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Detecting Human Gait Cycle Sub-Phases from Lower Limb Acceleration Signals using K-Means Algorithm

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***Abstract*— In this work, a novel method that aims to identify the seven well-known sub-phases of human gait cycle is presented. This is done through a six-dimensional clusterization of three lower limb acceleration signals and their derivatives. The proposed method is based on the k-means clustering algorithm aided with a logical post-processing filter. Particularly, acceleration signals from the knee and ankle joints on the sagittal plane were used. The capability of the method is demonstrated from the seven sub-phases identified in data obtained from trials performed by an amputee patient wearing a prosthetic knee. Also, the method was applied on data from an able-body subject during a gait analysis. The method was able to cope with different walking speeds in a robust way, and also detected standing periods which were associated with the 'mid-stance' sub-phase. Furthermore, most of the sub-phases detected were consistent with the corresponding gait cycle percentages reported in the literature. Indeed, from an analysis of variance, three of the sub-phases showed no significant differences when compared to the literature reference values ($p<0.05$).**

Keywords: gait cycle sub-phases, k-means algorithm, lower limb acceleration signals, intelligent knee prostheses, lower limb prosthetic devices.

I. INTRODUCTION

Characterization of gait cycle aims to identify the different stages of gait from signals captured on human body during walking. This may have several purposes, ranging from treating and evaluating different gait conditions in patients to applying a particular control strategy on a prosthetic device. Currently motion analysis based in optoelectronics systems used combined with force plates is considered the standard method to characterize normal and pathological gait as performed in gait lab facilities [1]. However, this technology is very expensive, lacks of portability and is impractical in terms of real-time applications [2]. On the other hand, in the last years accelerometers have been increasingly used in all kind of applications, which have turned them in very low-cost, miniature, light and portable sensors. In [3], Mansfield and Lyons were interested in detecting heel contact events from accelerometry to use it as a sensor in functional electrical stimulation for the correction of drop foot in hemiplegic patients. Aminian *et al.* also detected heel contact and toe-off events using lower-limb acceleration signals, from which they determined the stance and swing times to analyze gait improvement after hip arthroplasty [4]. Recently, Bishop and Li used shank-mounted accelerometers to estimate walking speed on able-body subjects as an alternative to traditional gait analysis systems [5].

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Accelerometers and gyroscopes have been introduced also as part of the instrumentation of electronic prostheses, particularly of prosthetic knees, to assist in the characterization of gait cycle required by such devices [5]–[7]. Control of intelligent knee prostheses for transfemoral (above-knee) amputees is based on the characterization of gait cycle performed by the microcontroller on-board. Up to date, these prosthetic devices mostly apply finite-state control, thus characterization of gait cycle is required to determine the current state on the prosthesis during walking [8]–[10]. Intelligent knee prostheses commercially available, such as the *C-Leg* by Otto Bock [11] and the *Rheo-knee* by Össur [12], use strain gages to characterize the gait cycle mainly in the stance and swing phases. Nonetheless, it has been found that accelerometer signals carry a lot of information that, adequately processed, could be as robust as the one from the strain gages [5], [6] and, even better, this information gives insight about the swing phase of the gait cycle [13], which is impossible to the strain gages whose signal becomes zero when the prosthesis is not in contact with the floor [14].

Detecting as many stages as possible along gait cycle is important because this allows to develop a more accurate control for the prosthesis. This is valid for both finite-state and continuous control strategies. For the finite-state strategy, it allows to adapt the prosthesis response as many times as stages are detected along a gait cycle [15]. For the continuous one, the tracker system coupled to the gait cycle phase is updated every time a sub-phase is detected, allowing a faster adaptation of the prosthesis response, especially to walking speed changes [16]. However, characterization of gait cycle on lower-limb intelligent prostheses may be performed identifying the stages detected or not, depending on the control strategy applied. Identifying the stages detected is the usual approach [15], [17], but Torrealba *et al.* have found that it is not necessary if only gait speed calculation is desired [6].

Most of the studies that perform gait cycle characterization using accelerometers and gyroscopes are limited to heel contact and toe-off detection [3]–[5], [18]–[20]. In [13], Torrealba *et al.* determined sub-phases of gait cycle on a sound leg during level walking from accelerometers data. Such characterization was accomplished by combining information from several lower limb acceleration signals besides the knee angle. As a result, seven events were detected throughout the gait cycle that mostly matched the percentages of sub-phases found in the literature [21]. However, the algorithm used back then was based on heuristically-determined thresholds applied to the signals. The need for automation of such algorithm was satisfied later by means of using recent signal statistics to automatically set the threshold levels on each signal [6]. Therefore, though the accelerometry-based detection algorithm yielt reliable results, the capability of using the implicit information carried by accelerometer signals processed together was neglected.

The present paper is addressed to develop an algorithm for detecting the human gait cycle sub-phases in an automated way, particularly tackling the shortcomings shown by previous algorithms presented in [6] and [13]. In section II, it is shown the development process of the technique whereas its capability is demonstrated in section III. Then, an extensive discussion of results is carried out in section IV and finally some important conclusions are summarized in section V. Also, a couple of future works are briefly introduced in section VI.

II. METHODOLOGY

For the analysis in this work data collected from two bi-axial accelerometers fixed to lower limbs in the sagittal plane was used. The accelerometers were placed at the knee and ankle joints height as shown in Fig. 1. Thus, four signals were available: a_{k_x}, a_{k_y}, a_{a_x}, a_{a_y}, with a_k referring the knee accelerations and a_a, the ankle ones. All data was captured at a sampling frequency of 60Hz, resampled to 120Hz and normalized. The following two gait conditions were used:

- Set A: Signals captured on an amputee patient wearing the prosthesis on a treadmill and in open areas [6]. The knee accelerometer was fixed to the stump (above-knee segment) at the knee axis height whereas the ankle accelerometer was attached to the pylon (below-knee segment) at the prosthesis ankle height.
- Set B: Signals captured on an able-body subject walking along an 8-m long walkway during a gait lab session [13]. The knee accelerometer was fixed to the thigh (above-knee segment) 7.5cm above the femoral condyles height whereas the ankle accelerometer was attached to the shank (below-knee segment) exactly at the malleollus height.

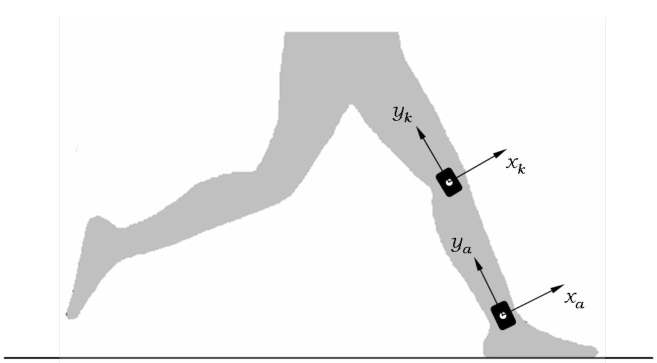


Fig. 1. Position and orientation of the accelerometers on the knee and ankle joints. The 'y'-axis of the accelerometers was aligned with the segment on which they were fixed, namely above-knee: thigh or stump, and below-knee: shank or pylon. The 'x'-axis was perpendicular to the latter with positive direction pointing forward.

A. Gait cycle characterization

From the well-known characterization of human gait cycle [21], it is divided in two major stages known as stance and swing phases. Typically, the stance phase goes from 0 to 60% of gait cycle in normal walking whereas the swing phase covers the remaining 40%. The stance phase is further divided in four sub-phases: load response (0-10% of gait cycle), mid-stance (10-30% of gait cycle), terminal stance (30-50% of gait cycle) and pre-swing (50-60% of gait cycle). The swing phase is also divided in three sub-phases: initial swing (60-73% of gait cycle), mid-swing (73-87% of gait cycle) and terminal swing (87-100% of gait cycle). Each of these seven sub-phases is characterized from the biomechanical point of view [21], therefore our endeavor to recognize the same sub-phases but from portable accelerometers data with all the associated advantages.

B. K-means algorithm

The k-means algorithm was used to obtain the centroids of N=7 clusters in the distribution using euclidean distance metrics. This was applied to the following signals: a_{k_x}, a_{a_x}, a_{a_y}, and their first derivatives: a'_{k_x}, a'_{a_x}, a'_{a_y}, thus yielding a six-dimensional space. The number of clusters was set in seven, corresponding to the number of sub-phases defined by the characterization of gait cycle detailed in subsection II-A. Then, the 7 seeds introduced to initialize the algorithm were the samples corresponding to the middle point of each sub-phase along a given gait cycle as shown in Fig. 3. Thus, a 6x7 matrix with 6-rows corresponding to the acceleration signals and 7-columns corresponding to the clusters (sub-phases of gait cycle) was defined as the seed matrix. Several k-means clustering runs were performed in order to avoid possible local minima in the resulting classification.

C. Cluster visualization

In order to visualize the clusters obtained after the k-means algorithm convergence, a 3D-plot was used with the signals a_{k_x}, a_{a_x}, a_{a_y}, plotting each cluster in a different color. Then, the same color chart was used to plot the clusters along the signals in order to visualize the temporal sequence of the sub-phases identified. Finally, a stair-like plot was also implemented to easily visualize the temporal sequence differentiated by these colors.

D. Logical filter

As the k-means clustering algorithm does not take into account the temporal sequence of the gait cycle sub-phases, some misclassifications can occur between contiguous gait sub-phases. In order to overcome this drawback, it was further developed a logical filter that operates on the k-mean clustered output. The filter can be described as the Finite-State-Machine (FSM) shown in Fig. 2.

In Fig. 2, it can be observed that there are three transitions for each sub-phase: the expected transition, the no-transition and the forbidden transition. Then, considering each sub-phase as a state of the FSM, there are three variables identified as the current state X_C, the expected state X_E, and the incoming state X_i. The X_C correspond to the last correctly assigned state. The X_E is the expected following state according to a normal 7 sub-phase gait cycle. Finally, the X_i is the following state suggested by the k-means algorithm. Based on this, now the logical filter operation can be described as follows:

- If $X_i = X_C$, there is no transition.
- If $X_i = X_E$, it is a valid transition, then: $X_C \leftarrow X_i$
- Else, there are two scenarios: missing sub-phases or a misclassified sub-phase, so:
  - If $X_i = X_C - 1$, it is a forbidden transition, then: ignore it!
  - Else, there are several missing sub-phases (≤ 5), then: $X_C \leftarrow X_i$

Finally, the output of the logical filter previously described is the obtained current state $X_C[n]$ for the sequence $X_i[n]$ received from the k-means algorithm.

E. Experiments

The experiments carried out in this work are summarized in Tab. I. In experiment 1, the aforementioned procedure was applied on trial T1 (A-set data) to obtain the centroids C1. Then, these centroids were used to classify the data of trial T2 (A-set data) in experiment 2, whereas the same data was also classified with centroids C2 obtained from the same trial in experiment 3. Finally, experiment 4 takes centroids C1 and apply them to classify the B-set data of trial T3.

F. Sub-phase length estimation

The length of the sub-phases after the logical filter were computed from the stair-like plot introduced in sub-section II-C. Later, this allowed to compare these results with the reference length of the human gait cycle sub-phases stated in sub-section II-A. This comparison was performed via analysis of variance ANOVA (multiple comparison test) in MATLAB, to determine if there were statistically significant differences ($p<0.05$) between the reference values and sub-phase lengths obtained from experiments 1, 2 and 3 (see Tab. I).

III. RESULTS

A. Algorithm training

The clusters obtained in experiment 1 before applying the logical filter are plotted in Fig. 4. It is observed a clear space classification from the centroid seeds selected from a given gait cycle of trial T1 as shown in Fig. 3. Then, Fig. 5(a) shows the clusters plotted along the acceleration signals. As can be observed, a color sequence is mainly recognized along the three signals though some misclassifications are also present. This is seen clearer in Fig. 5(b), in which each level of the stair correspond to a gait cycle sub-phase.

After applying the logical filter, the new cluster identification resulted as shown in Fig. 6. This classification shows a much more robust characterization of the gait cycle than the one presented in Fig. 5; showing in addition a logical temporal sub-phase sequence. Particularly from Fig. 6(a)-(1), it is seen that the second deepest valley of the signal is associated with the transition from the 'red' to the 'yellow' sub-phase in this plot. This transition is very important as it refers to the heel contact event which initiates the gait cycle [5], [13]. Likewise, the same occurs with the deepest valley, which is related to the toe-off event and hence to the start of the swing phase [5], [13]. In this case, this valley

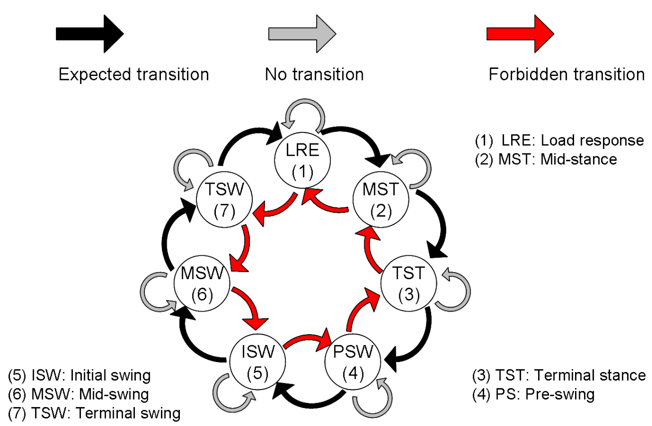


Fig. 2. Logical filter description as a Finite State Machine.

TABLE I
EXPERIMENTS PERFORMED

Experiment	Trial	Data set	Centroids
1	T1	A	C1
2	T2	A	C1
3	T2	A	C2
4	T3	B	C1

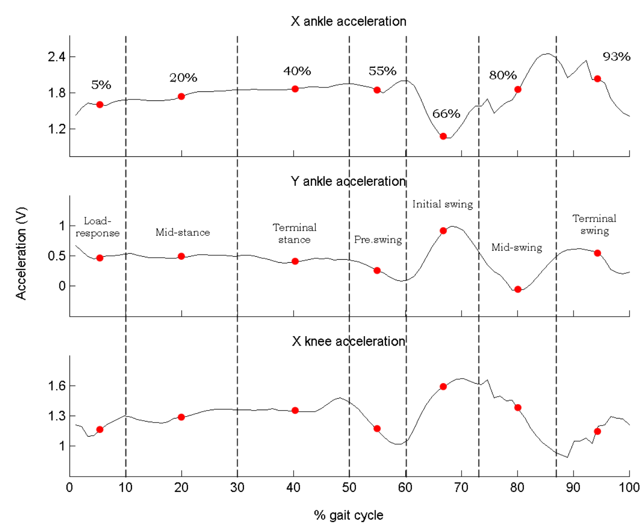


Fig. 3. Lower limb acceleration signals and seeds (red dots) introduced into the k-means algorithm. Gait cycle was divided in seven sub-phases and their corresponding middle-points were selected as the seven centroids required to feed the k-means algorithm. Centroids were also selected from the lower limb acceleration signal derivatives following this procedure.

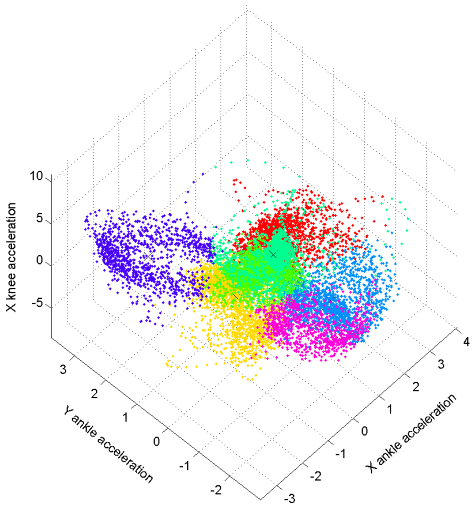
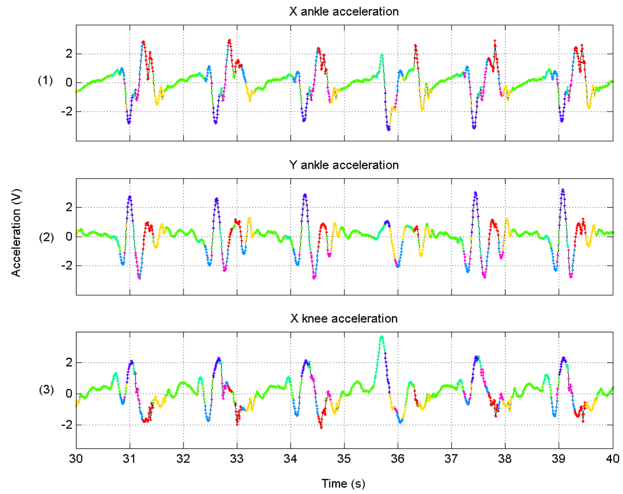
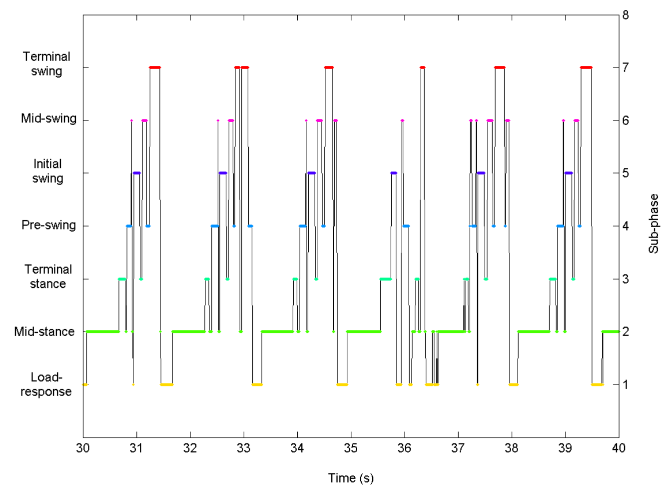


Fig. 4. 3D-plot of clusters obtained from the k-means algorithm



(a)



(b)

Fig. 5. Clusters plotted along the acceleration signals: (a) Superposition in time, (b) 'Stair'-plot showing the sub-phase sequence

is related to the transition from the 'light blue' to the 'dark blue' sub-phase.

In general, Fig. 6(a) highlights the hidden potential of lower limb acceleration data processed as a whole, since the transitions between sub-phases observed are otherwise almost impossible to be determined, for instance, by applying specific thresholds on each signal separately [6]. Regarding Fig. 6(b), this presents the benefits of applying the logical filter, resulting in a sub-phase temporal sequence that was almost perfect. The gait cycle periods along the trial were further computed from the 'load-response' sub-phase starts detected by the algorithm. Then, the gait cycle percentage covered by each sub-phase was calculated and compared to the reference values indicated in sub-section II-A. Such results correspond to experiment 1 shown in Tab. II and the length of sub-phases detected along each of the 78 gait cycles covered by the trial are shown in Fig. 7.

B. Algorithm testing

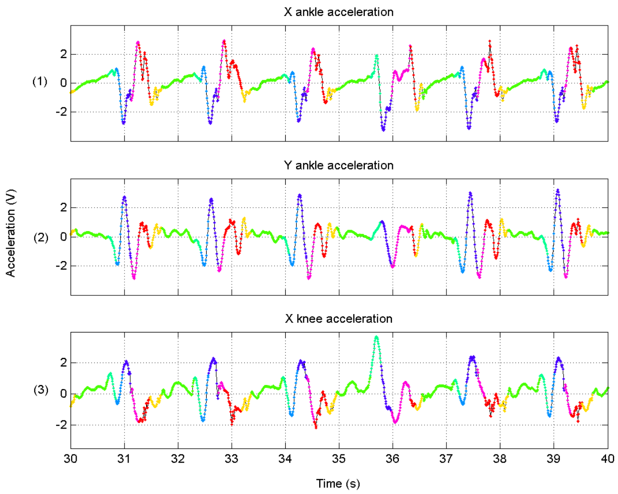
During the algorithm training it was found that, depending of the gait cycle from which the centroid seeds are selected, the clusters classification may result adequate or not in terms of the gait cycle sub-phase sequence expected. Looking for generalization, it was further tested the feasibility of using the centroids obtained from a given trial on a different one. Thus, the centroids found from trial T1 (experiment 1, see Tab. I) were used to classify the data distribution of trial T2 (experiment 2, see Tab. I). Fig. 8(a) shows the gait cycle periods that resulted from such experiment. Later, centroids were also obtained directly from trial T2 (experiment 3, see Tab. I) by applying the k-means algorithm as before (see sub-section III-A). Fig. 8(b) shows the resulting periods. As can be seen, gait speed was varied along the trial, and it is remarkable the similarity of the gait cycle period estimation from both experiments (see Fig. 8). Such similarity denotes the algorithm robustness to changes in walking speed. Also, it can be noticed that the outlier period of almost 9s corresponded to a pause presented along the trial. Also, the length of the gait cycle sub-phases that resulted from experiments 2 and 3 are presented in Tab. II.

Results from experiments 1, 2 and 3 shown in Tab. II were further used to perform an analysis of variance having as reference the length of sub-phases presented in sub-section II-A. For the 'load-response', 'mid-swing' and 'terminal swing' sub-phases, no statistically significant differences ($p<0.05$) between both the reference and detected sub-phases were found. However, the gait cycle percentages corresponding to the 'mid-stance' and 'terminal stance' were clearly different from the reference, whereas the resulting ones for the 'pre-swing' and 'initial swing' sub-phases barely differed from it. From Tab. II, it is important to notice that the sum of percentages of gait cycle corresponding to the seven sub-phases calculated in each experiment does not reach a 100%. This is because not all the sub-phases are found in every gait

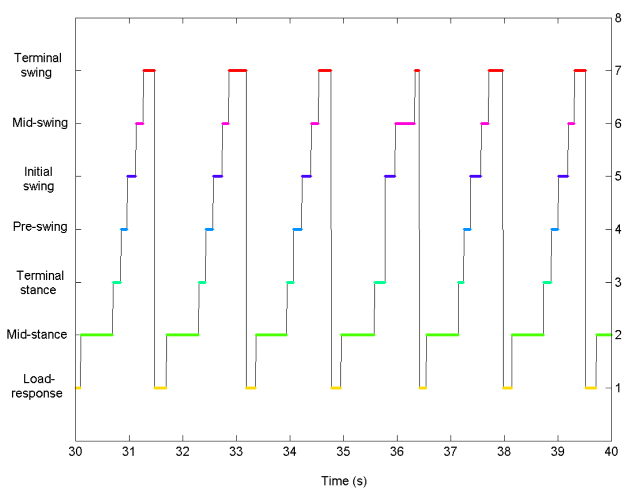
TABLE II

LENGTH OF SUB-PHASES FOUND FROM THE K-MEANS ALGORITHM IN PERCENTAGES OF GAIT CYCLE (MEAN)

Experiment	Load-Response	Mid-stance	Terminal stance	Pre-swing	Initial swing	Mid-swing	Terminal swing	TOTAL
Reference	10.0%	20.0%	20.0%	10.0%	13.0%	14.0%	13.0%	100.0%
1	13.9%	34.4%	9.5%	7.8%	11.6%	7.8%	13.8%	98.8%
2	7.3%	34.6%	6.8%	8.2%	11.3%	17.7%	13.1%	98.9%
3	21.3%	24.7%	7.4%	8.0%	9.6%	14.4%	13.5%	98.9%
Average E1-E3	10.6%	34.5%	8.1%	8.0%	11.4%	12.7%	13.5%	98.8%



(a)



(b)

Fig. 6. Clusters plotted along the acceleration signals after applying the logical filter: (a) Superposition in time, (b) 'Stair'-plot showing the sub-phase sequence

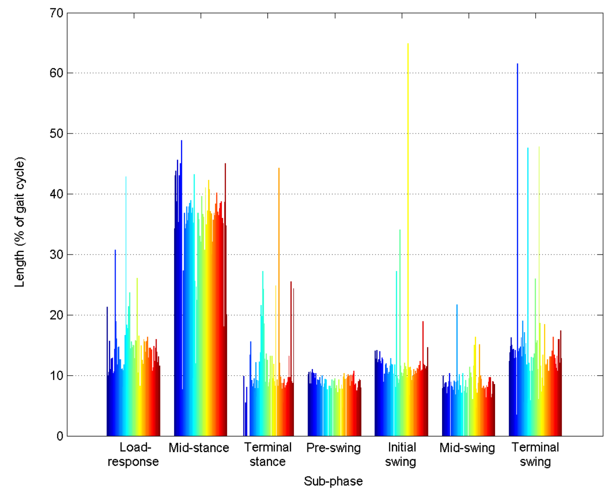
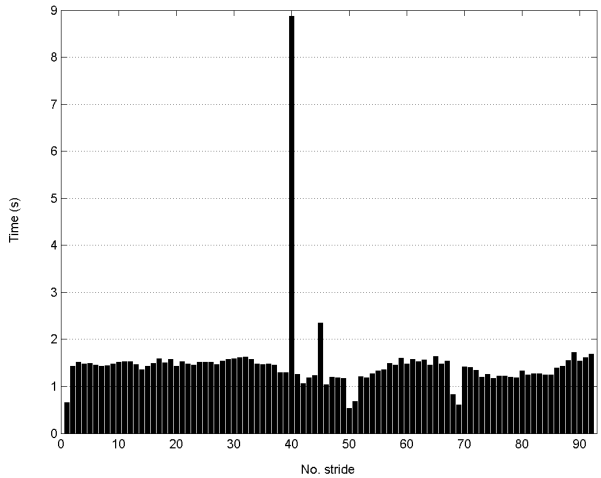


Fig. 7. Length of sub-phases found after applying the k-means algorithm and logical filter

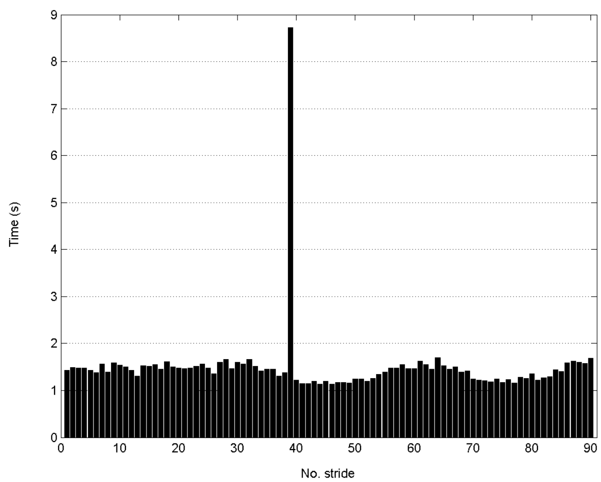
cycle of the trials. The difference, however, is only about 1% in long trials of more than 2min of length.

In addition, Tab. III presents the length of stance and swing phases computed in percentages of gait cycle from the experiments performed. It must be noticed that the average of the three experiments for these parameters are 61.2 and 37.6% of the gait cycle, respectively. These results practically match the reference values given by Perry in [21], when referring not the gross normal distribution (60% -stance; 40% -swing) but the one at the customary 80m/min rate of walking (62% -stance; 38% -swing).

Finally, the resulting sub-phase classification of experiment 4 is plotted in Fig. 9(a). As observed, the trial consisted of three complete gait cycles in which not all the sub-phases are detected from the cluster classification applied. Nonetheless, it is fair to mention that this experiment applied centroids from a prosthetic gait data trial (T1) on a completely different trial (T3) corresponding to a normal gait. Thus, such experiment was performed as an extreme test just to see the potential of the algorithm here developed. Bearing in mind that this trial (T3) was captured during a gait analysis, in which the subject begins to walk from one side of the walkway being standed and finishes across it in the same position, it resulted interesting how the algorithm correctly classified that position as a 'mid-stance' sub-phase. On the other hand, Fig. 9(b) presents the length of the sub-phases detected along the three strides of the trial. As before, not all the sub-phases are present in the three strides. Actually, only the 'load-response', nitial swing', 'mid-swing' and 'terminal swing' sub-pases are always present, though the percentages of gait cycle covered are not the right ones.

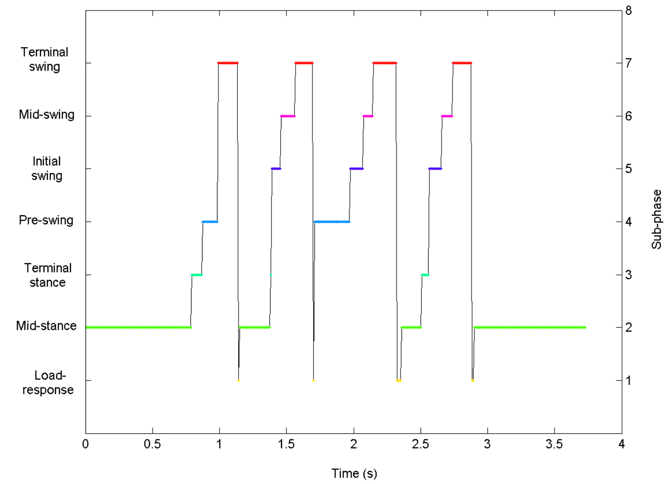


(a)

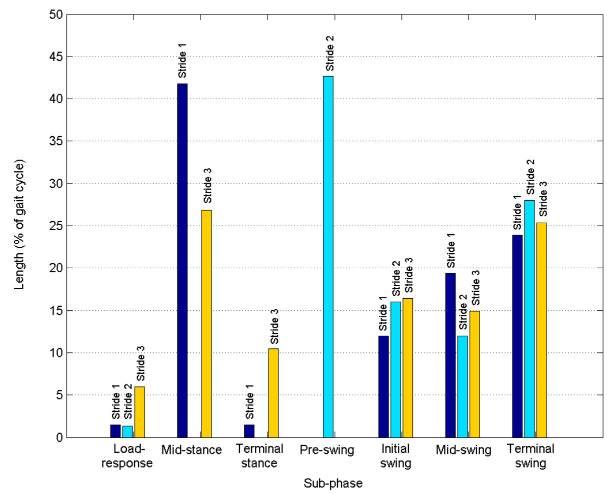


(b)

Fig. 8. Gait cycle periods computed from the 'load response' sub-phase starts detected by the algorithm along a trial: (a) After classification with centroids obtained from a different trial, (b) After classification with centroids obtained from the same trial



(a)



(b)

Fig. 9. Gait cycle sub-phases found by applying centroids obtained from a prosthetic gait trial on a normal gait one: (a) 'Stair'-plot showing the sub-phase sequence, (b) Sub-phase length in percentages of gait cycle

IV. DISCUSSION

Lower limb acceleration data captured during walking presents spikes that may correspond to single points if sampling frequency is not high enough. Furthermore, a positive spike could be inmediately followed by a negative one and, if the algorithm is trying to separate them in different clusters (sub-phases), one single sample may lead to a misclassification. To overcome this problem, data was resampled to 120Hz (twice the sampling frequency) resulting several points along the spikes before applying the k-means algorithm.

TABLE III
LENGTH OF STANCE AND SWING PHASES FOUND FROM THE K-MEANS ALGORITHM IN PERCENTAGES OF GAIT CYCLE

Experiments	Stance	Swing
Reference	60.0%	40.0%
1	65.6%	33.2%
2	56.9%	42.0%
3	61.4%	37.5%
Average E1-E3	61.2%	37.6%

As the signals a_{k_x}, a_{a_x}, a_{a_y}, had been the ones that were useful in [6], these were the three also employed here although the algorithm used back then was completely different. In addition, the first derivative of the signals was included to feed the algorithm with temporal dependence information. Derivatives of higher grade were discarded to prevent the reduction of the signal to noise ratio.

From Fig. 4, it can be observed that the sub-phases of gait cycle represented as clusters cover different regions of the space, thus reinforcing the hypothesis that acceleration signals looked as a whole carry implicit information that is overlooked when they are processed separately. However, the k-means cluster classification must be taken only as a preliminary one since such algorithm does not take into account the sub-phase temporal sequence. Therefore, many illogical sub-phase transitions may result as shown in Fig. 5, especially in points that fall between cluster frontiers. In such sense, the logical filter developed to provide the original k-means classification with a logical temporal sequence resulted to be very appropriate. As seen in Fig. 6, the apparently erratic classification of the k-means algorithm observed in Fig. 5 was transformed in a regular sequence of gait cycle sub-phases after applying the logical filter. This result demonstrated the effectiveness of the logical filter developed and allowed to calculate the length of the so-found sub-phases.

Basically, most of the sub-phase lengths shown in Tab. II resulted similar to the reference values reported by the literature though only three of the sub-phases found did not present statistically significant differences according to the ANOVA performed ($p<0.05$). In average, it seems that part of the 'terminal stance' sub-phase is absorbed by the 'mid-stance' one. This is probably because during the 'mid-stance' sub-phase here found all the acceleration signals processed seem to present a steady behaviour that is therefore detected as one single sub-phase (see Fig. 6). From Tab. III, it can be seen that the stance and swing phase lengths estimated from the sub-phase lengths presented in Tab. II are very similar to the values reported in the literature for these parameters. Furthermore, this result indirectly allows to conclude that the heel contact and toe-off events detected from the 'load response' and 'initial swing' sub-phases, respectively found from the k-means cluster classification, are correct. This is interesting as these events are the two most important ones of the gait cycle, allowing to determine several gait parameters.

Another important advantage of the algorithm here presented is that it can deal with different gait speeds. Previously, this had been an issue found by the authors when applying a correlation-based gait cycle tracker in [6]. It worked fine as long as the walking speed was constant but, whenever gait speed changed, it experienced problems that led to discard it. In this work, it was shown that the k-means algorithm as implemented here not only does not care about gait speed changes but also that it is equally applicable to different acceleration waveforms as long as the data had been previously normalized. Indeed, the algorithm was actually developed on a trial of prosthetic gait data and then applied to others of the same set of data and also of a different set (see Tab. I). Such experiments were performed to evaluate robustness of the algorithm, which resulted very promising for tackling different waveforms and gait speeds in lower limb acceleration data. Nevertheless, in any case the recommended procedure is of course to apply the algorithm here described to obtain the centroids of a given data distribution and then apply them to classify data of the same set on different trials (see sub-section III-A).

In this work, the number of signals used to characterize the gait cycle was reduced to three plus their corresponding first derivatives. This represents a big step when compared to the five signals initially used in [13], especially in terms of minimizing the information used to have a complete (seven sub-phases) characterization of the gait cycle. In addition, here there are specifically indicated the signals necessary to perform such characterization, particularly from sensors that can be embedded into lower limb prosthetic devices. On the other hand, it is worthy to mention that the results here found involve lower limb accelerations only, and they not include angles at the joints. This is very important to separate the characterization of gait cycle required by lower limb prostheses from the variables to be controlled, which are usually the joint angles.

Lower limb acceleration data not only bring in information about the swing phase but also allow to separate it in three different sub-phases. This is of great importance for the control of electronic knee prostheses, as during the swing phase the knee range of motion is wider and hence the actuator response should be majorly modulated [15]. Moreover, on the control of such prosthetic devices, detecting more stages along the gait cycle is desired whether a finite-state or a continuous strategy is intended. Here, seven sub-phases are identified by using the k-means algorithm, which might be used to define seven states or to update the gait cycle phase seven times along the gait cycle depending of the strategy applied.

V. CONCLUSIONS

As demonstrated in this work, lower limb acceleration data allows to perform a complete characterization of human gait cycle. It has been introduced the k-means clustering algorithm accompanied of a FSM-based logical filter to automatically identify seven sub-phases along the gait cycle, based on the biomechanical characterization reported in the literature. For the best of the authors' knowledge, it is the first time such method is proposed. This is a completely different approach to the problem of characterizing the gait cycle from lower limb acceleration data captured during walking, compared to what has been published to date.

The algorithm was trained and tested on prosthetic gait data. Most of the so-found sub-phases were similar in length (% of gait cycle) to the ones taken as reference from the literature, although only three presented no statistically significant differences ($p<0.05$) when compared to the reference values via analysis of variance. The algorithm was further tested by taking the centroids obtained from a prosthetic gait data trial on a normal gait data one. Despite such an extreme experiment, the algorithm was able to detect several sub-phases along the gait cycles, denoting its powerful capability to classify lower limb acceleration signals into gait cycle sub-phase clusters. Also, the algorithm demonstrated robustness to gait speed changes. This is a major asset of the method here proposed as people walks at several different gait speeds and therefore it is necessary to deal with this kind of changes.

Finally, among the sub-phases here recognized there were the 'load-response' and 'initial swing' sub-phases, whose start points correspond to the 'heel-contact' and 'toe-off' events, respectively. From these events, several temporal gait parameters may be determined as, for instance, the stance and swing lengths, or also the single and double-limb support times. Thus, the results of the algorithm presented in this work have a great potential not only to developers of lower limb prostheses, but also to be embedded into a portable device in order to estimate temporal gait parameters of importance in the study and diagnosis of normal and pathological gait in able-body and amputee subjects.

VI. FUTURE WORKS

The authors are currently developing the next prototype of the biomechatronic knee prosthesis presented in [6], in which the development here described will be introduced to performing the gait cycle characterization on the prosthesis. Once at this point, it is planned to test the prosthesis with several individuals and then, we will have opportunity to collect further data from which to continue evaluating the performance of the algorithm here shown. Hopefully, given the robustness of the algorithm as demonstrated in this work, upcoming results will be satisfactory too.

Also, though it was mentioned that the number of signals processed here was reduced in comparison with the ones used in [13], another possible work to undertake in the future is to incorporate the signal a_{k_y} into the group of acceleration signals used to perform the characterization of gait cycle on the prosthesis. Previously, this was left aside because it did not show a pattern with spikes that allowed to separate them as gait events by using thresholds as in [6], [13]. Now, from the algorithm here presented it might be useful to take such signal into account as well as its first derivative. In particular, from a very preliminary correlation analysis, it has been found that this signal and its derivative are little correlated to the others, therefore probably carrying different information from the ones already processed.

REFERENCES

[1] V. Racic, A. Pavic and J.M.W. Brownjohn, Experimental identification and analytical modelling of human walking forces: Literature review, *Journal of Sound and Vibration*, 326, 2009, pp. 1-49.

[2] H.K. Lee, K.J. Lee, S.P. Cho and J. You, Computational method and feasibility of detecting the whole body centre of gravity using an accelerometric device, *Electronics Letter*, 43(20), 2007, pp. 1068-1070.

[3] A. Mansfield and G.M. Lyons, The use of accelerometry to detect heel contact events for use as a sensor in FES assisted walking, *Medical Engineering & Physics*, 25, 2003, pp. 879-885.

[4] K. Aminian, K. Rezakhanlou, E. De Andres, C. Fritsch, P.F. Leyvraz and P. Robert, Temporal feature estimation during walking using miniature accelerometers: an analysis of gait improvement after hip arthroplasty, *Medical & Biological Engineering & Computing*, 37, 1999, pp. 686-691.

[5] E. Bishop and Q. Li, Walking speed estimation using shank-mounted accelerometers, *in Proc. 2010 IEEE Int. Conf. Robotics and Automation ICRA 2010*, May 2010, pp. 5096-5101.

[6] R.R. Torrealba, C. Pérez D'Arpino, J. Cappelletto, L. Fermín-León, G. Fernández-López and J.C. Grieco, Through the Development of a Biomechatronic Knee Prosthesis for Transfemoral Amputees: Mechanical Design and Manufacture, Human Gait Characterization, Intelligent Control Strategies and Tests, *in Proc. 2010 IEEE Int. Conf. Robotics and Automation ICRA 2010*, May 2010, pp. 2934-2939.

[7] B.G. Lambrecht and H. Kazerooni, Design of a Semi-Active Knee Prosthesis, *in Proc. 2009 IEEE Int. Conf. Robotics and Automation ICRA 09*, May 2009, pp. 639-645.

[8] R.R. Torrealba, G. Fernández-López and J.C. Grieco, Towards the development of knee prostheses: review of current researches, *Kybernetes: The International Journal of Systems & Cybernetics*, 37(9/10), 2008, pp. 1561−1576.

[9] D. Zlatnik, B. Steiner and G. Schweitzer, Finite-state control of a transfemoral (TF) prosthesis, *IEEE Trans. Control Systems Technology*, 10(3), 2002, pp. 408-420.

[10] A. Bar, G. Ishai, P. Meretsky and Y. Koren, Adaptive microcomputer control of an artificial knee in level walking, *Journal of Biomedical Engineering*, 5, 1983, pp. 145150.

[11] Otto Bock C-Leg. (2010, Jun 27). [Online]. Available: http://www.ottobock.com/cps/rde/xchg/ob_com_en/hs.xsl/1913.html.

[12] Rheo-Knee Support. (2010, Jun 27). [Online]. Available: http://www.ossur.com/?PageID=13449.

[13] R.R. Torrealba, J.M. Castellano, G. Fernández-López and J.C. Grieco, Characterisation of gait cycle from accelerometer data, *Electronics Letter*, 43(20), 2007, pp. 1066-1068.

[14] T. Watanabe, E. Ohki, Y. Kobayashi and M.G. Fujie, Leg-dependent Force Control for Body Weigth Support by Gait Cycle Estimation from Pelvic Movement, *in Proc. 2010 IEEE Int. Conf. Robotics and Automation ICRA 2010*, May 2010, pp. 2235-2240.

[15] H. Herr and A. Wilkenfeld, User-adaptive control of a magnetorheological prosthetic knee, *Industrial Robot: An International Journal*, 30(1), 2003, pp. 42-55.

[16] R.R. Torrealba, J. Cappelletto, L. Fermín, G. Fernández-López and J.C. Grieco, Cybernetic knee prosthesis: application of an adaptive central pattern generator, *Kybernetes: The International Journal of Systems & Cybernetics*, to be published.

[17] H. Dietl, R. Kaitan, R. Pawlik and P. Ferrara, C-Leg - A new system for prosthetic management of A/K amputations (C-Leg - Ein neues system zur versorgung von oberschenkelamputationen), *Orthopadie Technik*, 49, 1998, pp. 197-211.

[18] R.E. Mayagoitia, A.V. Neneb and P.H. Veltinkc, Accelerometer and rate gyroscope measurement of kinematics: an inexpensive alternative to optical motion analysis systems, *Journal of Biomechanics*, 35(4), 2002, pp. 537-542.

[19] K. Tong and M.H. Granat, A practical gait analysis system using gyroscopes, *Medical Engineering & Physics*, 21(2), 1999, pp. 87-94.

[20] K. Aminian, B. Najafia, C. Blab, P.F. Leyvrazc and P. Robert, Spatio-temporal parameters of gait measured by an ambulatory system using miniature gyroscopes, *Journal of Biomechanics*, 35(5), 2002, pp. 689-699.

[21] J. Perry, *Gait analysis: normal and pathological function*, SLACK Incorporated, Thorofare, NJ; 1992.

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