33rd Annual International Conference of the IEEE EMBS
Boston, Massachusetts USA, August 30 - September 3, 2011

A Hidden Markov Model-Based Technique for Gait Segmentation Using a Foot-Mounted Gyroscope

Andrea Mannini, *Student Member, IEEE*, Angelo Maria Sabatini, *Senior Member, IEEE*

Abstract—**In this paper, we describe an application of hidden Markov models (HMMs) to the problem of time-locating specific events in normal gait movement patterns. The use of HMMs in this paper is mainly related to the opportunity they offer to segment gait data collected at different walking speeds and inclinations of the walking surface. A simple four-state left-right HMM is trained on a dataset of signals collected from a mono-axial gyro during treadmill walking trials performed at different speed and incline values. The gyro is mounted at the foot instep, with its sensitivity axis oriented in the medio-lateral direction. A rule based method applied to gyro signals is used for data annotation. Sensitivity and specificity of phase classification detection higher than 95% are obtained. The estimation accuracy of heel strike, flat foot, heel off and toe off events is about 35 ms on average.**

I. Introduction

THE development of wearable sensor systems is an active research area in several fields including, among others, health care, physical medicine and rehabilitation, sport training. In-body motion sensors, such as gyros and accelerometers, are by far the most common choice to date for implementing wearable sensor systems applied to analysis and monitoring of human movement.

Beside the development of filtering algorithms and sensor fusion techniques for accurate measurement of human motion such as joint angle, body segment position and orientation in the three-dimensional space, other research directions concern the development of computational methods [1], to accomplish either automatic recognition of human activity [2] or walking feature assessment [3, 4], condition classification [5] and gait phase detection [6]. In this paper, we propose a statistical technique based on hidden Markov models (HMMs) for automatic segmentation of human gait using inertial sensor data.

Because of the role played by walking in human activities of daily living, evaluation of temporal and spatial parameters during walking is considered of the greatest importance in the clinical practice, e.g., to quantify improvement resulting from medical interventions, or to predict subsequent events, such as falls. The term gait is used to describe the way of walking and consists of consecutive gait cycles [7]. During each gait cycle a sequence of key events, referred to as temporal parameters, can be used to specify the transition from one gait phase to another. The key events occur at specific temporal locations in the gait motion pattern.

Many different sensor configurations and models for temporal parameter extraction have been used so far for gait segmentation in humans. Inertial sensors, accelerometers [8] and gyros, are attractive in this regard, because, since they provide movement data directly, the key events can be detected by analyzing patterns in the sensor data.

In [9], a mono-axial gyro placed on the thigh is used to estimate stride time, stride length, and walking speed. Using a gyro attached to both shanks and a thigh gait temporal parameters and other information such as stride length can be estimated [4]; a simple inverted-pendulum biomechanical model of the lower limb is formulated, and a wavelet-based method is proposed for signal feature detection.

In our previous work [3], a rule-based method is devised to determine four gait events (heel strike, flat foot, heel off, toe off), using a sensor unit composed of a mono-axial gyro and a bi-axial accelerometer fastened to the foot instep. While the gyro is used to extract the temporal parameters, the accelerometer is used to estimate stride length and inclination of the walking surface by strap-down integration.

Another approach is to extract gait parameters without calculating angle and position. Hidden Markov models (HMMs) – a stochastic pattern recognition technique that has been widely used in computer vision research for gesture recognition [10] and human movement analysis [11] – can be used to separate the movement into strides, as first proposed in [12] and further pursued in [6, 13].

The application described in this paper bears some similarity to these latter contributions. Our motivation to investigate HMMs for gait data segmentation lies in our current studies on automatic methods of human physical activity classification [14]. We are interested in merging two apparently distinct tasks a wearable sensor system would jointly fulfill: activity classification and estimation of parameters for the particular classified activity. In this sense, the main advantage of HMMs as classification tools can be seen in the simultaneous segmentation and classification process of sequential data [12]. In this paper, we introduce a HMM for normal gait, valid for a range of walking speeds and inclinations of the walking surface. While this model shall be considered in the future together with other models, valid for activities such as, e.g., upstairs/downstairs walking,

Manuscript sent April 12, 2011.

Andrea Mannini is with The BioRobotics Institute, Scuola Superiore Sant'Anna, Pisa, Italy (e-mail: a.mannini@sssup.it).

Angelo Maria Sabatini is with The BioRobotics Institute, Scuola Superiore Sant'Anna, Pisa, Italy (phone: +39-050-883415; fax: +39-050-883101; e-mail: sabatini@sssup.it).

cycling, or static postures and used in a hierarchical approach to Markov modeling, e.g., [15], we limit ourselves in this paper to test the performance of the HMM as a method useful to extract temporal parameters of normal gait.

II. MATERIALS AND METHODS

A. Dataset

The dataset used for HMM training, validation and testing was extracted from the dataset we used for carrying the research described in [3]. For the purpose of this paper, three healthy subjects performed two-minute trials of treadmill walking, at seven different speeds (from 3 to 6 km/h with 0.5 km/h steps), and four different inclines (0%, 5%, 10%, 15%). Signals from a foot-mounted mono-axial gyro with the sensitivity axis oriented in the medial-lateral direction were sampled at 200 Hz and low-pass filtered at 15 Hz using a forward-backward second-order Butterworth filter. Data from the gait cycles inside the interval [50 110] s of each trial were retained for statistical processing.

B. Hidden Markov Models for gait segmentation

A typical plot of foot-mounted gyro signals from our dataset is shown in Fig. 1. Two negative polarity *humps* (clockwise foot rotations as seen from a lateral view) are separated by a sort of signal *plateau*, when the foot is almost steady at zero angular velocity; the second negative polarity hump is followed by a positive polarity hump (counterclockwise rotation). This pattern of humps and plateaus is quite stable and repeats itself indefinitely during gait. Four gait phases, or states in the HMM language, are identified: phase S_1, from T_{HS} to T_{FF}; phase S_2, from T_{FF} to T_{HO}; phase S_3, from T_{HO} to T_{TO}; phase S_4, from T_{TO} to T_{HS} of the next stride.

We assume the following rules for defining the key events T_{FF}, T_{HO}, T_{TO} and T_{HS}. The transition S_1–S_2 (flat foot, FF) occurs at time T_{FF}, when the following condition on the measured angular velocity ω_k:

$$|\omega_k| \geq \lambda_{FF} \tag{1}$$

is verified (λ_{FF} is a given threshold value, λ_{FF} = 50 °/s). The transition S_2–S_3 (heel off, HO) occurs at time T_{HO}, when the condition:

$$|\omega_k| \geq \lambda_{HO} \tag{2}$$

is verified (λ_{HO} is a given threshold value, λ_{HO} = 50 °/s). The transition S_3–S_4 (toe off, TO) is assumed to occur at time T_{TO}, when the signal changes sign going from the negative polarity pulse to the positive polarity pulse. Although the foot is assumed to take off at the time instant when the angular velocity reaches the maximum value in the clockwise direction in [3], it is also known that the toe off detection is anticipated of about 35 ms as compared with the indication provided by footswitches. We choose the time instant T_{TO} when the angular velocity goes to zero before turning into the opposite direction, Fig. 1.

Finally, the transition S_4–S_1(heel strike, HS) occurs at time T_{HS}, which takes place just before the peak value of the first negative polarity hump, at the time instant when the absolute difference between the filtered and unfiltered gyro signal takes the maximum value, see Fig. 1 [3, 4, 16].

We assume that the gyro signals are modeled by a HHM with a finite number Q of states S_i (Q = 4). The time evolution of the Markov chain is ruled by the Q-dimensional prior probability vector $\boldsymbol{\pi}$, whose elements π_i give the probability that the chain occupies the state S_i at the initial time t_0:

$$\pi_j = \Pr[X(t_n) = S_i], \quad i = 1,\ldots,Q \tag{3}$$

and by the $Q \times Q$ matrix $\mathbf{A}$ (the transition probability matrix, TPM), whose elements a_{ij} give the transition probabilities from the state S_i at time t_n to the state S_j at time t_{n+1}:

$$\begin{cases} a_{ij} = \Pr[X(t_{n+1}) = S_j \mid X(t_n) = S_i], & i = 1,\ldots,Q \\ a_{ij} \geq 0, \quad \sum_{i=1}^{Q} a_{ij} = 1 \end{cases} \tag{4}$$

Each gait phase can only be observed through a set of raw sensor signals, the gyro signal in the present case. In other terms, the states are hidden and only a second-level process is actually observable. The observable outputs $z_n = z(t_n)$ are called emissions, and can be modeled using discrete or continuous random variables. In this paper, we opt for a continuous approach, by associating a univariate Gaussian probability density function (pdf) to each state. The i-th component of the emission vector $\mathbf{b} = [b_1,\ldots,b_Q]$ gives the Gaussian pdf associated to the i-th state:

$$b_j = N\left(z_n \mid \mu_i, \sigma_i^2, X(t_n) = S_i\right) \quad i = 1,\ldots,Q \tag{5}$$

with mean value μ_i and standard deviation σ_i. The HMM model is captured by the parameter set $\boldsymbol{\lambda} = (\boldsymbol{\pi}, \mathbf{A}, \mathbf{b})$. Given an observation sequence $\mathbf{Z} = [z_0, z_1, \ldots, z_N]$ and the parameter set $\boldsymbol{\lambda}$, learning/inference problems can be solved using few powerful algorithms, i.e., the forward-backward algorithm, which allows computing the likelihood $\mathcal{L}(\mathbf{Z}, \boldsymbol{\lambda})$, the Baum-Welch algorithm, which performs the maximum likelihood estimation of model parameters; of main interest in this paper, the Viterbi algorithm, which is widely used to

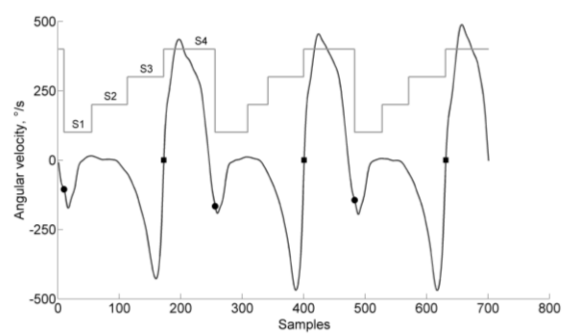

Fig. 1: Plot of foot-mounted gyro signal. Toe-off (■) and heel strike (•) obtained from applying the rule-based detection algorithm, are indicated for three consecutive strides. The state sequence S_1-S_2-S_3-S_4 of a particular stride is made explicit.

estimate the most likely sequence of states traced by the HMM [17].

We specify a four-state left-right HMM, as shown in Fig. 2. Skips are not allowed with this architecture. No attempt is made here to consider the number of states as a parameter to be optimized during cross-validation, as done, e.g., in [6, 12]. In normal gait, the state transitions are only self-transitions, or transitions between adjacent gait phases. In other words, the TPM must have the following form:

$$\mathbf{A} = \begin{bmatrix} a_{11} & a_{12} & 0 & 0 \\ 0 & a_{22} & a_{23} & 0 \\ 0 & 0 & a_{33} & a_{34} \\ a_{41} & 0 & 0 & a_{44} \end{bmatrix} \quad (6)$$

The diagonal elements represent the probabilities of self-transitions in gait phases, and the other non-zero elements indicate the transition probabilities between non-adjacent gait phases; the element a_{41} states the gait cyclical nature.

We remark that the HMM structure and the underlying definition of gait phases is instrumental to the motion patterns recorded by the gyro in our sensing configuration; it is not consistent with the suggestion by, e.g., [7], who divides the gait stride in eight phases: initial contact, loading response, mid-stance, terminal stance, pre-swing (stance); initial swing, mid-swing, terminal swing (swing). Roughly, S_1 embraces initial contact, loading response and mid-stance, together with S_2, whose transition to S_3 indicates the transition from mid-stance to terminal stance. Together with terminal stance, S_3 embraces the pre-swing phase, while initial swing, mid-swing and terminal swing all collapse in phase S_4.

C. Training and validation

A critical element that may influence the HMM training is the large number of parameters generally present in $\boldsymbol{\lambda}$. Moreover, the HMM maximum likelihood estimation problem is not convex: careful parameter initialization may thus help circumventing the problem of local maxima existing in $\mathcal{L}(\mathbf{Z},\boldsymbol{\lambda})$. The availability of a labeled training set comes to one's rescue in this regard. Labeling of observation sequences $\mathbf{Z}$ by label vectors $\mathbf{Y}$ requires the key event identification in the gyro signals, which is made by applying the rule-based method described in [3]. Of course, any sort of out-body or in-body sensors, e.g., optical markers or footswitches, would be used to perform data labeling. Rough estimates of state transition probabilities (a_{ij}) and priors (π_i) are possible using $\{\mathbf{Z}, \mathbf{Y}\}$ training data. The prior probability of the j-th state is estimated as follows:

$$\pi_j = N_j / N_{tot} \quad (7)$$

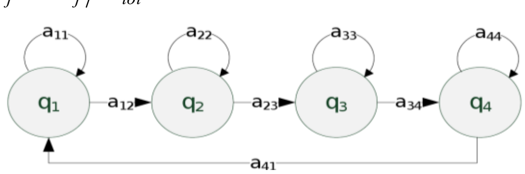

Fig. 2. Four states left-right model.

where N_j is the number of elements associated with the j-th label present in the N-dimensional vector $\mathbf{Y}$.

If we assume that only a single transition between adjacent states can occur in each gait cycle, the transition probability from the j-th state to the next state of the sequence is estimated as:

$$a_{ji} = C / N_j, \quad where \quad i = \mathrm{mod}(j+1, Q) \quad (8)$$

where C is the number of gait cycles in the training set. We can also write:

$$a_{jj} = 1 - a_{ji} \quad (9)$$

The parameters of the state emission Gaussian densities can be estimated by computing sample means and sample standard deviations from the observable outputs that are known emitted from any state:

$$\mu_j = \frac{1}{N_j} \sum_{t=1}^{t_T} Z(t) \Big|_{s.t. Y(t)=j} \quad (10)$$

$$\sigma_j = \sqrt{\frac{1}{N_j - 1} \sum_{t=1}^{t_T} \left(Z(t) - \mu_j\right)^2 \Big|_{s.t. Y(t)=j}} \quad (11)$$

Because of the nature of this work, which is intended to just scratch the surface of how HMMs would be applied in a context where activity classification and parameter estimation come together, we limit ourselves to the absolute minimum in the HMM structural complexity. We do not consider any process of feature extraction/selection, and we simply work on the signal sample values. Moreover, no use is made of multidimensional data, although two accelerometer signals are available together with the gyro signals in the original dataset. It is reasonable to expect that a combination of carefully chosen feature vectors, a greater number of states than four and different, more complex, state emission probabilistic models, would give rise to HMMs with outstanding performance as compared with the simple HMM developed in this paper, especially in case that we have to deal with different walking styles by different subjects, or by the same subject in different conditions of speed and inclination of the walking surface.

The leave-one-out cross-validation approach is applied in this paper using data from the P tested subjects ($P = 3$). This approach consists of training the model using data from P–1 subjects and testing it using data from the excluded subject. The cross-validation process is repeated P times, each time excluding one different subject. Results are then aggregated from the P different models. Such a validation allows testing the capability of the proposed method to segment gait phases without the need of any individual model calibration.

D. Implementation issues

Data processing and HMM learning/inference algorithms are implemented using Mathworks MATLAB (R2008a) and the HMM toolbox available from [18]. Some remarks about the application of the Baum-Welch (BW) algorithm are important. Usually, the BW algorithm is used to refine the parameter estimates produced during the initialization process. However, in our experiments the BW algorithm does not yield significant performance gains. Because of the higher computational costs and the risk of being trapped in local maxima of the likelihood function, we prefer not to apply the BW algorithm. As a consequence, the HMM parameters are fixed to those estimated during the initialization process. During the testing phase, the Viterbi algorithm is applied to gyro data, so as to estimate the most likely state sequence traversed by the chain (Viterbi decoding). In a simple left-right model, the decoding can be potentially plagued by two different errors: gait strides can be missed (deletions) or erroneously added (insertions). With regard to the latter problem, a heuristic strategy is cascaded to the Viterbi decoder: simply, this strategy is based on the reasonable assumption that, in the range of tested speeds and inclines, gait strides lasting less than 0.35 s cannot be observed.

E. Performance assessment

Classification performance is calculated evaluating insertions and deletions. Since the influence on the gait segmentation performance of any mismatching between Viterbi decoded and actual labels is intuitively related to the temporal distance existing between detected and annotated key events, classification errors are computed when they occur outside acceptance windows centered on the annotated key events with the following widths: 0, 20 and 30 ms. The sensitivity and the specificity of the method are evaluated for each model state in terms of correct classifications (true positives, TP and true negatives, TN) and misclassifications (false positives, FP and false negatives, FN):

$$\mathrm{Se} = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FN}} \qquad \mathrm{Sp} = \frac{\mathrm{TN}}{\mathrm{TN}+\mathrm{FP}} \tag{12}$$

A single value of sensitivity and specificity value is then computed by aggregating results achieved for all model states. To assess how close in time are the Viterbi decoded and annotated key events, we finally compute mean and standard deviation of their difference.

III. Results and Discussion

Model parameters for one of the leave-one-out cross-validation runs, when testing is made on subject #3 are reported in Table I. Similar results are obtained for the other two tested subjects. Classification outcomes are reported in Table II. Different acceptance window sizes are considered (0, ±10 ms, ±30 ms) for sensitivity and specificity computation. Sensitivity and specificity of gait phase classification are high for every validated subject. With the larger rejection window value almost all data are correctly classified. We can conclude from this that most key events can be detected with a maximum difference of 30 ms (6 data samples at a sampling rate of 200Hz). In Table III bias and standard deviation for each difference between Viterbi decoded and annotated key events are reported.

Not surprisingly, the less accurate results concerned the determination of the key events that involved the state S_1. It is expected indeed that the gyro signal pattern may subtly change, so as to reflect the differences existing in the strategies adopted by different subjects in placing the foot to ground, in different conditions of speed and inclines of the walking surface. For some unknown reasons, the number of insertions is particularly high for Subject 1. However, all insertions are successfully detected and fixed by the previously described heuristic strategy. Moreover, it is interesting to note that no deletions occurred.

Another observation concerns the critical behavior of the HMM in dealing with the transitions S_1-S_2 and S_2-S_3. Not surprisingly, the problem of detecting when the foot is steady is critical to any detector used to prescribe, e.g., when zero-velocity updates have to be applied in a foot-mounted pedestrian navigation system [16, 19].

In Fig. 3 we report a Bland-Altman plot of the difference

TABLE I
Model Parameters, Training on subjects 1-2, testing on subject 3

	P1	P2	P3	P4
Prior probabilities (π)				
	0.123	0.266	0.281	0.329
Transition probability matrix (A)				
P1	0.954	0.046	0	0
P2	0	0.981	0.019	0
P3	0	0	0.983	0.017
P4	0.014	0	0	0.986
Emissions mean values (μ) [°/s]				
	-116.8	-22.6	-236.4	262.9
Emissions standard deviations (σ) [°/s]				
	83.0	17.6	163.2	137.1

TABLE II
Classification Results, %

	Subject 1	Subject 2	Subject 3	Aggregated
Without rejection windows on transitions				
Se	94.4	92.6	93.0	93.3
Sp	98.2	97.5	97.7	97.8
With ±10 ms rejection windows on transitions				
Se	96.9	95.6	95.9	96.1
Sp	99.0	98.5	98.6	98.7
With ±30 ms rejection windows on transitions				
Se	98.6	98.1	98.2	98.3
Sp	99.5	99.4	99.4	99.4
Insertions	29.8	1.6	4.4	12.0
Deletions	0	0	0	0

TABLE III
Event Bias, Mean (std) [samples]

	HS	FF	HO	TO
Subject 1	-1.2 (4.1)	2.6 (7.4)	-3.1 (4.1)	-0.1 (0.3)
Subject 2	4.6 (3.6)	3.0 (9.2)	-2.6 (1.0)	-0.7 (0.6)
Subject 3	5.5 (5.5)	4.5 (6.5)	-3.3 (0.8)	-0.7 (1.1)
Aggregated	3.7 (4.8)	3.3 (7.9)	-3.0 (2.5)	-0.5 (0.8)

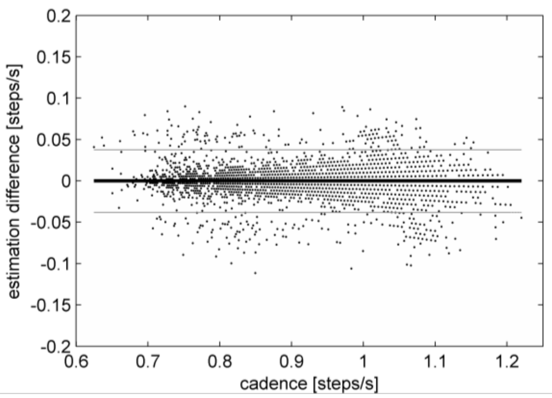

Fig. 3. Bland-Altman plot of the cadence estimation (all subjects aggregated data).

in the cadence values estimated by the HMM-based segmentation procedure and the rule-based segmentation upon which the data labeling procedure is based (the gold standard in this paper). No over (or under) estimation of the cadence is observed and the standard deviation of the difference is about 0.034 steps/s (2.7% of the maximum value of cadence).

In most applications of HMM to activity recognition, data windowing is done in preparation of the feature extraction step. Window sizes do not generally conform to human periodic movements, including gait. When, for instance, frequency-domain techniques are applied with the aim to capture the inherent periodicities in walking signals, extremely long windows have to be considered to avoid truncation effects in the estimation of the dominant frequencies [20]. This is at the expense of the temporal resolution of the analysis. An advantage accrued by using HMMs as tools for classification and segmentation is that individual strides are detected, with the possibility to improve the interpretation process of gait data and to ease the process of classification into gait categories.

IV. Conclusions and Further Developments

A statistical tool for human gait segmentation based on a supervised HMM has been illustrated; two distinct advantages of the method are that (a) a fast training phase allows specifying the model and (b) an individual model calibration is not mandatory. In this paper, the system is based on a very simple on-body sensor configuration. The promising results shown in this paper encourage us to enlarge the scope of our work, by, e.g., incrementing the number of tested subjects and planning a data acquisition campaign in a wider set of experimental conditions, including over-ground walking. In particular, we intend to use an optoelectronic motion analysis system to generate reference kinematic data useful for algorithm learning, rather than using reference data produced by the same sensor configuration associated with the HMM. Moreover, we are porting the HMM-based segmentation method to a target hardware platform, in order to test the method performance in on-line conditions.

References

[1] A. M. Sabatini, "Inertial sensing in biomechanics: a survey of computational techniques bridging motion analysis and personal navigation," in *Computational Intelligence for movement sciences, neural networks and other emerging techniques*, R. Begg and M. Palaniswami, Eds., ed: IGP Idea Group Publishing, 2006, pp. 70-100.

[2] M. J. Mathie, A. C. F. Coster, N. H. Lovell, and B. G. Celler, "Accelerometry: providing an integrated, practical method for long-term, ambulatory monitoring of human movement," *Physiol. Meas.,* vol. 25, pp. 1-20, 2004.

[3] A. M. Sabatini, C. Martelloni, S. Scapellato, and F. Cavallo, "Assessment of walking features from foot inertial sensing," *IEEE Trans. Biomed. Eng.,* vol. 52, pp. 486-494, 2005.

[4] K. Aminian, B. Najafi, C. Bula, P. F. Leyvraz, and P. Robert, "Spatio-temporal parameters of gait measured by an ambulatory system using miniature gyroscopes," *J. Biomech.,* vol. 35, pp. 689-699, 2002.

[5] H.-Y. Lau, K.-Y. Tong, and H. Zhu, "Support vector machine for classification of walking conditions using miniature kinematic sensors," *Med. Biol. Eng. Comput.,* vol. 46, pp. 563-573, 2008.

[6] E. Guenterberg, A. Y. Yang, H. Ghasemzadeh, R. Jafari, R. Bajcsy, and S. S. Sastry, "A method for extracting temporal parameters based on hidden Markov models in body sensor networks with inertial sensors," *IEEE Trans. Inform. Technol. Biomed.,* vol. 13, pp. 1019-1030, 2010.

[7] 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.

[8] A. T. M. Willemsen, F. Bloemhof, and H. B. K. Boom, "Automatic stance-swing phase detection from accelerometer data for peroneal nerve stimulation," *IEEE Trans. Biomed. Eng.,* vol. 37, pp. 1201-1208, 1990.

[9] S. Miyazaki, "Long-term unrestrained measurement of stride length and walking velocity utilizing a piezoelectric gyroscope," *IEEE Trans. Biomed. Eng.,* vol. 44, pp. 753-759, 1997.

[10] A. D. Wilson and A. F. Bobick, "Parametric hidden Markov models for gesture recognition," *IEEE Trans. Patt. Anal. Mach. Intell.,* vol. 21, pp. 884-900, 1999.

[11] N. M. Oliver, B. Rosario, and A. P. Pentland, "A Bayesian computer vision system for modeling human interactions," *IEEE Trans. Patt. Anal. Mach. Intell.,* vol. 22, pp. 831-843, 2000.

[12] T. Pfau, M. Ferrari, K. Parsons, and A. WIlson, "A hidden Markov-model based segmentation technique applied to equine inertial sensor trunk movement data," *J. Biomech.,* vol. 41, pp. 216-220, 2008.

[13] M. Chen, B. Huang, and Y. Xu, "Human abnormal gait modeling via hidden Markov model," presented at the Proc. Internat. Conf. on Information Acquisition ICIA '07, Jeju City, Korea, July 9-11, 2007.

[14] A. Mannini and A. M. Sabatini, "Machine learning methods for classifying human physical activity from on-body accelerometers," *Sensors,* vol. 10, pp. 1154-1175, 2010.

[15] J. Lester, T. Choudhury, N. Kern, G. Borriello, and B. Hannaford, "A hybrid discriminative/generative approach for modeling human activities," presented at the Proc. 19th Internat. Joint Conf. Artif. Intell., Edinburgh, Scotland, 2005.

[16] A. M. Sabatini, "Wearable sensor systems in biomechanics: assessment of unrestrained walking features," presented at the Pr. 21st IEEE Instrum. and Meas. Technol. Conf., IMTC 04, Como, 2004.

[17] L. R. Rabiner, "A tutorial on hidden Markov models and selected applications in speech recognition," *Proc. IEEE,* vol. 77, pp. 257-286, 1989.

[18] K.Murphy.*http://www.cs.ubc.ca/~murphyk/Software/HMM/hmm.html*

[19] I. Skog, P. Handel, J. O. Nilsson, and J. Rantakokko, "Zero-velocity detection—an algorithm evaluation," *IEEE Trans. Biomed. Eng.,* vol. 57, pp. 2657-2666, 2010.

[20] H. Vathsangam, A. Emken, D. Spruijt-Metz, and G. S. Sukhatme, "Toward free-living walking speed estimation using Gaussian Process-based Regression with on-body accelerometers and gyroscopes," resented at the 4th Int. Conf. Perv. Comp. Technol. for Healthcare (PervasiveHealth), Munich, 22-25 March 2010.