Segmentation and Classification of Gait Cycles

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***Abstract*—Gait abnormalities can be studied by means of instrumented gait analysis. Foot-switches are useful to study the foot–floor contact and for timing the gait phases in many gait disorders, provided that a reliable foot-switch signal may be collected. Considering long walks allows reducing the intra-subject variability, but requires automatic and user-independent methods to analyze a large number of gait cycles. The aim of this work is to describe and validate an algorithm for the segmentation of the foot-switch signal and the classification of the gait cycles. The performance of the algorithm was assessed comparing its results against the manual segmentation and classification performed by a gait analysis expert on the same signal. The performance was found to be equal to 100% for healthy subjects and over 98% for pathological subjects. The algorithm allows determining the atypical cycles (cycles that do not match the standard sequence of gait phases) for many different kinds of pathological gait, since it is not based on pathology-specific templates.**

***Index Terms*—Atypical gait cycles, classification, foot–floor contact, foot-switches, gait analysis, gait event detection, gait phases, signal segmentation, stride-to-stride variability.**

I. Introduction

THE STUDY of the foot–floor contact during gait is crucial in the management of many orthopedic and neurological disorders. An accurate detection of the gait phases is fundamental in clinical gait analysis to interpret kinetic and kinematic data [1]. Focusing on one lower limb, each gait cycle is typically divided into two periods called stance and swing. *Stance* designates the entire period during which the foot is on the ground, while *swing* applies to the time the foot is in the air for limb advancement. In normal gait, most of the gait cycles consists of the sequence of the following three sub-phases of stance: heel contact (H), flat foot contact (F), push off (or heel off) (P), followed by the limb swing (S) [2]. In a pathological gait, other sequences of gait phases may be observed. In subjects with an equinus foot, the gait cycle usually starts with a forefoot contact instead of a heel strike. In many neurological and degenerative diseases—including stroke, multiple sclerosis, muscular dystrophy, and Parkinson's disease—a foot-drop may be observed during the swing phase. In general, detecting the gait events that mark the transition from one gait phase to another, as well as the sequence of gait phases, is essential to evaluate gait abnormalities.

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During a walk consisting of a large number of strides (100–250), both normal and pathological subjects use different sequences of gait phases. In other words, a subject does not show the same type of gait cycle throughout the walk. This is due to the inherent variability of the human gait [3]. In literature, there is a growing interest in the study of intra-subject gait variability. Among other applications, gait variability is used to assess fall risk in elderly people [4], [5]. The stride-to-stride variability of the spatio-temporal parameters is frequently used to quantify gait performances. However, the stride-to-stride variability of the foot–floor contact sequence is usually not considered and the presence of different types of gait cycle, occurring during a subject's walk, is disregarded. As a matter of fact, many studies consider only a few consecutive gait cycles (due to the limitations of the laboratory setting), and discard cycles that do not match the "standard" cycle observed for the specific subject under test. A second reason why this variability is often disregarded is the lack of algorithms that automatically recognize the sequence of gait phases in a "long" walk (lasting 2–3 min).

Designing gait tests in which a large number of strides is recorded is fundamental in "statistical gait analysis" [6]–[9] to handle intra-subject variability. A key point, in this approach, is the possibility of analyzing the gait cycles automatically and in a user-independent way.

The analysis of long walks allowed us to evidence the presence of "nonstandard" sequences of gait phases even in normal subjects. We called *atypical cycles* those gait cycles that do not match the "standard" foot–floor contact pattern: heel contact, flat foot contact, push off, swing (HFPS). From the study we conducted on 100 healthy children, we observed an occurrence percentage of atypical cycles around 10% [7]. In pathological subjects, depending on the pathology, the percentage of atypical cycles may significantly grow with respect to the normal [9], [10], reaching 100% in subjects with severe gait abnormalities. In mildly impaired patients, the percentage of atypical cycles can be used as a reliable outcome measure in evaluating subtle changes of a patient's condition.

A reliable evaluation of the gait events is fundamental in the study of the foot–floor contact. Many different sensors are used for timing the gait cycles [2]. They can be divided into two categories: sensors that allow for a *direct* measure of the gait events and those that *indirectly* reconstruct the timing of these events. Foot-switches [6]–[10] and force-sensitive resistors [11], [12] allow acquiring directly the foot–floor contact, while accelerometers [13]–[15], gyroscopes [16], and inclinometers [2] require a customized signal processing to gain the information on the gait events. Here, we are interested in a direct measure of the foot–floor contact by means of foot switches.

In this paper, we address the *segmentation* of the foot-switch signal, which is the partition of the signal into separate gait

cycles and the gait cycle *classification*, i.e., the definition of the gait cycle types observed during a walk. The segmentation and classification of gait cycles may become difficult in pathological gait. This problem is often faced focusing on the signs of the specific pathology under consideration and establishing pathology-specific templates for the foot–floor contact patterns. The advantage of the approach presented here is that it does not require any *a priori* knowledge on the sequence of phases forming a gait cycle. This means that the same algorithm can be applied to many different pathologies, since the segmentation process is carried out without the need to define foot–floor contact templates.

The aim of this paper is to describe the structure and validation process of an algorithm for the segmentation of the foot-switch signal and the classification of the gait cycles in an automatic and user-independent way.

II. Foot-Switch Signal

A. Signal Acquisition and Four-Level Coding

The foot-switch signal is acquired as follows. A subject is instrumented with three foot-switches under the sole of the foot, positioned beneath the heel, the first and the fifth metatarsal heads. He is asked to walk barefoot back and forth along a straight walkway, for 2–3 min, at self-selected speed. Foot-switches (size: $10\ \mathrm{mm} \times 10\ \mathrm{mm} \times 0.3\ \mathrm{mm}$, STEP32, DemItalia, Italy) are activated by a force of 3 N.

The three digital signals are combined by means of a digital-to-analog converter to obtain $2^3 = 8$ different foot-support conditions (eight-level signal). However, the eight-level signal is too variable and "detailed" to be used in a statistical analysis of gait, and it is usually simplified into a four-level signal [6], [7]. The four levels correspond to the gait phases H, F, P, and S.

During the H-phase only the foot-switch under the heel is closed. During the F-phase the heel foot-switch is closed, and at least one of the foot-switches under the forefoot is also closed. During the P-phase the foot-switch under the heel is open, and at least one of the foot-switches under the forefoot is closed. During the S-phase all the foot-switches are open. Fig. 1 schematizes the four on/off combinations of the foot-switches and the corresponding gait phases.

B. Signal Preprocessing

Once the foot-switch signal has been recorded, an anti-causal anti-bounce filter is applied to it, to remove spurious spikes due to switch bounces.

C. Examples of Foot-Switch Signal

Examples of foot-switch signals are shown in Fig. 2. These signals were recorded during a gait test, at self-selected speed, from: (a) a healthy subject, (b) a patient affected by Parkinson's disease, (c) a child with hemiplegic cerebral palsy (affected side). The three cases show different patterns of foot–floor contact. These examples demonstrate that a specific subject does not show a single characteristic cycle, but different cycle types.

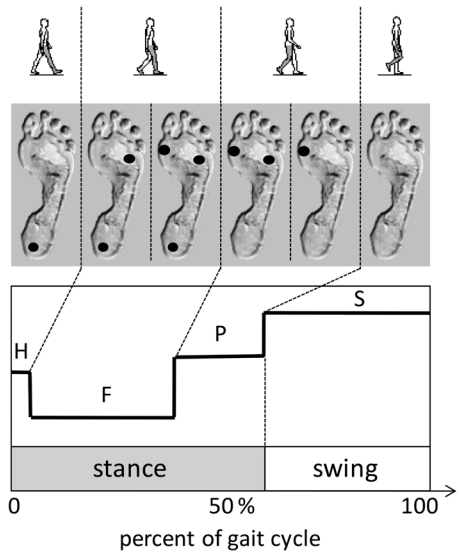

Fig. 1. Foot-switches: four level coding. Gait phases (for one leg): heel contact (H), flat foot contact (F), push-off or heel off (P), swing (S).

III. Description of the Algorithm

The foot-switch signal is segmented into separate gait cycles and each cycle is classified as belonging to a class characterized by a specific sequence of gait phases. The algorithm begins by defining a preliminary segmentation. Then, it tries to merge cycles that are too short to be considered as a valid cycle. A schematization of the algorithm is given by Fig. 3. The algorithm is detailed in the following.

A. Preliminary Segmentation

Let us define the foot-switch signal as the time-series $X = [x_1, x_2, \ldots, x_n]$, where each time sample x_i assumes one of four separate voltage values, corresponding to F, H, P, S, in ascending order of amplitude. The preliminary segmentation of the foot-switch signal is obtained through the following steps:

1) Beginning of Gait Phases: Determine the beginning of each gait phase as the transition between adjacent phases. Define the vector $\mathrm{PhaseInSample} = [y_1, y_2, \ldots, y_m]$, finding the positions in X for which $x_i - x_{i-1}$ is different from zero.

2) Phase Duration: Calculate the duration of each gait phase (in samples) $\mathrm{PhaseDur} = [y_2 - y_1, \ldots, y_j - y_{j-1}, \ldots, y_m - y_{m-1}]$.

3) String of Phases: Obtain the string of characters defining the sequence of gait phases of length $m-1$, e.g., $\mathrm{SequenceString} = [\mathrm{SHFPSPSHFPSHFPSHFPS}\ldots]$.

4) Initial-Cycle Candidates: Find, in *SequenceString*, the "initial-cycle candidates," that is the indexes of the array elements in which a cycle is likely to start. These indexes are obtained by applying the following rule: *a cycle begins at the first detection of foot contact*. In the four-level coding this is represented by a *transition from a specific level to a lower one* (e.g., from S to H, from S to F, from S to P, etc.). If there are two consecutive transitions, only the first one is considered as a valid cycle start, i.e., all the one-phase cycles are merged with the

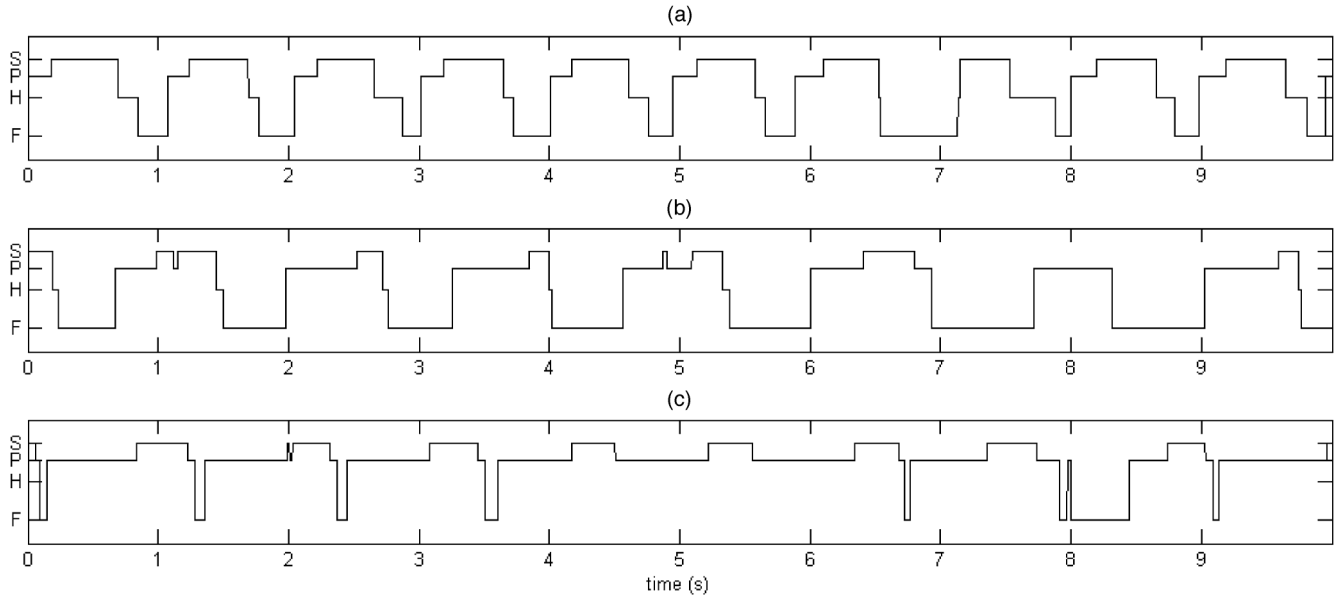

Fig. 2. Examples of foot-switch signal during gait (10 s extracted from the original signals are displayed). (a) Healthy subject. (b) Parkinson's disease. (c) Hemiplegic child.

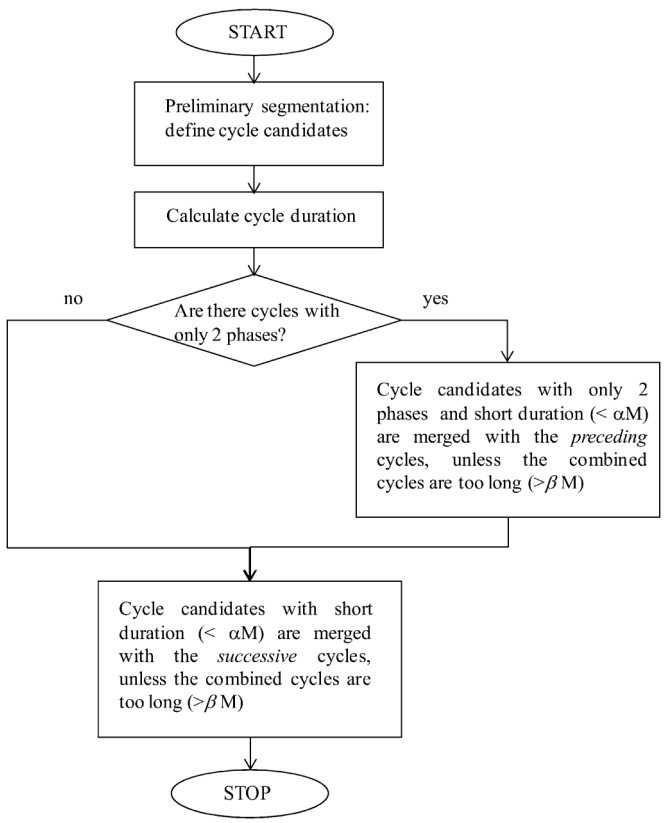

Fig. 3. Schematization of the algorithm.

cycle that follows. To clarify this rule, Fig. 4 represents an example of initial-cycle candidate selection. Focusing on the first few levels shown in the figure we observe: 1) a transition from S to H, and 2) a consecutive transition from H to F. Applying the above mentioned rule, the second transition is neglected: the first cycle candidate begins with an H-phase and extends for four phases. The following transition can be found between S and P:

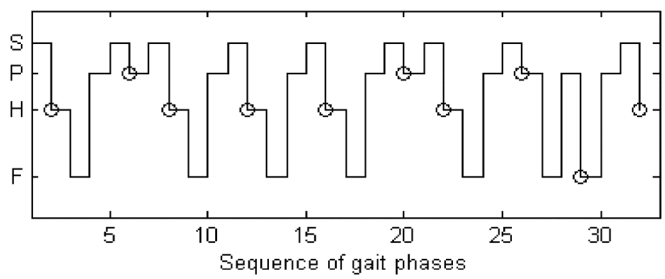

Fig. 4. Preliminary segmentation: initial-cycle candidates are marked with a circle.

the second cycle candidate begins with a P-phase and extends for two phases, etc. In this example, the vector of the initial cycle candidates $\mathrm{CycleInit} = [I_1, I_2, \ldots, I_k, I_{k+1}, \ldots, I_N]$ is equal to [2, 6, 8, 12, 16, ...].

5) Gait Cycle Candidates: Each gait cycle is defined as the substring of gait phases whose indexes range from $\mathrm{I_k}$ to $(\mathrm{I_{k+1}} - 1)$. Hence, referring to the same example, the candidate cycles are HFPS, PS, HFPS, HFPS, ... Each different substring is the prototype of a class: $\mathrm{Class}\{1\} = \mathrm{HFPS}$, $\mathrm{Class}\{2\} = \mathrm{PS}, \ldots$. Each cycle is assigned to the corresponding class.

The number of cycles assigned to each class is counted, thus obtaining the absolute frequency (Freq) of each class. A "segmentation vector" of length $m - 1$ is initialized to zero. Then, each element corresponding to the beginning of a cycle is set to a number different from zero: this number indicates the class of the cycle, that is 1 if the cycle belongs to $\mathrm{Class}\{1\}$, 2 if it belongs to $\mathrm{Class}\{2\}$, etc., e.g., $\mathrm{Segments} = [0\ 1\ 0\ 0\ 0\ 2\ 0\ 1\ 0\ 0\ 0\ 1\ 0 \ldots]$.

B. Duration of Gait Cycles

The average duration of the gait cycles is calculated (in samples), separately for each class: e.g., $\mathrm{CycleDur}\{1\}$, $\mathrm{CycleDur}\{2\}$, etc.

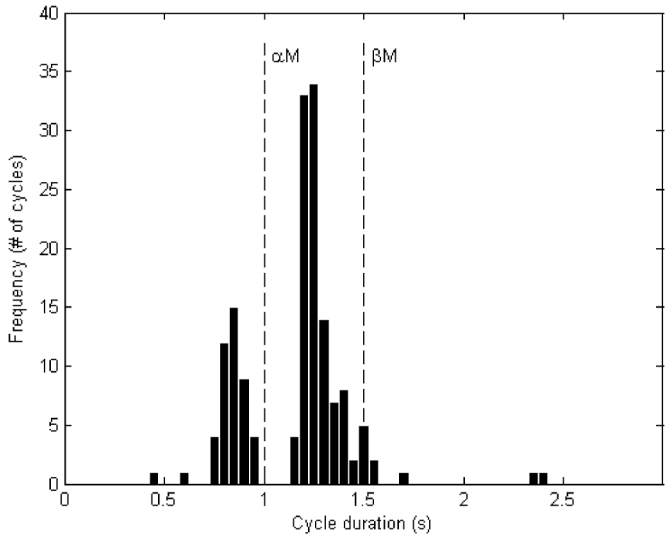

Fig. 5. Histogram of cycle duration for a pathological subject (Parkinson's disease). The mode of the histogram is $M = 1.25$ s. The two thresholds $\alpha \cdot M$ and $\beta \cdot M$ are indicated with a dashed line for $\alpha = 0.8$ and $\beta = 1.2$.

C. Cycles With Only Two Phases

At this stage the algorithm searches, iteratively, a cycle with more than two phases (e.g., HFPS) followed by a cycle with only two phases (PS), and merges them into the composite cycle (HFPSPS) by means of the following rule: *if the two-phase cycle is short and the composite cycle is not too long, then the composite cycle is considered as a valid cycle candidate*. This implicates the definition of two thresholds. More specifically, we calculate the mode M of the duration of cycles with more than two phases. If the duration of a two-phase cycle is less than a given percentage of the mode, $\alpha \cdot M$ (with $0 < \alpha < 1$), and if the duration of the composite cycle is not greater than $\beta \cdot M$ $(1 < \beta < 2)$, than the composite cycle is a valid cycle candidate (see Fig. 5). More specifically, we consider a cycle to be valid if its duration is neither shorter nor longer for more than 20% of the mode M defined above, hence choosing $\alpha = 0.8$ and $\beta = 1.2$. The vectors *Segments*, *CycleDur*, and the absolute frequency *Freq* of the involved classes are updated accordingly. If needed, a new class is created.

D. Leftover Cycles With Short Duration

The algorithm searches for the leftover cycles with short duration, independently from the number of phases (i.e., not limiting to cycles with only two phases). Iteratively, the algorithm takes one of these cycles and merges it with the following cycle, provided that the duration of the composite cycle is not greater than $\beta \cdot M$.

IV. Validation of the Algorithm

The algorithm described here is based on a set of rules that represent the way in which an experienced "user" works to segment the signal. The validation process is aimed at demonstrating that the algorithm is as good as the human expert. We used one expert (Knaflitz) to define the rules and another one (Agostini) to validate the algorithm. We applied the described algorithm to a dataset of 10 foot-switch signals, collected from five healthy and five pathological subjects. For the latter, we searched retrospectively our clinical database to cover the more common gait alterations observed in different pathologies, e.g., foot drop in swing, producing cycles with forefoot (PS, PFPS,. . .) or flatfoot (FPS,. . .) initial contact, or cycles in which the forefoot, already detached from the floor, falls down, and touches the floor again before reaching a sufficient foot clearance (HFPSPS). Both healthy and pathological subjects walked 2–3 min at self-selected speed. Therefore, a slightly different number of cycles was collected for each of them during the gait test. The average number of cycles collected and analyzed was 135 ± 17 for healthy and 129 ± 36 for pathological subjects. The algorithm was validated on a total of 1320 gait cycles (674 from healthy and 646 from pathological subjects): 1005 cycles showed a normal sequence of gait phases (HFPS), while 315 showed an atypical sequence (different from HFPS). A total of 19 cycle types were recognized: the HFPS class and other 18 atypical classes.

A. Comparison With Manual Segmentation

For each signal, we compared the gait cycle classification obtained from: 1) the algorithm, 2) the "manual" segmentation performed by the gait analysis expert (Agostini). The manual segmentation was performed through the following steps:

1) Visualization of the (filtered) foot-switch signal from the acquisition system interface, setting the visualization options so that only a few cycles (5–10) at a time are displayed.
2) Insertion of a segmentation line with a mouse double click.
3) Visual recognition of each cycle class (e.g., HFPS, etc.). When a new cycle is classified, a cross is added on a sheet of paper near the correspondent class name.
4) Counting of the crosses assigned to each cycle class.

We calculated the mismatching cycles between the procedures (algorithm and manual segmentation), if present. The performance of the algorithm was defined as the number of gait cycles matching the manual segmentation, divided by the total number of gait cycles.

B. Results and Performance of the Algorithm

Applying the algorithm to the sample dataset, we obtained the results reported in Table I. More specifically, for each examined subject we indicated the subject's health condition, the class and number of gait cycles obtained through the automatic segmentation, and the class and number of cycles obtained through the manual segmentation. The last column reports the percentage of correct classifications. The algorithm recognized 100% of the cycles in healthy subjects, and over 98% in pathological subjects.

A one-factor sensitivity analysis was performed to evaluate the robustness of the values chosen for α and β. Changing the (input) value of α in the range 0.75–0.85 we obtained exactly the same classification in seven subjects. In the remaining three subjects the classification was different only for less than 3% of the gait cycles. Similar results were obtained changing the parameter β in the range 1.15–1.25.

TABLE I
VALIDATION DATASET

N	Subjects: health condition	Algorithm classification[a]		Manual classification[a]		Percentage of correct classification
		Gait cycle class	# of cycles	Gait cycle class	# of cycles	
1	Healthy	HFPS	118	HFPS	118	100 %
		HS	1	HS	1	
		HFHS	1	HFHS	1	
		HFHFPS	1	HFHFPS	1	
2	Healthy	HFPS	145	HFPS	145	100 %
		PFPS	2	PFPS	2	
3	Healthy	HFPS	152	HFPS	152	100 %
		HFHFPS	3	HFHFPS	3	
4	Healthy	HFPS	131	HFPS	131	100 %
		HFHFPS	2	HFHFPS	2	
		FPS	1	FPS	1	
		PFPS	1	PFPS	1	
5	Healthy (elderly)	HFPS	106	HFPS	106	100 %
		PFPS	7	PFPS	7	
		PFHS	2	PFHS	2	
		FPS	1	FPS	1	
6	Hemiplegic child (Winters Group I)[b]	HFPS	63	HFPS	63	100 %
		PFPS	18	PFPS	18	
		HFHS	4	HFHS	4	
		PFHS	2	PFHS	2	
		PFPSPS	1	PFPSPS	1	
		HFHFHS	1	HFHFHS	1	
		FPS	1	FPS	1	
7	Hemiplegic child (Winters Group II)[b]	PFPS	88	PFPS	88	98.0 %
		PFPSPS	38	PFPSPS	38	
		PS	9	PS	9	
		PFPSPSPS	6	PFPSPSPS	6	
		PFPFPS	**3**	**PFPFPS**	**4**	
		PSPS	3	PSPS	3	
		FPS	**3**	**FPS**	**2**	
		PFP	**2**	**PFP**	**1**	
8	Parkinson's disease	HFPS	81	HFPS	81	98.7 %
		HFPSPS	43	HFPSPS	43	
		PFPS	**11**	**PFPS**	**10**	
		FPS	**9**	**FPS**	**10**	
		PFP	7	PFP	7	
		HFP	3	HFP	3	
		FP	2	FP	2	
		HFPSPSPS	1	HFPSPSPS	1	
		HFPFHFPS	1	HFPFHFPS	1	
		FPSPS	1	FPSPS	1	
9	Vestibular schwannomas resection	HFPS	70	HFPS	70	100 %
		HFHFPS	17	HFHFPS	17	
		HFHS	1	HFHS	1	
		HFPSPS	1	HFPSPS	1	
10	Total hip arthroplasty	HFPS	139	HFPS	139	100 %
		PFPS	16	PFPS	16	
		PFPFPS	1	PFPFPS	1	

[a] A mismatch between the algorithm and the manual classification is highlighted in bold.
[b] Winters Group I and II refer to the severity of children hemiplegia as classified by Winters *et al.* [17].

C. Atypical Cycles

The percentage of atypical cycles was calculated as the total number of cycles that do not match the standard HFPS-sequence, divided by the total number of segmented cycles. This parameter is reported in Table II, for each subject. The percentage of atypical cycles was 1%–3% in the healthy adults and 9% in the elder subject. This percentage ranged from 11% to 100% in pathological subjects.

V. DISCUSSION

The described algorithm automatically segments a foot-switch signal through a set of rules, with the purpose of mimicking the human expert. The results showed that the cycles defined by the algorithm were interchangeable with those determined by the human assessor in 100% of cases for normal gait, and at least 98% of cases for pathological gait.

This algorithm identifies the different types of gait cycles present in a walk. Since it is not based on predetermined templates for the sequence of phases forming a gait cycle, it is potentially capable to handle any kind of atypical cycle, provided that foot-switches are used accurately. This characteristic makes this algorithm usable in the study of many pathologies that affect the gait function. Caution should be taken in the study of pathologies involving severe foot deformity, e.g.,

TABLE II
ATYPICAL CYCLES

N	Subjects: health condition	Percentage of atypical cycles
1	Healthy	2%
2	Healthy	1%
3	Healthy	2%
4	Healthy	3%
5	Healthy (elder)	9%
6	Hemiplegic child (Winters Group I)	30%
7	Hemiplegic child (Winters Group II)	100%
8	Parkinson's disease	48%
9	Vestibular schwannomas resection	21%
10	Total hip arthroplasty	11%

Charcot–Marie–Tooth, since the foot-switch signal may become unreliable.

Spastic hemiplegic children usually show a drop foot in the swing phase (Winters group I), together with a tight heel cord in the stance phase (Winters group II) [17]. A study we carried out on 26 hemiplegic children allowed us to classify their foot–floor contact patterns [10]. Globally, their percentage of atypical cycles ranged from 19% to 100% (average: 73% $\pm$ 28%), in group I, and from 53% to 100% (average 96 $\pm$ 12%) in group II.

The possibility to calculate the percentage of occurrence of atypical cycles may be relevant in clinical applications, particularly when it can evidence subtle changes in gait performances, not clinically detectable. In a previous study, considering atypical cycles, we were able to demonstrate the benefits obtained from a light-intensity physical activity program undergone by 27 patients affected by type 2 diabetes [9]. The cadence of these patients did not change after the program completion, but the percentage of atypical cycles decreased from 9.9% to 4.8%, for the left lower limb, and from 7.7% to 4.4%, for the right one, quantifying a small, but measurable, improvement in their gait performances. The sensitivity of this parameter in grasping subtle changes of gait instability was highlighted also in other recent studies we conducted on patients after total hip arthroplasty [18], [19], and in normal pressure hydrocephalus [20], but the final results of these studies are not yet published. The proposed algorithm could also be applied to the assessment of fall risk in elderly people [4], [5], since it provides an objective measure of the stride-to-stride variability in the foot–floor contact patterns.

A reliable estimation of gait parameters is usually obtained by averaging the values from many gait cycles (recorded in the same test or in repeated tests), in order to reduce the intra-subject variability. However, averaging cycles that belong to different classes may be misleading, since these cycles may have different biomechanical determinants. For this reason, in *statistical gait analysis* [6], [7], [9], [19], averaging procedures aimed at reducing intra-subject variability are applied only to cycles belonging to the same class. Hence, the application of the proposed algorithm is a useful preprocessing step to perform a statistical analysis of gait, since it provides the required classification.

The algorithm presented here was applied to foot-switch signals. A single foot-switch provides a signal of either foot contact or lack of contact (on/off). This binary characteristic directly produce a "sharp" timing of the gait phases, useful in gait event detection. Other techniques, e.g., those relying on foot plantar pressure measurements [21], are based on many tiny sensors that allow for a detailed monitoring of the foot–floor pressure. However, they do not directly provide sharp indications on the sub-phases of stance. Preprocessing the insole pressure signal (see e.g., [22]) the proposed algorithm might be extended to insole pressure measurements. Future work may investigate this possibility.

VI. CONCLUSION

We proposed a general purpose algorithm for the classification of the gait cycles, usable in clinical gait analysis independently from the pathology considered, provided that a reliable foot-switch signal may be collected. We demonstrated the ability of this algorithm in recognizing the different types of gait cycles. The algorithm allows determining the atypical cycles present in a patient's walk.

REFERENCES

[1] J. Perry, *Gait Analysis. Normal and Pathological Function*. Thorofare, NJ: Slack, 1992.
[2] J. Rueterbories, E. G. Spaich, B. Larsen, and O. K. Andersen, "Methods for gait event detection and analysis in ambulatory systems," *Med. Eng. Phys.*, vol. 32, pp. 545–552, 2010.
[3] D. A. Winter, *The Biomechanics and Motor Control of Human Gait*. Waterloo, Canada: Univ. Waterloo Press, 1987.
[4] J. M. Hausdorff, D. A. Rios, and H. K. Edelberg, "Gait variability and fall risk in community-living older adults: A 1-year prospective study," *Arch. Phys. Med. Rehabil.*, vol. 82, no. 8, pp. 1050–1056, Aug. 2001.
[5] J. Verghese, R. Holtzer, R. B. Lipton, and C. Wang, "Quantitative gait markers and incident fall risk in older adults," *J. Gerontol. A Biol. Sci. Med. Sci.*, vol. 64A, no. 8, pp. 896–901, 2009.
[6] V. Agostini and M. Knaflitz, "Statistical gait analysis," in *Distributed Diagnosis and Home Healthcare (D2H2)*. Valencia, CA: American Scientific, 2012, vol. 2, pp. 99–121.
[7] V. Agostini, A. Nascimbeni, A. Gaffuri, P. Imazio, M. G. Benedetti, and M. Knaflitz, "Normative EMG activation patterns of school-age children during gait," *Gait Posture*, vol. 32, pp. 285–289, 2010.
[8] M. G. Benedetti, V. Agostini, M. Knaflitz, V. Gasparroni, M. Boschi, and R. Piperno, "Self-reported gait unsteadiness in mildly impaired neurological patients: An objective assessment through statistical gait analysis," *J. Neuroeng. Rehabil.* vol. 9, no. 64, pp. 1–7, 2012.
[9] V. Agostini, R. De Luca, L. C. Mansin, and M. Knaflitz, "Reduction of gait abnormalities in type 2 diabetic patients due to physical activity: A quantitative evaluation based on statistical gait analysis," *J. Mech. Med. Biol.*, vol. 12, no. 5, pp. 1–10, 2012.
[10] V. Agostini, A. Nascimbeni, A. Gaffuri, and M. Knaflitz, "Analysis of abnormal gait cycles in hemiplegic children," in *Proc. III Nat. Congr. Biomed. Eng.*, Rome, Italy, 2012, pp. 1–2.
[11] B. T. Smith, D. J. Coiro, R. Finson, R. R. Betz, and J. McCarthy, "Evaluation of force-sensing resistors for gait event detection to trigger electrical stimulation to improve walking in the child with cerebral palsy," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 10, no. 1, pp. 22–29, Mar. 2002.
[12] M. M. Skelly and H. Jay Chizeck, "Real-time gait event detection for paraplegic FES walking," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 9, no. 1, pp. 59–68, Mar. 2001.
[13] J. M. Jasiewicz, J. H. J. Allum, J. W. Middleton, A. Barriskill, P. Condie, B. Purcell, and R. C. T. Li, "Gait event detection using linear accelerometers or angular velocity transducers in able-bodied and spinal-cord injured individuals," *Gait Posture*, vol. 24, pp. 502–509, 2006.
[14] H. Lau and K. Tong, "The reliability of using accelerometer and gyroscope for gait event identification on persons with dropped foot," *Gait Posture*, vol. 27, pp. 248–257, 2008.
[15] M. S. H. Aung, S. B. Thies, L. P. J. Kenney, D. Howard, R. W. Selles, A. H. Findlow, and J. Y. Goulermas, "Automated detection of instantaneous gait events using time frequency analysis and manifold embedding," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 21, no. 6, pp. 908–916, Nov. 2013.

[16] A. Mannini and A. M. Sabatini, "A hidden Markov model-based technique for gait segmentation using a foot-mounted gyroscope," in *Proc. IEEE 33rd Ann. Int. Conf. EMBS*, Boston, MA, 2011, pp. 4369–4373.
[17] T. F. Winters, J. R. Gage, and R. Hicks, "Gait patterns in spastic hemiplegia in children and young adults," *J. Bone Joint Surg.*, vol. 69, pp. 437–441, 1987.
[18] V. Agostini, L. Cane, K. Facchin, D. Ganio, G. Gindri, S. Moreira Carneiro, and M. Knaflitz, "Statistical gait analysis in the follow-up of patients after hip replacement surgery," in *Proc. III Nat. Congr. Bioeng.*, 2012, pp. 1–2.
[19] V. Agostini, D. Ganio, K. Facchin, L. Cane, S. M. Carneiro, and M. Knaflitz, "Gait parameters and muscle activation patterns at 3, 6 and 12 months after total hip arthroplasty," *J. Arthroplasty*, 2013, submitted for publication.
[20] M. Campagnoli, M. Carlone, I. Azzolin, M. P. Schieroni, M. Lanotte, A. Ducati, V. Agostini, and M. Knaflitz, "Valutazione strumentale con gait analysis e stabilometria in pazienti affetti da idrocefalo normoteso: Casistica clinica e considerazioni riabilitative," in *Proc. 9th Mediterrean Congr. PRM*, 2012, pp. 117–118.
[21] A. H. Abdul Razak, A. Zayegh, R. K. Begg, and Y. Wahab, "Foot plantar pressure measurement system: A review," *Sensors*, vol. 12, pp. 9884–9912, 2012.
[22] S. M. M. De Rossi, S. Crea, M. Donati, P. Reberšek, D. Novak, N. Vitiello, T. Lenzi, J. Podobnik, M. Munih, and M. C. Carrozza, "Gait segmentation using bipedal foot pressure patterns," in *Proc. IV IEEE RAS/EMBS Int. Conf. Biomed. Robot. Biomechatron.*, Rome, Italy, 2012, pp. 361–366.

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