EC PAEDIATRICS
Research Article

Automatic Non-Invasive Method to Investigate Human Swing of the Gait Cycle

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Abstract

The purpose of this study was to analyse the electromyogram (EMG) signal processing and its application to identify human swing phase of the gait cycle so to develop an automatic, intuitive, low-cost and not invasive EMG device. Electromyography is traditionally used for diagnosis of neuromuscular disorders. EMG signals acquired from muscles require advanced tools and methodologies. However, with the advent of increasingly powerful and low cost sensors and microcontrollers, the study of EMG has found its place in robotics, in the creation of advanced prostheses and in rehabilitation techniques. In this study, a single channel surface EMG signal was studied from human muscles using non-invasive electrodes. After amplification stage, the EMG signal was digitized through analogue and digital (A/D) converter to have accurate and clear signal. Many paediatric neuromuscular disorders are analogous to those seen in the adult and the electrodiagnostic evaluation provides an important extension to the neurological examination. A total of 140 EMG amplitudes were recorded corresponding to 4 lower limb muscles of 35 subjects aged between 12 and 70 years was generated. For each record, the subject made a coordinated paused walk based on a sequence of audible tones to indicate each step. Results show that the amplitudes obtained in each swing sub-phase of the gait records are coherent with the normal swing phase. These findings allow to recommend the use of the EMG acquisition prototype for studies addressed to the detection of motion intention. Future studies will be carried out to extend this methodology to the study of gait in paediatric subject in order to create systems for the diagnosis of deviations from normal gait using non-invasive rehabilitation techniques.

Keywords: *Electromyogram; Non-Invasive; Human Swing; Gait Cycle; EMG Signal; Surface EMG*

Introduction

Electromyography (EMG) is the method of measuring electrical activity within muscle fibers activated by the central nervous system [1]. The first experiments regarding electromyography date back to the mid-1600s with the studies of Francesco Redi. Redi discovered a highly specialized muscle of the electric ray fish generated electricity [2]. Such momentary differences in the electric charges can be detected with two (or more) electrodes [3].

In the world of biomedical, the acquisition of myoelectric signals from the human body has always required a considerable engineering effort. Through electromyography the suffering of one or more nerve roots, one or more nerves and the lesions of one or more nerve trunks can be highlighted. The electromyography (EMG) has practical results in a myriad of fields, from the diagnosis of neuromuscular deficits to the study of the peripheral nervous system [4,5], for assisting weak or the elderly [6].

In children, EMG can serve to diagnose many disorders: spinal muscular atrophy, brachial plexus injury, neuromuscular transmission disorders, myopathy, muscular dystrophy etc [6]. However, until a few decades ago, the use of directly implanted on-site electrodes was the de facto standard, making the EMG examination invasive and problematic. Parallel to the EMG, in recent years a new promising technique, called surface EMG (sEMG), is being developed. SEMG is not invasive, because it uses surface electrodes (a simple electrode resting on the skin) [7]; the simplicity of this technique has created new applications outside the diagnostic field, making the study (and realization in some cases) of human-machine interfaces and robotic prostheses much more current respect at one time [6,7]. The facility to study makes the use of SEMG feasible even in paediatric subjects and it is widely used in the field of motor disability rehabilitation. [5-7].

In this study, I presented an EMG signal acquisition and process non-invasive system based on Arduino and Bluetooth technology to characterize the swing phase of normal gait cycle. The signals were detected from the muscles using non-invasive electrodes. Appropriate algorithms and methods for EMG signal analysis have been developed, improving detection techniques to reduce noise and acquire accurate EMG signals.

The device is been projected for the analysis of possible lack of strength or sensitivity of muscle activation in the swing phase, which is an important process in determining the start of the gait cycle and the intention of the neuro-musculoskeletal movement.

Finally, a total of 140 EMG signals were registered, corresponding to 4 lower limb muscles of 35 healthy subjects (15 Male - 20 Female) with ages 12/70 years old gave their written informed consent to participate in the study. Accordingly, the objective of this study was to assess the interactions between fatigue-induced changes in intrinsic muscle mechanical and electrical properties and the resulting neurological compensatory responses.

Other studies

In literature are present a number of articles about the EMG signal processing and classification techniques focused on gait cycle.

M. A. Mikulski in [8] proposed algorithms for EMG signal processing for the control of an exoskeleton used for physiotherapy and rehabilitation.

M.N. Shah., *et al*. in [9] has introduced an automated device for activities on patients requiring physiotherapy treatment.

H. He and K. Kiguchi in [10] proposed an EMG-based control for a robotic exoskeleton with the aim of helping the movement of the lower limbs for patients with physiological difficulties in walking.

Yusuke Hashimoto., *et al*. in [11] developed a gait aid device built with pneumatic artificial muscles that uses the input EMG signal.

Jun-ichiro Furukawa., *et al*. [12] has developed a new rehabilitation system using the signals acquired by the muscles during normal activity.

Materials and Methods

System design

EMG signal acquisition is an increasing aspect in the field of bionics and clinical rehabilitation research The hardware for EMG signal acquisition [6] can be divided into several parts which are instrumentation amplifier, filtering, rectifier, analogue digital converter (ADC), microcontroller and display unit. Figure 1 shows the whole system realized in this study.

To acquire the EMG signal from the muscles were used Ag-AgCl surface electrodes with a passive electrode cable, used for reasons of compatibility with the shield EKG-EMG. This cable is composed by an audio shielded cable with a stereo connector in one end, and in the

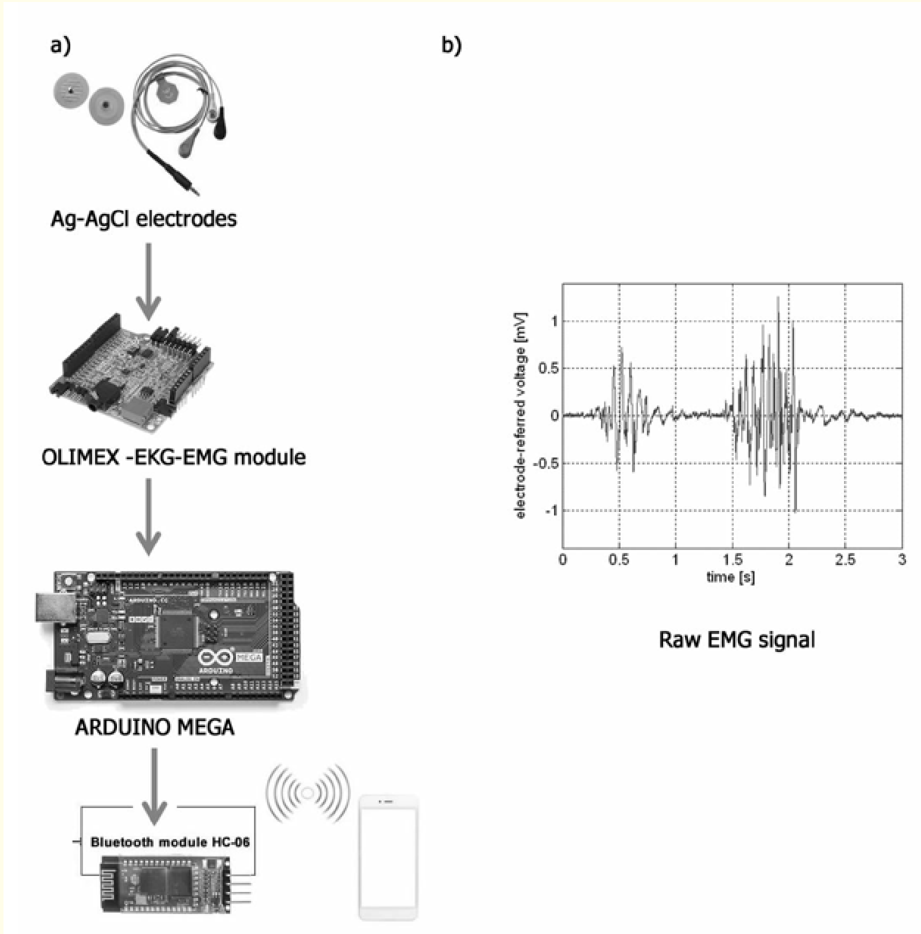

Figure 1: Pictorial representation of the System a) Ag-AgCl surface electrodes were used in the transducer stage. A cable connects the electrodes with the processing board, the shield EKG-EMG manufactured by Olimex, and compatible with Arduino. The A/D converter of the Arduino Mega is used with a resolution of 10 bits and a conversion rate of 1 KHz, finally the Bluetooth module HC-o6 send the data on a mobile device to show results on a graphical interface (GUI) B) The raw surface EMG signal acquired by the system.

other, three crocodile connectors. The cable connects the electrodes with the processing board an EKG-EMG manufactured by Olimex, compatible with Arduino (Figure 1). The EKG-EMG board converts 2-point analog differential signal into a single data stream as output (a single channel). SEMG signal received by the muscle has a very low amplitude [13] therefore it is required an amplification of the signal. Then the ADC of the Arduino Mega is used with a resolution of 10 bits and a conversion rate of 1 KHz to digitalized the signal. Finally, the raw EMG signal is send by Bluetooth module HC-06 to a device mobile to process the signal and display the results.

In this system two 9V disposable Lithium battery is used for making the device portable. For safety and short circuit protection, a voltage regulator LM7805 is used.

EMG signal acquisition

The firmware software implemented on the Microcontroller Arduino Mega, is written in assembly C language. Figure 2 depicts a flow chart to acquisition and send to mobile device the EMG signal. The flow starts getting inputs by the shield EKG-EMG via Ag-AgCl electrodes. The microcontroller Arduino (ATmega2560) checks whether all inputs are given properly. If someone of the inputs is not detected well, the system send a warning; if all inputs are detected, the Arduino firmware send the digitalized signal thought the Bluetooth module HC-06 at an app android used to signal process and to show the results on a mobile device (smartphone, tablet pc) with a graphical interface (GUI).

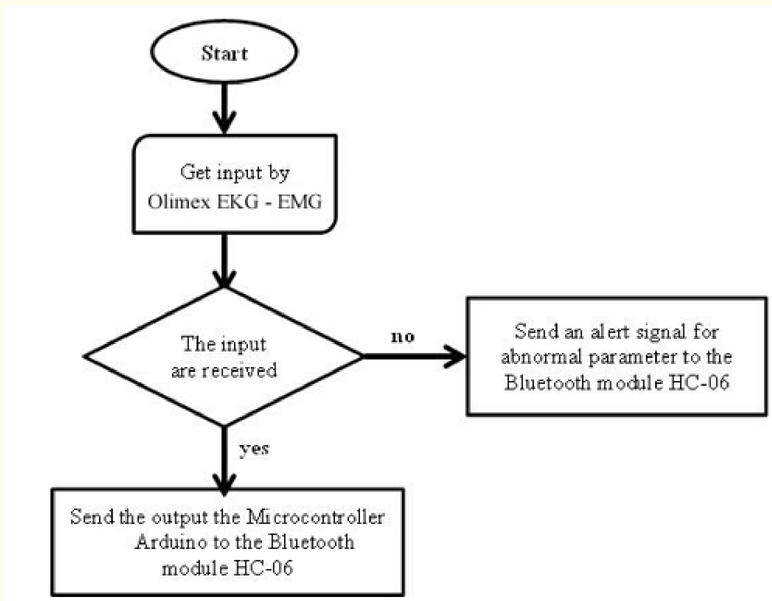

Figure 2: *Block diagram of the applied acquisition EMG signal firmware.*

The Android application receives the digitized signals, handles the processing and extrapolation of EMG data for varying degrees of measurement and interpretation and displays all of the data to the user via a custom GUI.

The raw data corresponding to the EMG signal are centred on a voltage level, with variations around the average value. Therefore, the signal must first be filtered and segmented. The noise in the EMG signal may come from other physiological signals: electrode contact noise or motion artefacts [13,14]. These noises could be modelled as white noise [13]. Some authors apply a high-pass filter to remove the artefacts. For example: Solnik., *et al*. [15] use a 6th order, high pass filter at 20 Hz, for surface EMG from vastus lateralis muscle.

After the filtering the signal, it is necessary the rectification step to get the envelope of the EMG signal. Attenuating the unadjusted signal does not lead to any result. Because the EMG signal is by its nature close to zero, with rapid oscillations on both sides of the zero. If you attenuate such a signal, you get only zero. The rectification brings negative oscillations into positive oscillations. The rectified signal is low pass filtered, with in the 5 - 100 Hz range, and the result looks like the "envelope" of the original signal [15]. One way to low pass filter a signal is to simply take the mean value, in a window which "slides" along the signal [16]. A moving window is an example of a finite impulse response filter. To not alter the phase, or timing, of the signal, the window must to be symmetric and centred. An alternative way to filter the rectified low pass signal is to use a discrete version of a low pass filter as Butterworth. The combination of rectification and low pass filtering is also called finding the "linear envelope" of the signal, since the filtering operation meets the mathematical definition of linearity, and, because it is low pass, it captures the "envelope" of the signal.

The raw signals acquired are shown in figure 3a.

A filter Butterworth 10th order passband with a cutoff frequencies of 50 and 400 Hz is used [18] (Figure 3b):

1. I fixed raw signal=x(t),
2. I make the mean of the signal: xm=mean(x(t)). If it was used an high-pass or passband filter, to filter raw signal then the mean will be zero already.
3. I assume: y(t) = |x(t)-xm)|
4. Then I use a: 10th order passband Butterworth filter for both directions, forward and reverse: zButter(t) = y(t).
5. Finally to compute the envelope I use this approach: envelope(t)=(Sum of y(t) from t-T_w/2 to t+T_w/2)/N_w, where T_w: the window width, N_w: the seconds.

Figure 3c show the EMG signal envelope.

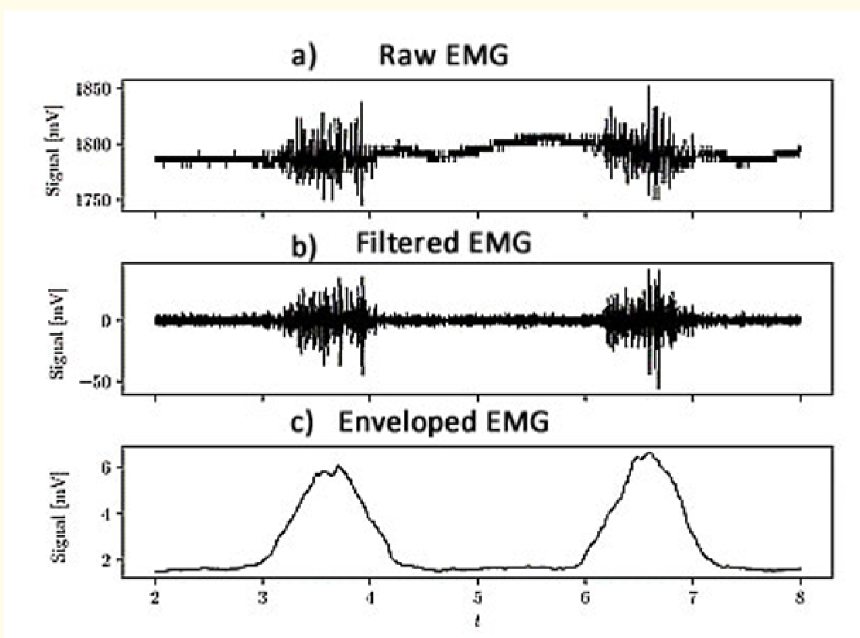

Figure 3: *a) The EMG signal acquisited; b) The EMG filtered with a Butterworth 10th order IIR passband digital filter; c) the EMG signal enveloped.*

Measuring the times when the signal enveloped exceeds a given threshold, the algorithm can estimate automatically the times at which muscles "turn on" and "turn off" The time results are shows on graphical display. The value of the threshold was calculated by follow equation:

Threshold=μ+Kσ

Where μ and σ are respectively the mean and standard deviation of the envelope signal, and K is a constant. The value of the constant K was fixed to 3 as described in Di Fabio [16].

If the muscle is not at a constant level of activation for the entire period of signal acquisition, the frequency content of the signal must be calculated for short time instants. To achieve this I have to use a floating window (any smooth window, not rectangular, is a reasonably good choice: Gaussian, Hamming, or Hanning). Each time the window is moved, it necessary to calculate the signal power spectrum within the window [17-20]. This will cause the generation of an entire family of power spectra, one for each position of the floating window. The power spectrum describes the frequency content of the signal [20]. I used an Hamming windows, whose width determined the frequency resolution (FR):

Width window = FR.

Having a large window means averaging a longer signal segment, and therefore being more likely to have multiple different signal segments included. A larger window also means that there is a poorer resolution in the time domain [17].

The window shift has been fixed within a range between a quarter and a tenth of the width of the window. Because it is known that small steps produce little new information, and therefore the subsequent shift of the window will see practically the same input data. The frequency resolution used was $\Delta f = 1/T_w$, where T_w is the width of the window. Figure 4 shows the general block diagram of the whole system.

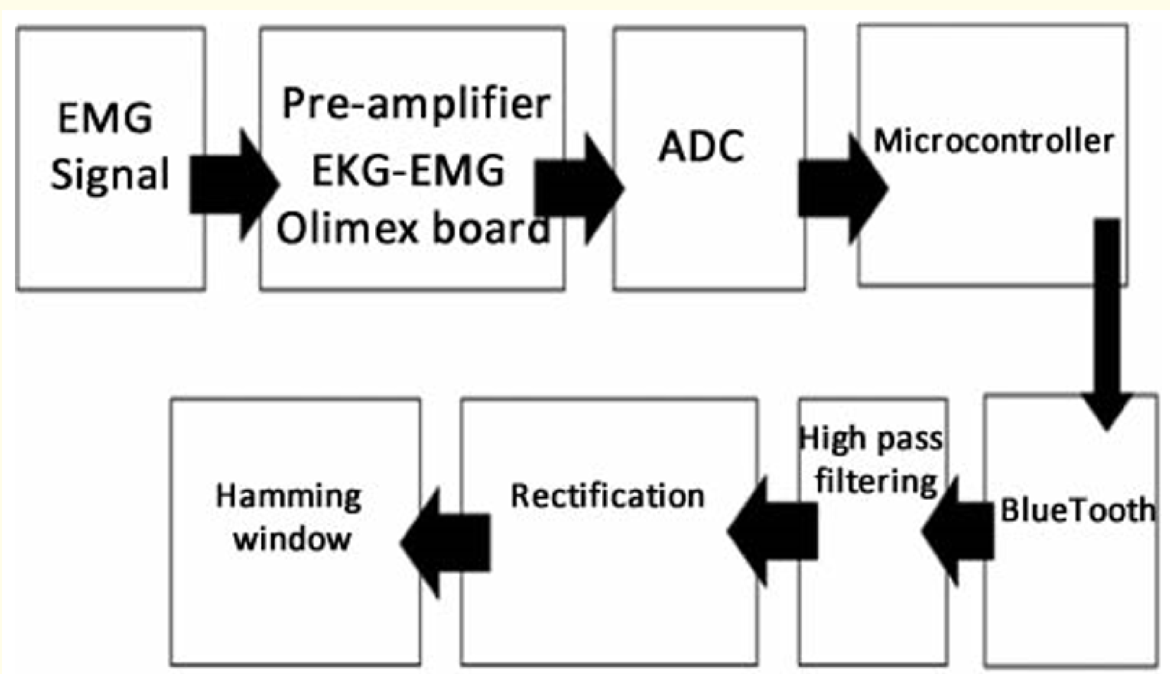

Figure 4: *Block diagram of the applied method.*

Results and Discussion

The gait cycle is a periodic cycle that involves the two lower limbs. On the way, the limbs repeat a sequence of movements that bring the body forward, maintaining a stable position. The swing phase corresponds to 40% of the human gait cycle and is synonymous with stride length and includes three sub-phases (Figure 5):

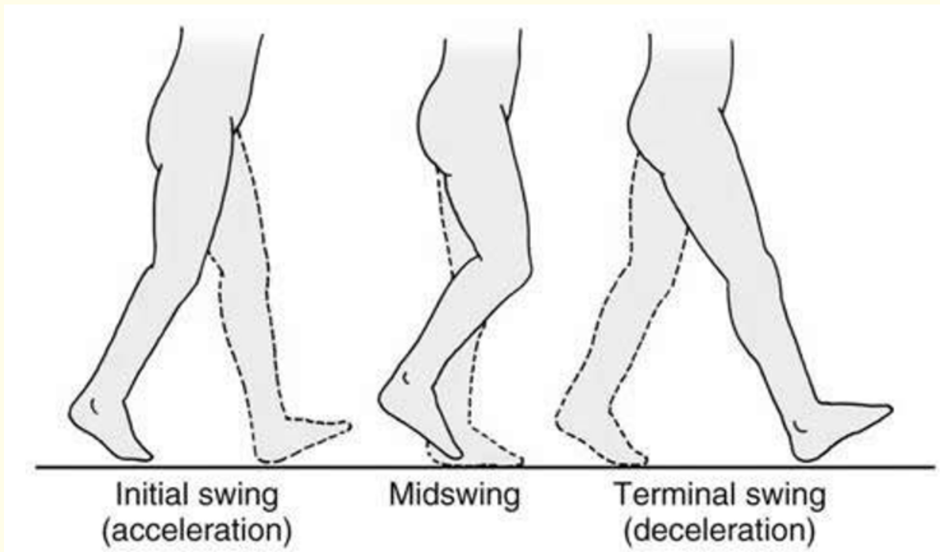

Figure 5: *In the swing-phase we can recognise two extra phases - acceleration and declaration. The acceleration phase goes from toe-off to midswing, while deceleration goes from midswing to heel strike. In the acceleration phase, the swing leg makes an accelerated forward movement with the goal of propelling the bodyweight forward.: Initial swing occurs when the foot is lifted off the floor. Then when the swing leg is adjacent to the weight-bearing leg we have the Midswing. Finally, the Terminal swing, when the swinging leg slows down in preparation for initial contact with the floor.*

1) Initial swing: This sub phase starts when the foot is raised off the ground. During a normal gait, rapid knee flexion and ankle dorsiflexion occur to allow the limb to swing and accelerate forward. In some pathological conditions, loss or alteration of knee flexion and ankle dorsiflexion leads to gait alterations. The initial oscillation corresponds to 34% of the oscillation phase. The muscles involved in the initial swing are: biceps femoris sartorius and rectus femoris.
2) Midswing: This sub phase occurs when the swinging leg is adjacent to the support leg. It starts at the maximum flexion of the knee and culminates when the tibia is placed perpendicular to the floor. Midswing corresponds to 26% of the swing phase. The muscular activity of the midswing involves: knee joint (biceps femoris, semitendinosus, and semimembranosus); hip joint (psoas major and iliac).
3) Terminal Swing: This sub occurs when the swinging leg slows down in preparation for contact with the floor and there is a deceleration of the motion. The muscles of the quadriceps control the extension of the knee and the posterior muscles of the thigh control the amount of flexion of the hip. Begins in the vertical position of the tibia, continues as the knee extends fully and ends when the heel makes contact with the floor. Terminal swing correspond to 40% of the swing phase. The muscle activity involves: knee joint -quadriceps (rectus femoris, vastus medialis, and vastus lateralis), and hamstrings (biceps femoris, semitendinosus, and semimembranosus) hip joint hamstrings (biceps femoris, semitendinosus, and semimembranosus).

Table 1 reports the average maximum amplitude values for the following muscles analysed: rectus femoris, vastus lateralis, vastus medialis and biceps femoris; and the p values between the right and left limb.

Muscles		Maximum Amplitude			p		
		Initial Swing	Mid swing	Terminal Swing	Initial Swing	Mid swing	Terminal Swing
Rectus Femoris	R	0.11	0.15	0.14	0.0012	0.0527	0.0527
	L	0.15	0.17	0.15			
Vastus Lateralis	R	0.11	0.16	0.14	0.0035	0.5629	0.0663
	L	0.18	0.18	0.16			
Vastus Medialis	R	0.12	0.16	0.15	0.0018	0.1249	0.0103
	L	0.14	0.18	0.19			
Biceps Femoris	R	0.11	0.19	0.15	0.0061	0.0346	0.0147
	L	0.17	0.21	0.18			

Table 1: *Maximum amplitude for follow muscles: Rectus femoris, Vastus lateralis, Vastus medialis and Biceps femoris. Swing sub-phases: Initial Swing, Midswing and Terminal Swing.*

In the initial swing phase, maximum amplitude of the left leg muscles is significantly greater especially for the biceps femoris and vastus lateralis, this is due to the fact that the hip flexor moment generated by these muscles favors knee flexion and with this, the advancement of the lower extremity; as well as the vastus medialis and rectus femoris since the concentric action of these muscles promotes the angular acceleration in the direction of the flexion of the hip and knee joints.

In the midswing phase, this difference is only observed for the biceps femoris, which is expected, since it is the most involved muscle during this phase because it starts to act eccentrically to slow the extension of the knee.

During the terminal swing sub-phase, all the muscles studied are involved, however the difference becomes smaller and is significant for two muscles: biceps femoris and vastus medialis, since in the first half of this phase they slow down the flexion of the muscles. The knee promotes joint stability, in the second half they contract concentrically to facilitate the full extension of the knee in synchrony with the pelvis and prepare the next initial contact. As expected, the average amplitude of the left extremity is greater than that of the right as each step starts with the left leg.

A further test was to alternate normal walking with walking with obstacles. The relative muscle activity is presented in figure 6. The EMG diagrams of the activity of the biceps femoris showed a higher activity corresponding to the burst of muscle power in normal walking conditions, walking with obstacles and walking after passing the obstacle. All the other muscles: rectus femoris, vastus lateralis and vastus medialis, showed qualitatively similar behaviors to each other in all conditions.

The methodology proposed in this manuscript have allowed to describe satisfactorily the whole human swing of the gait cycle in each sub-phases. Although more research is required to understand any clinical relevance of these present findings, given the differences in the underlying control of the leading and trailing limbs, it could be clinically relevant to train each side in leading and trailing functions to improve dynamic balance.

Conclusion

This document introduces a new methodology to characterize the human swing phase of the gait cycle in an automatic and non-invasive way. The proposed methodology was found to be effective for analysing the EMG signal and effective control of the prosthesis.

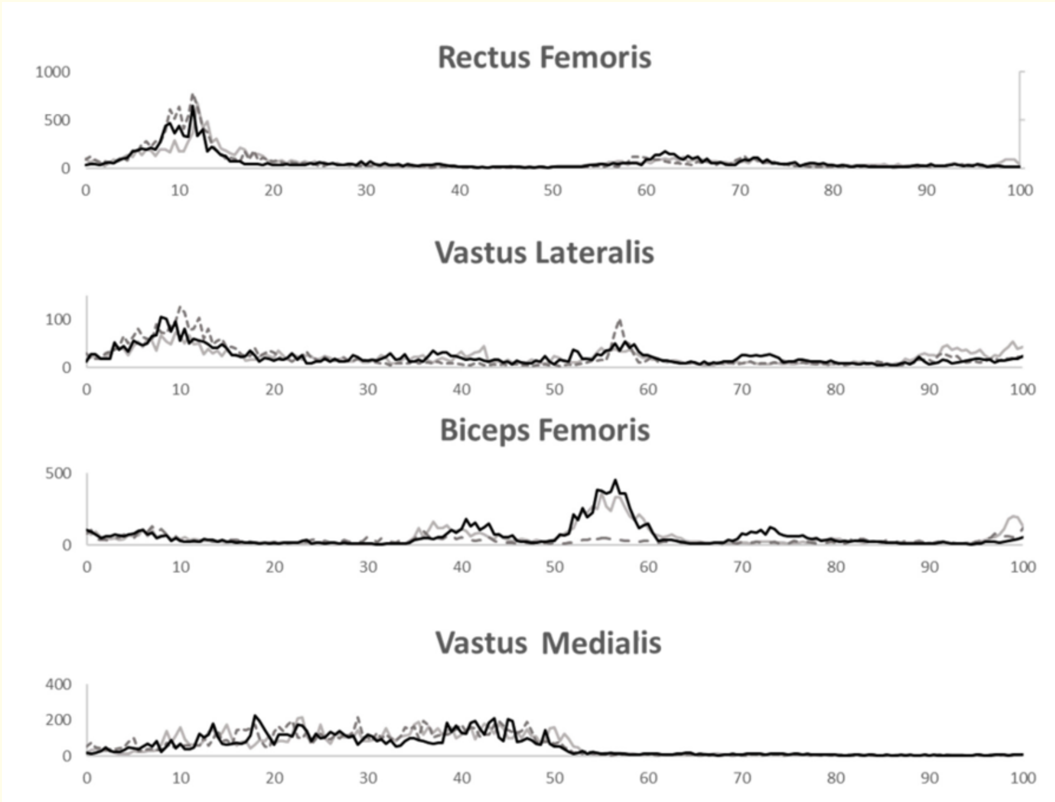

Figure 6: *Surface EMG of four lower limb muscles of one representative subject across conditions of unperturbed (gray), presence of obstacle (dashed line) and overcoming obstacles (black line) conditions.*

The purpose of this paper is to detect the swing phase in order to acquire useful muscle signals for rehabilitation and help purposes and to diagnose neuromuscular disorders. The swing phase of gait cycle allows you to monitor movement, specifically the patient's walk, and to quantitatively measure different aspects of walking. It is a fundamental tool of investigation in the analysis of movement and posture. In the future, I intend to further refine the optimization and classification approaches presented so to extend the study to paediatric subjects. More specialized and distinctive features and updated machine learning methods can increase the success of muscle strength analysis which would also improve the overall success of the methodology. In particular, methods can be devised to analyse the EMG signal not only of the lower limbs but of the whole body and to distinguish the different muscles involved in the movement processes. All this would improve the success rate in trauma rehabilitation cases.

Various aspects of the algorithm can be optimized to handle the specific problem at hand.

Conflict of Interest

The author declare is no exist any financial interest or any conflict of interest.

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