Functional Electrical Stimulation Ankle Orthotic

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Abstract

Every year, millions of people suffer from stroke, spinal cord injury, traumatic brain injury or other neurological or traumatic conditions that affect the peroneal nerve's motor pathway and lead to the weakness of the Tibialis Anterior (TA) and the incapacity to dorsiflex the foot during swing, a condition called Drop Foot (DF). One solution to mitigate the effects of DF is to use Functional Electrical Stimulation (FES) to stimulate the TA, promoting foot dorsiflexion and toe clearance during swing. Nowadays, some FES-based orthoses are available commercially but rely on an Open-loop architecture. Closed-loop systems have only been presented in the academia with a time resolution of one step. The goal of this thesis was to increase this time resolution to one third of the step to improve the adaptation capacity of the already existing controller. To do that the new controller follows a similar strategy than the one proposed by Seel et al. [1] of using the foot orientation to correct the stimulation profile, but uses a three-part division of the swing phase to scale and correct this profile, avoiding some instability issues that arise from variations in the gait pattern. The controller was implemented and tested in a neuromusculoskeletal model and achieved Root Mean Square Error values of less than 2° outperforming the previous one. Furthermore, the sensing strategies were tested with data from in vivo tests and proved to be accurate and precise.

Keywords: Drop Foot, Functional Electrical Stimulation, Ankle Orthosis, Closed-Loop Control, Gait Pathology

1. Introduction

Drop Foot (DF) (also called Foot Drop) is a gait pathology described by the medical community as the weakness or even paralysis of the dorsiflexor muscles (Tibialis Anterior, Extensor Hallucis Longus, Extensor Digitorum Longus) leading to an incapability of lifting the foot during the gait [2]. The most common cause of this disease is a lesion on the motor pathway from which the Common Peroneal Nerve is part of. This can happen due to Upper Motor Neurons (UMN) lesions, resultant of neurological conditions such as stroke, cerebral palsy, multiple sclerosis, traumatic brain injury or spinal cord injury [2]. Other traumatic experiences that compress the CPN (Lower Motor Neuron lesion), such as L5 radiculopathy, anterior horn cell disease, partial sciatic neuropathy, tibio-fibular fractures, or simply a long period of leg crossing, have also been reported as common causes for DF [3, 4]. Lesion in the dorsiflexor itself can also lead to the pathology [5].

The incapacity to dorsiflex leads to two main conditions called Toe-Drag and Slap-Foot. The former, resulting from the absence of the activation burst that starts slightly before the foot leave the ground, is described as the lack of toe clearance during swing phase leading to stumbling or even falling. The latter, happens due to the absence of a second burst that happens during first contact between the heel and the ground and lasts until a little after the foot is flat on the ground, might cause foot ulcers [2].

The inversion capability of the TA is also compromised leading to instabilities during Heel-Strike.

One common way patients find to compensate for Toe-Drag is to use increased hip or knee flexion developing a "steppage pattern" with a circumductive leg swing [6, 7].

To cope with, or even treat the condition, different approaches are available as the use of pharmacetics, surgery or the usage of some kind of orthotic device [5]. These devices can be mechanical Ankle-Foot Orthoses (AFO), neurostimulators as Functional Electrical Stimulation (FES) systems, or even Hybrid Orthoses that combine both of the previously mentioned solutions.

The most commonly used, is an AFO that constrains the movement of the foot during swing avoiding Toe-Drag [7]. These can be passive, designed to maintain the ankle at a neutral position during gait, or active where the magnitude of the
joint angle and the energetic dynamics by the means of a motor, pump or actuator [8]. These present some disadvantages related to the lack of mobility and comfort or the cosmetic burden they present [7].

When the lesion is in the UMN and the electrical excitability of the associated peripheral nerves is still intact, an alternative to the use of a classic AFO is the use of a FES-based orthosis. This technology was presented first in 1961 by Liberson and consists in applying an electrical charge to the Peroneal Nerve during swing, stimulating the dorsiflexors, promoting a proper dorsiflexion [9].

In some cases, as in cases of full paraplegia, FES-assisted patients need to use parallel bars, walkers or crutches for support. The usage of both FES and a lower limb orthotic brace can overcome this limitation and reduce the muscle fatigue induced by the high energy consumption [10]. This combination of FES and AFO is called an Hybrid Orthosis.

As the goal of this thesis is to develop a controller for a FES-based orthosis, these will be further introduced.

Unlike normal action potentials, FES induced potentials follow the principal of reverse recruitment where the larger fibers are recruited first and then the smaller ones. Adjusting the FES parameters (Amplitude, pulse width and frequency), will then change the recruited nerve fibers and hence the contraction force characteristics [11]. In cases of Drop Foot, the typical stimulation profile has a trapezoidal shape with symmetrical charges being applied (the positive amplitude is equal to the negative amplitude) in order to avoid electrochemical imbalances that could lead to tissue damage. The ramping helps to avoid sudden responses and, after the Heel-Strike, help with the controlled plantarflexion [2].

Nowadays several commercial devices using FES are available, but only with an open-loop architecture, similar to the one presented by Liberson in his work, where the stimulation profile is pre-tuned and doesn’t change during the usage. Some examples of these commercially available devices are the Ostock Dropped Foot Stimulator, Bioness Ness L300, Walkaide, or the partially implantable ActiGait or STIMuSTEP [2].

Closed-loop strategies, able to adapt, have been presented in the academia but this adaptation is done only on a step-to-step basis not being able to adapt to perturbations within the same step. These controllers use sensory feedback, not only to trigger the stimulation, but also to modulate certain parameters [2, 12].

One example of a closed-loop controller is the one developed by Thomas Seel and his team [1], and in which this thesis is based upon. Using the information of a 6D Inertial Measurement Unit (IMU) attached to the shoe and a double FES electrode setup, they developed an Iterative Learning Controller (ILC) for modulating the intensity of the FES applied to the patient. Integrating the information from the IMU to obtain the foot’s orientation and velocity, they developed a Finite State Machine that detects the gait phase in which the foot is at. Once swing is detected, the paretic foot’s pitch is stored and compared to a reference measurement in order to obtain the stride error. This error is then used to update a FES amplitude profile, through an ILC algorithm, that is applied in the next stride. Starting with a trapezoidal profile, they managed to converge within only two steps and achieve a FES profile that results in a physiological gait pattern. One advantage of this adaptive technique is the ability to compensate for muscle fatigue by increasing the intensity of the signal as it detects a decrease in the foot’s pitch profile.

As mentioned, this controller rely on the kinematic information of the foot and obtain it through IMU sensors. The problem with these sensors is that the information of the accelerometer, gyroscope and magnetometer can’t be used to determine position or orientation without any external measurement or assumption. This happens because every sensor is prone to errors, and the drift error on an Inertial Navigation System grows proportionally to the cube of the operation time [13].

Regarding Human Gait, and more precisely, the motion of the foot during gait, one can make the assumption that, during Stance, the foot is stationary. This, combined with the fact that the time distance between Stance phases is short, can be used to correct the estimation. This technique is called the Zero-Velocity Update (ZUPT) and is widely used in foot-mounted INS. There are “soft” and “hard” ZUPT. In “soft” ZUPT, the knowledge of a model for how position, attitude and velocity evolve with time, more precisely their errors evolve, together with the detection of zero-velocity periods, is used to correct the navigation solution and calibrate the navigation algorithm. “Hard” ZUPT are used for gait analysis where only the motion during individual strides is important and a ”hard” reset is enough to restart the estimator without compromising the data [13].

With all this in mind, this thesis proposes to develop a control strategy that is an extension of the one presented by Seel [1] and increases its time resolution by adapting the FES profile on a step-to-step basis, but also within the same step. The sensorial blocks of the controller have then to be tested with real data collected with a control board for a FES-based orthosis developed by André Couceiro [14] to evaluate whether or not it is fit for real life applica-
2. Controller Development

As mentioned, the developed controller was based on the one presented by Seel [1] and aimed to increase its time resolution. It’s development followed the subsequent steps:

- Development of a Gait Phase Detector (GPD) based on the information of the FSR;
- Development of an Orientation Estimator (OE) for the foot, shank and thigh;
- Integration of the shank and thigh orientation information to divide the swing phase in three sub-phases;
- Implementation of an inter-step FES adaptation controller based on the one already existing;
- Implementation of an intra-step FES adaptation strategy;
- Adaptation of the GPD and OE code to fit the orthosis.

The controller was implemented in Simulink and tested in a reflex-based neuromusculoskeletal model developed by Geyer [15]. This model allows for the replacement of the TA’s stimulus by an artificial one, simulating a DF patient with a FES-based orthosis. It has two important limitations: It takes a few strides for it to stabilize; It doesn’t take into account the weight acceptance preparation that happens in the human gait and is responsible for the avoidance of *Slap Foot*.

The OE and GPD were then tested using data from the orthosis. The device is equipped with 4 9DoF IMU and 5 Force Sensitive Resistors that are connected to a control board able to log the data at a maximum rate of 333Hz [14].

The current sections describe the methodology behind each of the development steps.

2.1. Gait Phase Detector

For the purpose of this controller, a Gait Phase Detector (GPD) was developed. The GPD can be seen as having two layers: an outer layer controlled by the FSR information divides each stride in four main phases - Foot Flat, Pre-Swing, Swing, and Loading Response - and an inner layer, controlled by the shank and thigh orientation, that further divides the swing phase in three different sub-phases. Its outer layer is implemented with a Finite State Machine architecture depicted in Fig. 1.

Like it was introduced, the outer layer uses the On/Off information of both the Heel and Toe FSR to segment the stride. This is done through the detection of the following four events:

- T1 - Heel-Rise - Heel FSR off, Toe FSR on;
- T2 - Toe-Off - Heel FSR off, Toe FSR off;
- T3 - Heel-Strike - Heel FSR on, Toe FSR off;
- T4 - Full-Contact - Heel FSR on, Toe FSR on;

In order to avoid false transitions, each event is only detected if the transition conditions remains true for a pre-determined number of samples. In the case of the Simulink simulation, run at a sample frequency of 250Hz, 5 samples were needed for a transition to be confirmed.

The inner layer was created based on the gait segmentation proposition of Meng [16]. In order to do the division, knee angle and shank pitch were estimated being the knee angle computed through the shank and thigh pitch as shown in Fig.2. With this information, it is possible to detect two transitions:

- TS1 - Knee angle reaches a minimum;
- TS2 - Shank pitch turns positive;

Within the scope of the GPD, there were two more situations that had to be addressed. Toe-Off had to be predicted so the stimulation could start a pre-defined time period before it happened allowing for good toe clearance. Although, the proposed controller wouldn’t be using it, Heel-Strike should also be predicted in order to cope with the lack of weight acceptance preparation already previously reported or to actively control the Controlled Plantarflexion for *in vivo* applications. Both of these predictions were made based on the same principle described in [1] for the Toe-Off prediction. Assuming each stride phase to have a relative constant duration, the onset of an event can be predicted based on the onset of the previous event and the duration of the corresponding phase in the last N strides. Some accommodations have to be done for the N-1 first strides. A generic methodology for the prediction of Toe-Off (is the same for Heel-Strike), is then the following:

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**Figure 1: GPD Finite State Machine.** T1 - T4 represent the events detected through the information of the FSR and TS1 and TS2 are orientation dependent events.
2.2. Orientation Estimation

The controller uses the foot pitch to correct the FES intensity profile and the GPD uses the shank and thigh pitch to change between sub-phases of swing. In order to assess the needed pitches, an Orientation Estimator (OE) was developed.

The estimator integrates the gyroscope information from an initial position assumed to be 0° for each segment so that the algorithm was not dependent on the sensor’s initial position. As the foot, thigh and shank pitch profile during gait have different characteristics, different correction strategies had to be used to cope with the usual drift that occurs during such integration.

For the foot, a simple "hard" ZUPT strategy was used. The gyroscope measures were integrated using a trapezoidal integration and set to zero when a zero-velocity period was detected. In this case the zero-velocity detector was the GPD that determined the foot to be stationary when foot flat was detected.

When working with both shank and thigh a problem arises as no stationary period can be detected during the stride can be detected. The alternative found was to use the maximum and minimum, respectively, found during swing and pre-swing to do the corrections.

In a walk on a flat surface without any major velocity changes, the mentioned features shouldn’t change much so they are assumed to be always the same. This being said, during the first few strides, the value of one of these peaks is recorded and saved as reference. During the next strides, when the respective peak is detected, its value is compared with the reference and, if the difference is smaller in modulus than a defined threshold, the difference is added to the current pitch and the drift is eliminated. The correction is “silent” during all the stride except for the instant in which the peak is detected.

Once all the corrections are made, the angle measurements are done like it is depicted in Fig.2.

2.3. Stimulation Adaptation

Once the GPD and the Orientation Estimator are implemented, one can now start developing the FES adaptation system. This system was developed in a two step fashion. Firstly, Seel’s work [1] was adapted and a controller able to adapt the FES intensity profile from stride to stride was implemented. Once the inter-step adaptation was done, an intra-step controller was developed that used the information of the elapsed portion of the step to correct possible errors that would occur in the remaining part.

2.3.1 Inter-Step Adaptation

The basic principle behind this controller is the following: Higher FES intensities result in higher dorsiflexion. With this in mind, the pitch can be recorded during one stride’s swing, compared with a reference recording and the FES profile of the next stride is corrected. This is done by increasing or decreasing the intensity of FES in areas where the recorded pitch is lower or higher that what it should’ve been respectively. It is considered an inter-step adaptation process as the information of one step will only be used in the next one.

There are two problems that arise when this rationale is applied that are related with a delay between stimulation and action that must be taken into account if a relation between both is to be considered and the fact that The pass length \( n_j \) of the current stride can’t be pre-determined and in order to work with vectors, dimensional coherence must exist.

The problem of the delay is solved using the Toe-Off prediction feature of the GPD. Once the Heel-Rise is detected, time of Toe-Off can be estimated and a time \( t_1 \) can be calculated anticipating \( t_{TO} \) by a time factor \( \tau_1 \). Once \( t_1 \) is achieved, the stimulation is triggered. In the simulation done \( \tau_1 = 0.05 \)s.

The variable pass length problem is solved by

\[
\begin{align*}
\text{Step 1:} & \quad t_{TO,1} = t_{HR,1} + \delta \\
\text{Step 2 to Step N-1:} & \quad t_{TO,j} = t_{HR,j} + \sum_{i=1}^{j-1} \frac{t_{TO,i} - t_{HR,i}}{N} \\
\text{Step N and forward:} & \quad t_{TO,j} = t_{HR,j} + \sum_{i=1}^{N} \frac{t_{TO,i} - t_{HR,i}}{N}
\end{align*}
\]

Where \( \delta \) is a pre-set time period, chosen based on the phase duration information of healthy subjects.

Using the information of a 600s model simulation, the pre-swing duration was found to be around 0.315s and the swing duration around 0.475s. Based on these findings \( \delta_{\text{Toe-Off}} \) was set to 0.3s and \( \delta_{\text{Heel-Strike}} \) to 0.5s.
defining limits for the possible values of \( n_j \). This length, although variable, doesn’t get arbitrarily large or small and can be bounded between a lower bound \( n \) and an upper bound \( \bar{n} \) such that \( n_j \in [n, \bar{n} - (\tau_l/t_s)] \) where \( t_s \) is the sampling time. For simulation purposes, \( \bar{n} = 150 \) and \( n = 100 \) and \( t_s = 0.004ms \).

Now that both problems are solved, one needs to define a “canvas” for the FES intensity profile \( u_j \) and a reference pitch recording \( r \). The intensity profile is defined as a column vector with length \( \bar{n} \) and is normalize with respect to the patient maximum tolerated intensity, \( \bar{q} \). The reference recording is also a vector of size \( \bar{n} \) obtained by averaging the time-scaled recordings of the swing of a large number of steps of one or multiple healthy subjects. For the simulation \( \bar{q} = 0.25 \) and \( r \) was obtained using the information of a 600s run of an unaltered model.

Once everything is properly constructed and defined, one can start to build the controller. The first part of the controlling scheme is to compare the pitch angle, \( \alpha_j \) recorded during swing with the reference pitch. In order to compare, the reference measurement has to be time-scaled so that we don’t find ourselves comparing miss-fitting information. Once \( r \) is time-scaled to have the same \( n \) samples that \( \alpha_j \), originating \( r_j \), a measure tracking error vector can be computed considering \( e_j \) = \( r_j - \alpha_j \).

This error vector \( e_j \) will have a length of \( n \) and needs to be extended so that it has a length of \( \bar{n} \). In order to do that, a column vector of zeros with length \( \bar{n} - n \) is appended to \( e_j \). The new extended vector is then multiplied by a learning gain matrix \( L \in \mathbb{R}^{\bar{n} \times \bar{n}} \) such that \( L = \gamma \times I^{\bar{n} \times \bar{n}} \) with \( \gamma \) being a scalar gain factor. Once this gain is applied to the extended error vector, it can be deduced from the current FES profile originating \( \tilde{u}_{j+1} \). For the simulation, a value of \( \gamma = 0.01 \) was used.

The obtained \( \tilde{u}_{j+1} \) is then multiplied by a filtering matrix \( Q \in \mathbb{R}^{n \times \bar{n}} \) that is a Toeplitz structure containing the Markov parameters of a low pass 2nd order Butterworth filter with cut-off frequency of \( f_Q \). These Markov parameters are obtained by applying the filter to the impulse response, inverting the obtained vector and reapplying the filter and reverting the final vector. This allows us to remove the discomfort of working with sudden intensity changes without adding any kind of delay to the process. Here, a value of \( f_Q = 10Hz \) was used.

Once the filtering is done, a process of element-wise saturation is applied to the resulting vector so that every intensity is within the tolerable range for the patient. The resulting learning law is the one depicted in Eq.1.

\[
\tilde{u}_{j+1} = \text{sat}_{\bar{q}}^q \left[ Q \left[ u_j + L \left[ e_j 0_{(\bar{n} - n_j)} \right] \right] \right]
\]  

(1)

2.3.2 Intra-Step Adaptation

The presented inter-step controller relies on the assumption that the swing phase will have the same duration from stride to stride. When this doesn’t happen, a miss-match between FES profile and pitch profile arises. This miss-match causes some instabilities that need to be addressed.

In an attempt to increase the stability of the controller an Intra-Step Adaptation strategy, based on time scalings of the FES profile, was adopted. This strategy relies on the detection of certain events during swing to adjust the FES profile computed in the Inter-Step Adaptation to fit a predicted duration for the swing in the current stride.

To achieve this goal, the Inter-Step Adaptation block had to be further adapted. In this second adaptation, the pitch vector is time scaled to have \( \bar{n} \) samples before being compared with the reference pitch of the same size. Once the vectors are compared, the FES profile is also time scaled to the same size and equation 1 is applied. Once the correction is done, the FES profile is further time scaled to have the same duration as the swing phase of the previous stride. A schematic representation of the adapted Inter-Step controller is depicted in Fig.3.

![Intra-Step correction pipeline when integrated with the Intra-Step controller](image)

The Intra-Step Adaptation is performed, in part, by correcting the prediction of the duration of the swing that happens during the Inter-Step procedure. This is done by assuming that there is a certain number of events that occur at a specific percentage of the swing phase. The duration of the current swing phase (\( t_{\text{swing}} \)) is then computed by considering \( t_{\text{swing}} = \frac{t_e}{P_{\text{event}}} \), where \( t_e \) is the elapsed time since the beginning of the swing, \( P_{\text{event}} \) is the percentage of swing at which the event happens.

These percentages are computed simply by dividing the time elapsed from the beginning of swing until the event by the total duration of the swing phase in the same step. At the beginning of each stride, the swing percentage at which each event will occur is admitted to be the average of the same percentage in the last \( n \) strides (3 in this case). The computation is done in a similar fashion of the one
of $t_{TO}$ or $t_{HS}$.

Besides the FES profile time scale correction that happens, during these correction events, FES amplitude is also corrected. To do this, foot pitch recorded between the previous and the current event is compared with a reference pitch of the correspondent portion of the swing recorded from a healthy person, the same way it is done in the Inter-Step Adaptation. Once the error vector is obtained, the values after the last zero-crossing are averaged. This average is then multiplied by a pre-determined gain $g$ and added to the FES profile already properly scaled. Only the values after the last zero-crossing are considered as these are the ones that represent the trend of the pitch for the remaining step. In this project, a value of $g = 0.002$ was used.

In this case, the events considered were the transitions between each of the swing sub-phases detected by the GPD. The pipeline of the correction at each event is the following:

- 1- The FES profile is scaled to have a new duration $t_{swing}$;
- 2- A reference pitch vector is scaled to have the same duration as the recorded pitch vector;
- 3- The error vector is computed;
- 4- The values after the last zero-crossing are averaged and multiplied by $g$ to obtain the correction factor;
- 5- The correction factor is added to the scaled FES profile values corresponding to the time after the event.

Like it was previously mentioned, to cope with the response delay of the muscles, the stimulation has to begin shortly before the swing phase. Since, due to the scale corrections, they are programmed to have the same duration, the stimulation would end $\tau_1s$ before HS. To cope with this, the last value of the FES profile vector is held for $\tau_1s$.

2.4. Orthosis Preparation

Now that the controller is prepared, accommodations must be done so that it can be transferred from the in silico environment to the orthosis. These changes have to deal with the non-ideal behaviour of the sensors and are presented next.

Gyroscope Calibration

The gyroscope measurements present an offset that needs to be removed through calibration. The calibration is done by keeping the gyroscopes stationary during a short period of time and averaging the angular velocity measurements in each dimension. The measured value is considered to be the offset and is subtracted from the measurements.

FSR Calibration

To cope with the fact that the used FSR are not ideal, nor in an ideal situation, leading to residual pressures to be detected, and still use the On/Off methodology to access whether or not the foot is on the ground thresholds have to be used. To define these thresholds without any previous information on the user, they are defined for each FSR at the start of the orthosis operation period. In order to do that, after keeping the foot still on the ground for a few seconds, one should lift the foot for another short period of time. The average of the measurements of the FSR $n$ in each of these periods will allow to define an maximum ($l_{n,\text{max}}$) and minimum ($l_{n,\text{min}}$) load respectively. Once these measurements are done, the threshold for FSR $n$ ($th_n$) is defined by Eq.2 where $c$ is a tolerance factor. During the experiments done a value of $c = 0.6$ was used.

$$th_n = l_{n,\text{min}} + c \times (l_{n,\text{max}} - l_{n,\text{min}})$$ (2)

Once the thresholds are defined, the FSR are grouped into the Heel Group (FSR 0 and FSR 1) and the Toe Group (FSR 6). Each group is On when one of its FSR is On avoiding contact misdetections.

3. Results

3.1. Stimulation Adaptation

The proposed controller was tested by replacing the model’s Tibialis Anterior’s stimulation signal with an artificial signal computed by the implemented algorithm. This replacement was done only after the first three strides so that the model has time to stabilize. Two 60s runs were performed, in the first, the ground was kept flat through the whole run, during the second run a depression in the ground is applied in order to disturb the system and test the adaptation capacity of the controller. In this section, the results of these tests will be presented and discussed.

3.1.1 Comparison with the Healthy Subject

One first way to assess the performance of the controller and its feasibility as and orthosis controller is to compare the obtained FES profile and foot pitch profile with the one from a healthy subject (the model without the signal replacement).

After a few strides, the controller stabilizes and the obtained profile is the one in the left plot of Fig.4. Comparing the achieved FES profile with the one from a healthy subject (the model without the signal replacement).

Although the learned burst is slightly lower, it is also longer, which will then produce the same foot pitch outcome when compared
with the model, as they will produce the same force. After the 80% mark, the profiles diverge, being that the one achieve with the controller presents a second burst before Heel-Strike, absent in the original stimulation profile. This second burst happens so that the Initial Contact is done with the heel and not with the toe. It can be compared with the weight acceptance preparation mentioned by Geyer, but it affects only the way the foot approaches the ground, being that, with this controller, 

\textit{Slap-Foot} still happens as there would be no way to learn by pitch comparison how to properly tune the Controlled Plantarflexion stimulation. Despite the differences presented by the FES profiles, the foot pitch profile achieved with the controller is similar to the one presented by the unaltered model as it can be seen in Fig.5.

Figure 4: Comparison between the learned FES profile (left) with the one from the model (right)

Figure 5: Comparison between the foot pitch during a stride obtained with the controller (blue) with the one from the model (orange)

3.1.2 Comparison with the existing controller

With the goal of assessing the controller’s performance and comparing it with the one with only Inter-Step Adaptations, to test for improvements, both were submitted to the previously mentioned 60s runs. After each run, the recorded pitch vector at each swing phase was scaled to have \( n \) samples and a Root Mean Square Error (RMSE) measure was computed comparing the new scaled vector with the reference vector. The results comparing the performance of the new (presented here) and original (presented by Seel [1] and adapted to work with the neuromusculoskeletal model) are presented in Fig.6 (for the run without perturbations) and Fig.7 (for the run with perturbations).

Observing, Fig.6, it is clear that there is an improvement in performance when comparing both controllers. Although they have similar stabilization times and are able to achieve physiological RMSE values before the 5\textsuperscript{th} stride (the pitch angle of healthy subjects can vary by 7\textdegree{} [1]), the new controller achieves RMSE values that are less than half the ones obtained by the original (around 1\textdegree{} for the new and 3.5\textdegree{} for the original). This difference is mainly due to the swing duration adaptation that is introduced with the Intra-Step Adaptation. Without the constant adaptation of the length of the FES intensity vector, the controller is sensitive to changes in the swing duration from one stride to the other and big changes can really invalidate all the learning that was previously done.

Another perturbation that compromises the performance of the original controller are variances in the duration of pre-swing. When this duration varies much from one stride to the next, the TO will be miss-predicted, which will cause the stimulation to start either too early (if one stride’s PS is longer than the previous) or too late (if it is shorter). This shift will cause the foot’s angle to be higher or lower than it should during the whole stride if not corrected. The new controller uses the first third to correct for this, making it more robust.

Figure 6: Comparison of the evolution of the Root Mean Square Error for the new algorithm (blue) and the one originally proposed by Seel (orange) in a perturbation free environment.

Looking at Fig.7, it is possible to see that once stabilized, the new algorithm is robust and is able to withstand small perturbations.

3.2. Orthosis Tests

To assess the feasibility of the GPD and OE in \textit{in vivo} applications, a subject was equipped with the orthosis and did a walk with around 50 steps where FSR and IMU data was collected and then processed in Matlab in order to simulate both the GPD and OE performance with real data.
3.2.1 Gait Phase Detection

**Outer Layer**

Fig. 8 shows the duration of the Main Gait Phases detected by the GPD’s Outer Layer using the obtained FSR data and the mean values and deviations are detailed in Table 1. By looking at the plots and analysing the table, one can see that, although there are some deviations in the values for the pre-swing and foot flat phases, the detected phases mean durations are very similar to the ones presented by Gage in [17] being that the swing phase comprises almost 40% of the stride, the loading response only a little over the reported 10% and the foot flat and pre-swing the remaining 50%, and the errors in the swing phase (the phase of most importance for this algorithm) are relatively small (less than 10%) and are not gigantic in the other phases (the highest relative error is the negative one on the PS and happens only on the final stage of the run).

This consistency on the swing phase and accuracy when compared with the relative durations reported in literature, are characteristics that value this Outer Layer of the GPD designed within this thesis’ scope.

**Inner Layer**

In order to properly use the Intra-Step Adaptation block, not only the GPD’s outer layer must be consistent, but also its inner layer.

Like in the previous section, Fig. 9 and Table 2 represent, both graphically and numerically, the mean duration of each of the detected sub-phases, the absolute deviations around that mean and the percentage of the swing that each represents. Through the analysis of the presented results, more specifically the deviation errors, one can see that the detection of each sub-phase is done in a quite consistent way being that the biggest error is of 25% on the third sub-phase, which won’t play an active role on this correction process as the corrections are done based on the other two sub-phases. This bigger deviation present in S3 could be assigned to more sudden terminations or elongations of the swing.

**Toe-Off & Heel-Strike Prediction**

The last feature of the GPD to be tested was the ability to predict the onset of Toe-Off and Heel-Strike. Fig. 10 shows the values for the time elapsed between $t_1$ and $t_{TO}$, and $t_2$ and $t_{HS}$ for the several strides of the run. If one observes the mean values

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**Table 1: Main Gait Phase mean durations, positive and negative errors, and relative durations**

<table>
<thead>
<tr>
<th>Phase</th>
<th>Mean Duration [s]</th>
<th>$e^{-}$ [s]</th>
<th>$e^{+}$ [s]</th>
<th>%</th>
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<tbody>
<tr>
<td>FF</td>
<td>0.3556</td>
<td>-0.09562</td>
<td>0.09771</td>
<td>30.07442</td>
</tr>
<tr>
<td>PS</td>
<td>0.2628</td>
<td>-0.1428</td>
<td>0.09382</td>
<td>22.2598</td>
</tr>
<tr>
<td>S</td>
<td>0.433</td>
<td>-0.02632</td>
<td>0.04095</td>
<td>36.62043</td>
</tr>
<tr>
<td>LR</td>
<td>0.131</td>
<td>-0.03431</td>
<td>0.04903</td>
<td>11.07916</td>
</tr>
</tbody>
</table>

**Table 2: Swing Sub-Phases mean durations, positive and negative errors, and relative durations**

<table>
<thead>
<tr>
<th>Phase</th>
<th>Mean Duration [s]</th>
<th>$e^{-}$ [s]</th>
<th>$e^{+}$ [s]</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td>S1</td>
<td>0.114</td>
<td>-0.01736</td>
<td>0.01264</td>
<td>26.32794</td>
</tr>
<tr>
<td>S2</td>
<td>0.1901</td>
<td>-0.0134</td>
<td>0.0166</td>
<td>43.903</td>
</tr>
<tr>
<td>S3</td>
<td>0.1289</td>
<td>-0.02222</td>
<td>0.0311</td>
<td>29.76905</td>
</tr>
</tbody>
</table>

Despite the small deviations, the presented values indicate that the inner layer is robust enough to be used within the scope of the Intra-Step Adaptation block.

---
for the duration of each period are really close ones set previously - 0.0459s for the TO (set to 0.05s) and 0.0972s for the HS (set to 0.1s). Unfortunately such small intervals are prone to fast small changes in the gait pattern adopted by the subject, hence the high relative variance, more noticeable on the TO prediction as the whole pre-set duration of the interval is smaller than the variations noticed for the PS phase.

Figure 10: Duration of the period between $t_1$ and $t_{TO}$, and $t_2$ and $t_{HS}$ as measured using the orthosis data

Although there are limitations mentioned above, if the algorithm is able to do corrections in the first part of the swing phase these variations in the onset of the TO won’t be a problem and this strategy can be considered fit for the goal of this project.

3.2.2 Orientation Estimator

In order to test the feasibility of the OE with data obtained from the orthosis, accuracy and precision tests were made. To do the accuracy test, the tracking software Kinovea [18] was used. This software allows the tracking of points within a video and the computation of the angle between the lines delimited by these points. At the same time the video was recorded, the orthosis was also recording kinematic data so that it could be compared. Once both data-sets were obtained, the offsets were removed and the angle profile was compared.

The previously explained accuracy test’s results can be seen in Fig. 11. As one can see, the measurements done with the OE based on the IMU/FSR information are quite similar to the ones measured by the Kinovea. The fact that all the events present in this portion of the stride are observed and that the angle achieved values are not much different (the differences are in the order of 5°) than the ones presented by Winter in [19] (2°) indicates that the OE presents good accuracy.

To test for the precision of the OE the whole recording was cut into separate steps and scaled to have the same nominal size. In Fig. 12 one can see the result of the test. The step to step variation is not too big, being in the order of 5° when compared to the average and going as high as 10° during swing phase.

The variation from step to step can be attributed to the natural inter-step variation present in Human gait and although higher than the one reported by Winter in [19] (2°) is not very high considering that the subject was walking with the control board attached to the leg.

These results indicate that the OE used, although simple, is precise and accurate enough to be used in the control strategy presented in this thesis.

4. Conclusions

As stated at the beginning, the proposed goal for this thesis was the adaptation of the Drop Foot FES-based orthosis controller proposed by Seel, improving its time resolution and use that to further improve the correction capacities.

A Gait Phase Detector is presented that divides the stride in four main phases and the Swing phase in three sub-phases, improving the number of total phases from four, in the original controller, to six, in the new one. Although the apparently simple approach, the GPD was able to detect all the phases and sub-phases with a relatively high degree of precision. Besides differentiating between gait phases, the GPD is also able to predict the onset of events like Toe-Off and Heel-Strike with a certain degree of certainty (lower for the TO). This detection is still very dependant on the duration of the
Pre-Swing and Swing phases of the previous strides but proved to be useful integrated in the controller.

An Orientation Estimator was implemented that, through the data of only one gyroscope in the thigh, the shank and the foot, is able to track the orientation of the foot during Swing and detect the selected features of the knee and shank angle profile during the same phase needed by the GPD with a high level of accuracy and precision.

Lastly, and the main goal and contribution of this thesis, a controller able to adapt the FES profile based on the foot orientation with a time resolution of one third of the Swing was developed and implemented. It was able to outperform the one in which it was based of that had a time resolution of a full stride while maintaining the necessary stability of the neuromusculoskeletal model on which it was tested. The presented Drop Foot FES controller represents then one step further to the achievement of the ideal fully closed-loop controller where the data from the sensors is used to adjust the stimulation in real-time with the time resolution being dependent only on the housing micro-controller’s processor capability.

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References


