide information about the spatial parameters. The output is a binary signal representative of the stationary and non-stationary threshold, and stance and swing phase are calculated, respectively, by adding on the stationary phase durations and subtracting on the swing phase durations the value of the systematic bias computed during the validation process. The temporal parameters are then directly calculated as the difference between the HS and TO occurrence time. But the spatial parameters require additional steps before being computed. The use of an orientation

estimation filter could be a way for assessing the spatial parameters from the acceleration signal.

After evaluating its performance, the algorithm was applied in post-stroke individuals in order to observe the potential effect of the Wheeleo © in comparison to the classic cane. A significant difference was observed for spatiotemporal parameters and provided better results for the Wheeleo © cane. The swing-stance symmetry ratio was also better when patients walked with the wheeled cane. No significant effect in term of gait variability estimators, which are clinical indicators of the gait stability and fluidity, was observed. However, this potential non-significance may be explained by the fact that the measurements conditions were not optimal, and that some external factor may have impacted the variability measures. Further investigation, with a larger number of participants and better external conditions could be considered to assess the the variability estimator. In addition, study including long-range autocorrelation could also be a lead for assessing stability.

7.2 Conclusion

For concluding, we can say that the technique and algorithm designed in the framework of this thesis constitute a promising tool for gait spatiotemporal parameters decomposition, and open a wide range of leads in post-stroke gait analysis.

In parallel, new positive effects related to the use of the Wheeleo © cane were highlighted thanks to measures carried out through this project. This suggests, once again, that the Wheeleo constitutes a walking aid and a rehabilitation tool particularly suitable for post-stroke patients.

On a personal note, the work undertaken as part of this Master thesis constituted a in rewarding experience. Indeed, I have been asked to apply, and to learn from a series of engineering skills, including the discovery and the depth knowledge of a sensor, the design and test of a new measurement tool and the use of advanced techniques in signal processing. Furthermore, this thesis gave me the opportunity to combine engineering skills and the sensibility that I acquired during my previous study in physiotherapy. Working on a biomedical issue directly associated with patients' rehabilitation was for me a source of motivation which foster my work throughout this thesis.

Appendices

Appendix 1 Design of the clinical study comparing the effects of the classic four-points cane and the wheeled cane

Document obtained from Geoffroy Dellicour

1. Critères d'inclusion et d'exclusion

Critères d'inclusion

- Patient AVC nécessitant une canne multipode à la marche
- Marche autonome possible sur 10 m

Critères d'exclusion :

- Troubles cognitifs limitant la compréhension des consignes
- Besoin d'un soutien important pour la marche (présence de sécurité autorisée)

Nous visons l'inclusion de 100 patients répartis sur 2 sites (CHN William Lennox et CHU Dinant Godinne/UCL Namur)

2. Ligne du temps

Jour 1 : Familiarisation avec canne quadripode à roulettes. Réalisation du SIAS.

Jour 2 : Test de marche de 10 m et test de marche de 6 minutes (si possible) avec canne quadripode ou canne quadripode à roulettes.

Jour 3 : Test de marche de 10 m et test de marche de 6 minutes (si possible) avec canne quadripode à roulettes ou canne quadripode.

Le jour 2 et le jour 3 pourront être espacés de maximum une semaine. Un temps de repos de minimum 10 minutes sera respecté entre les tests de marche de 10m et le test de marche de 6 minutes

3. Randomisation

L'ordre de passage entre les aides techniques (canne quadripode ou quadripode à roulettes) est randomisé. La randomisation se fera « par paquets ».

Appendix 2 Gait tracking with X-IO : Matlab source code

```
% Gait tracking with X-IO
% Authors = X-IO technologies
% -----
% Select dataset (comment in/out)
filePath    =    'C:\Users\Mathilde\Desktop\Memoire\Gait-Tracking-With-x-IMU-
master\Gait Tracking With x-IMU_xio\Datasets\StraightLine';
startTime = 6;
stopTime = 26;

% -----
% Import data
samplePeriod = 1/256;
xIMUdata      =      xIMUdataClass(filePath,      'InertialMagneticSampleRate',
1/samplePeriod);
time = xIMUdata.CalInertialAndMagneticData.Time;
gyrX = xIMUdata.CalInertialAndMagneticData.Gyroscope.X;
gyrY = xIMUdata.CalInertialAndMagneticData.Gyroscope.Y;
gyrZ = xIMUdata.CalInertialAndMagneticData.Gyroscope.Z;
accX = xIMUdata.CalInertialAndMagneticData.Accelerometer.X;
accY = xIMUdata.CalInertialAndMagneticData.Accelerometer.Y;
accZ = xIMUdata.CalInertialAndMagneticData.Accelerometer.Z;
clear('xIMUdata');
% -----
indexSel = find(sign(time-startTime)+1, 1) : find(sign(time-stopTime)+1, 1);
time = time(indexSel);
gyrX = gyrX(indexSel, :);
gyrY = gyrY(indexSel, :);
gyrZ = gyrZ(indexSel, :);
accX = accX(indexSel, :);
accY = accY(indexSel, :);
accZ = accZ(indexSel, :);
% -----
% Detect stationary periods
% Compute accelerometer magnitude
acc_mag = sqrt(accX.*accX + accY.*accY + accZ.*accZ);
% HP filter accelerometer data
filtCutOff = 0.001;
[b, a] = butter(1, (2*filtCutOff)/(1/samplePeriod), 'high');
acc_magFilt = filtfilt(b, a, acc_mag);
% Compute absolute value
acc_magFilt = abs(acc_magFilt);
% LP filter accelerometer data
filtCutOff = 5;
[b, a] = butter(1, (2*filtCutOff)/(1/samplePeriod), 'low');
```

```

acc_magFilt = filtfilt(b, a, acc_magFilt);
% Threshold detection
stationary = acc_magFilt < 0.05;
% -----
% -----
% Compute orientation
quat = zeros(length(time), 4);
AHRSalgorithm = AHRS('SamplePeriod', 1/256, 'Kp', 1, 'KpInit', 1);
% Initial convergence
initPeriod = 2;
indexSel = 1 : find(sign(time-(time(1)+initPeriod))+1, 1);
for i = 1:2000
    AHRSalgorithm.UpdateIMU([0      0      0], [mean(accX(indexSel))
mean(accY(indexSel)) mean(accZ(indexSel))]);
end
% For all data
for t = 1:length(time)
    if(stationary(t))
        AHRSalgorithm.Kp = 0.5;
    else
        AHRSalgorithm.Kp = 0;
    end
    AHRSalgorithm.UpdateIMU(deg2rad([gyrX(t)  gyrY(t)  gyrZ(t)]), [accX(t)
accY(t) accZ(t)]);
    quat(t,:) = AHRSalgorithm.Quaternion;
end
% -----
% Compute translational accelerations
% Rotate body accelerations to Earth frame
acc = quaternRotate([accX accY accZ], quaternConj(quat));
% % Remove gravity from measurements
acc = acc - [zeros(length(time), 2) ones(length(time), 1)]; % unnecessary
due to velocity integral drift compensation
% Convert acceleration measurements to m/s/s
acc = acc * 9.81;
% -----
% Compute translational velocities
acc(:,3) = acc(:,3) - 9.81;
% Integrate acceleration to yield velocity
vel = zeros(size(acc));
for t = 2:length(vel)
    vel(t,:) = vel(t-1,:) + acc(t,:) * samplePeriod;
    if(stationary(t) == 1)
        vel(t,:) = [0 0 0]; % force zero velocity when foot stationary
    end
end
% Compute integral drift during non-stationary periods

```

```

velDrift = zeros(size(vel));
stationaryStart = find([0; diff(stationary)] == -1);
stationaryEnd = find([0; diff(stationary)] == 1);
for i = 1:numel(stationaryEnd)
    driftRate = vel(stationaryEnd(i)-1, :) / (stationaryEnd(i) -
stationaryStart(i));
    enum = 1:(stationaryEnd(i) - stationaryStart(i));
    drift = [enum'*driftRate(1) enum'*driftRate(2) enum'*driftRate(3)];
    velDrift(stationaryStart(i):stationaryEnd(i)-1, :) = drift;
end
% Remove integral drift
vel = vel - velDrift;
% Compute translational position
% Integrate velocity to yield position
pos = zeros(size(vel));
for t = 2:length(pos)
    pos(t,:) = pos(t-1,:) + vel(t,:) * samplePeriod; % integrate velocity
to yield position
end

```

Appendix 3 Gait cycle segmentation algorithm

```

function [ stationary ] = gait_segmentation( magn, vect_arg, step_vel, freq)
% Gait segmentation algorithm for post-stroke subjects
% INPUT : magn is a column vector containing the acceleration magnitude
%         vect_arg is the vector of algorithm paramters (nb_group,
%         group_swing, p_wv, CM, critical nb and penalty value
% OUTPUT : a binary signal with 1 corresponding to stationary phase and zero
% corresponding to non-stationary phase
% Author : Schinckus Mathilde

samplePeriod_c = 1/freq;

% Changed paramters
nb_group = vect_arg(1);
group_swing = vect_arg(2);
PWf = vect_arg(3);
window_width = round((1/step_vel)*freq*PWf) ;
PIf = vect_arg(4);
window_incr = round(PIf* window_width);
window_nb = round(window_width/ window_incr);
critical_mean = vect_arg(5);
critical_nb = vect_arg(6);
pr_pen = vect_arg(7);

penalty_value = pr_pen*max(magn);

```

```

[peaks, locs] = findpeaks(magn');

% K-means algorithm
minc = min(peaks);
maxc = max(peaks);
initialcenters = repmat(minc, nb_group, 1) + bsxfun(@times, (0:nb_group-1).',
(maxc - minc) ./ (nb_group-1));

[idx, centroid] = kmeans(peaks',nb_group, 'start', initialcenters);
[centroid_sorted, index] = sort(centroid);
idx = idx';

modified_mag = NaN(1,length(magn ));

for k = 1 : nb_group;
group{k} = locs(idx == index(k));
modified_mag (1,group{k}) = k;
end

% Attribute a penalty value
modified_mag (1, modified_mag (1, :) > group_swing )= penalty_value;
modified_mag (1, modified_mag (1, :) == 1 )= 0;

% Sliding window algorithm
stat_mat = zeros(window_nb + 2,length(magn ));
mean_mat = zeros(window_nb + 1,length(magn ));

for w = 0 : window_nb - 1;
    for j = 1+ w * window_incr : window_width : length(magn )- window_width -
w*window_incr ;
        mean_mat (w+1, j: j+window_width)= nanmean(modified_mag (1,j : j+
window_width));

        if mean_mat (w+1, j: j+window_width) < critical_mean;
            stat_mat (w+1, j: j+window_width) = 1;

        else stat_mat (w+1, j: j+window_width) = 0;
        end
    end
end

% Compute the stationary period

stat_mat (window_nb + 1, :) = sum(stat_mat (1:window_nb, :), 1);
stat_mat (window_nb + 2, :) = stat_mat (window_nb+1, :) > critical_nb;
stationary = stat_mat (window_nb + 2, :);

end

```


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