Gait Quality Monitoring Using an Arbitrarily Oriented Smartphone

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Abstract. Gait sensing by means of accelerometers yields quasi-periodic signals that can be analyzed in order to extract useful information. This paper introduces a method based on a Fuzzy Finite State Machine with temporary restrictions for tracking and recognizing the different states of human walking. Such operation is a mandatory task prior to perform a subsequent analysis on gait quality. Besides, the method described here allows to achieve this recognition when the sensing device, i.e. a smartphone, is being carried by the user in arbitrary orientations related to his/her body's natural axes.

1 Introduction

Human gait analysis and the development of practical applications with the extracted information represent a huge challenge for engineers, physical therapists and doctors alike. This is partly because human walking is an extremely complex process that changes from a given person to another, but also change for the same person walking under different physical —surface, footwear— or psychological conditions.

However, gait analysis is a valuable source of knowledge about the health condition of a patient. It might be a key part in clinical assessment of several pathologies, ranging from those merely physical to complex diseases like Parkinson [1] or, most notably, cerebral palsy [2]. Unfortunately this often requires a considerable amount of resources —professionals, laboratory time, expensive equipment, etc— and the monitoring scope is limited. In addition it is a well-known fact that people under a test environment do not behave in the same way as they would normally do [3].

Recent efforts have been made to apply intelligent systems to gait analysis in order to cope with some of these drawbacks, specially the need for a passive, long-term monitoring system. Computer vision [4] is one of these techniques, however it introduces other disadvantages in the shape of high complexity, limited spatial scope and, most importantly, privacy issues.

Another option is the acceleration-based gait sensing. This technique is able to record the human walking with an acceptable degree of accuracy and therefore to extract meaningful —although limited— information about its quality in a long-term tracking period. Previous researches in this field have opted to use a

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triple axis accelerometer attached to the user's body to measure gait quality [5], so the directions of those axes are aligned with the natural axes of the person. This represents a considerable setback when the goal is to design systems in order to be as less obtrusive as possible. In these systems users are forced to constantly take care of the position of the device because the system would not work if it is not properly placed.

The approach taken in this paper, by contrast, is to explore the possibility of monitoring the gait quality of the user without any condition regarding the orientation of the device, and therefore without significantly change his/her habits or behaviors. An important role in this vision is the device itself. Nowadays many people in the western countries —where also fast population ageing is becoming an important concern— carries some sort of mobile device, namely a smartphone or a PDA, for long periods of time each day. These gadgets usually have a built-in accelerometer, good computational performance and internet access capabilities, so they are potentially very interesting tools for the purpose of monitoring human activity.

Section 2 describes briefly our approach to Fuzzy Finite State Machines; section 3 describes how to apply this concept to model the human gait; section 4 presents a way of defining the gait quality; section 5 describes a basic experimentation and finally, section 6 contains the conclusions.

2 Fuzzy Finite State Machine with Temporary Restrictions

Once the acceleration data is acquired, the question that remains is how to effectively treat it to be able to identify the different states of gait. Many possibilities arise, being Hidden Markov Models maybe the most common method due to its extensive and successful employment in gait recognition [6]. Our approach on this matter, however, diverges from machine learning solutions and it is inspired instead by the concept of Linguistic Fuzzy Modeling [7].

Linguistic Fuzzy Modeling allows to describe a system from a qualitative point of view by means of linguistic variables, i.e. variables whose values are taken from natural language, and by the relations between these variables in the shape of conditional fuzzy statements. Given that variables and relations are established by an expert designer based on his/her knowledge and experience, the models tend to be reliable yet conceptually easy to understand, which is a desirable feature when dealing with complex processes like human gait.

Another feature of gait is that it produces quasi-periodic signals when magnitudes like acceleration are measured. This means that these values roughly repeat in time under a period that may not be constant either. Given such conditions —complexity and quasi-periodicity—, a suitable linguistic model that has already been successfully applied in previous works [8][9] is the Fuzzy Finite State Machine (FFSM). Here, a refinement of this type of model is proposed taking into account that human walking is a process subject to some obvious physical limitations. This means that additional knowledge can be added to the model in the form of "intuition" about what will happen next. We call this model Fuzzy Finite State Machine with temporary restrictions and it is defined by the following tuple:

$$\{Q, S, S', U, Y, f, g\}$$

where:

- Q is the set of states defined by the designer based on his/her perceptions about the behavior of the system.
- S is a vector that contains the degree of activation of each state at a given moment.
- S' is a vector that contains the predicted degree of activation of each state at given moment. It also relies on the designer's interpretation of phenomena.
- U is a vector containing the numerical values of the input variables.
- Y is the output vector of the system.
- f is the transition function that yields the next activation vector given the input and the current and predicted degrees of activation. $S[t+1] = f(S[t], S'[t+1], U[t])$.
- g is the output function: $Y[t] = g(S[t], U[t])$.

The key part of the model is the transition function which is defined through a set of fuzzy conditional statements. There is potentially one statement per each possible change of state and these statements operate over inputs as linguistic variables. The number of statements and their content are up to the designer but, generally, a rule for changing from state i to state j is shaped as follows:

$$R_{ij} = R_k : \text{ IF } (S[t] \text{ is } Qi) \text{ AND } (C_{ij}) \text{ AND } (S'[t+1] \text{ is } Qj)$$
$$\text{THEN } S[t+1] \to Q_j$$

Where C_{ij} is the set of fuzzy statements that evaluates to what degree the input variables meet the criteria of the given transition.

After assessing the antecedent of every rule, a set of firing degrees $\{w_k\}_{k=1}^{N}$ is obtained. Each degree represents the likelihood of transition to a given state and the combination of all of them yields $S[t+1]$.

3 A Human Gait Model

As said before, the approach proposed here needs a designer, who, using his experience and knowledge, has to choose the parameters of the FFSM. The most relevant are, perhaps, the number of considered states and their meaning because they define how the system is expected to behave.

Human gait can be explained as a cyclic process involving several phases. The most widely accepted models consider up to 7 different states for each leg [10], which, in addition, overlap in time. To avoid such complexity, we propose a simpler model that has only two states, namely *double support* and *swing*. *Swing* refers to the leg that moves forward. By contrast, if the leg in contact with

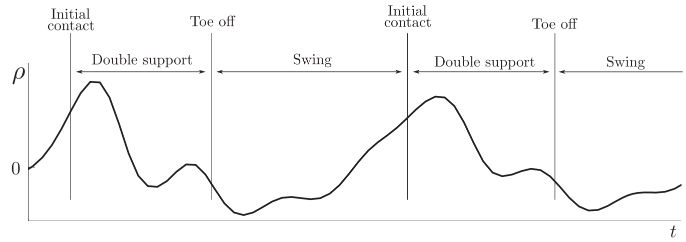

Fig. 1. Human gait model

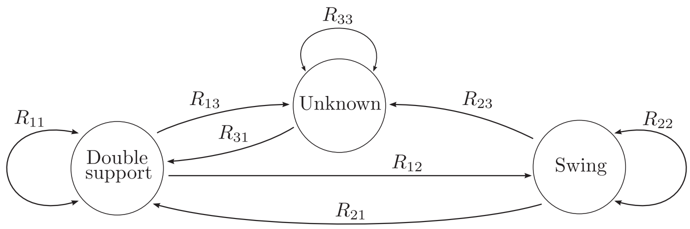

Fig. 2. States and transitions of the FFSM

the ground is considered, the state should be called *double support*. This way of defining states is slightly based on the former models, but it is also backed up by the orientation-independent resultant acceleration signal ($\rho = \sqrt{a_x^2 + a_y^2 + a_z^2}$), in which both states can be easily recognized (Figure 1).

Double support starts when one of the legs is finishing its swinging state and the heel is about to make the initial contact. As the hit happens, the acceleration becomes greater until it reaches a maximum and then, the person starts to move his/her body weight towards the forward leg. The state ends when the back foot takes off and the forward foot lays flat. This produces an slightly upwards thrust —spotted as the second local maximum— that will lift the body on the following swing phase, leading it to reach its highest point on the cycle. While the acceleration is kept low, the back leg starts to move forward until the heel hits the ground again and a new cycle starts.

On the other hand, an additional state has to be added in order to build a practical FFMS that takes into account the case in which the acceleration signal doesn't meet the double support nor the swing state conditions. When the user starts an activity other than walking, the sensed signal has nothing to do with the typical gait signal. Therefore, the FFSM has to acknowledge this situation and transition to the referred unknown state.

Once the states are defined, the connections between them have to be established —again from the designer's experience and knowledge—. In this case the scheme chosen is shown in Figure 2. There is a transition from each state to the rest, except for the case of the unknown state, in which it is only possible to go to the double support state, considered as the start of the cycle. This decision has been made in order to make the system simpler and more robust.

The inputs considered are the above-mentioned resultant acceleration signal, ρ, and its successive derivatives, ρ' and ρ''. All signals are axes independent and thus they are suitable for the proposed goal of modeling human gait irrespective of the orientation of the sensing device. These signals are previously low pass filtered in order to get rid of the spurious accelerations that appear at high frequencies and are not naturally produced by the human gait. A fair cut off point could be 5 Hz as it is unlikely that a person is able to perform movements with a period lower than 200 ms. Sampling frequency in cutting edge smartphones is around 60 Hz —i.e. way more than twice the considered bandwith of 5 Hz— so capturing every meaningful movement is assured. In addition, the gravity influence is canceled and the signal is normalized in order to ease and simplify the FFSM.

An important issue that has not been tackled yet is how the predicted state vector, S', is built. In this case, the first thing to do is estimate the step period (T_{step}). This can be achieved by performing a Fast Fourier Transform (FFT) on the resultant acceleration and subsequently detecting its dominant frequency. Once the step period is known, it is necessary to split it according to the percentage of time spent in each of both gait states. Based on previous experience, a reasonable balance might be 30% for double support and 70% for swing.

$S'[t + T_{step}]$ is then constructed by chaining two fuzzy membership functions that represent the expected lasting time of each state. This has to be done every time the FFSM transitions to double support state at time t.

Figure 3 shows how the FFSM is able to recognize the temporal evolution of the gait while it is shifting between the two states.

4 Gait Quality Parameters

Taking into account the obvious limitations of dealing with just the resultant acceleration, four quality parameters are proposed: Double Support Symmetry (DSS), Swing Symmetry (SS), Double Support Homogeneity (DSH) and Swing Homogeneity (SH). Here, this vector of four parameters can be considered the output Y of the FFSM.

The first step is to segment the total walking signal using the FFSM. Once the segmentation is done, three values are extracted for each k set and state: average acceleration ($\bar{\rho}_k$), duration (Δt_k) and peak acceleration ($max(\rho_k)$ or $min(\rho_k)$) (Figure 3). Comparing these values across different sets of samples will allow to obtain the above-mentioned parameters.

4.1 Symmetry

Symmetry aims to capture how balanced the gait is by comparing two set of acceleration samples that belong to the same state. These two sets of samples have to appear one after another so they represent different legs. Duration and acceleration values are then computed for each couple (Figure 4) through a function that yields a value between 0 and 1, with 1 meaning a total match between sets.

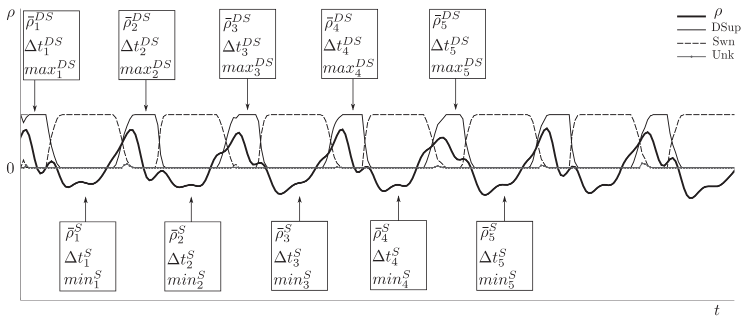

Fig. 3. State segmentation and comparing values

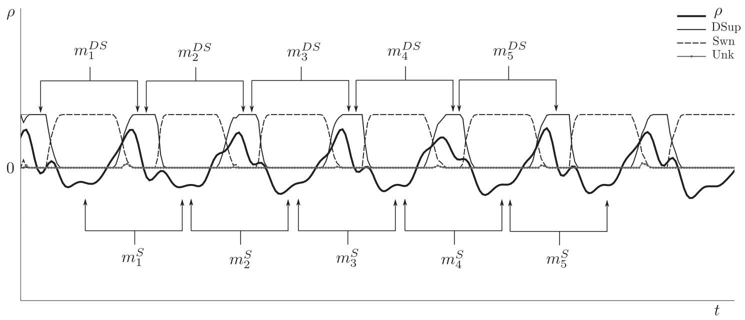

Fig. 4. Symmetry

At the end, two vectors, $\mathbf{m}^{DS}$ and $\mathbf{m}^{S}$, are obtained, with their lengths depending on how long the total walking signal is. Symmetry's parameters, DSS and SS, can be then calculated as:

$$DSS = mean\left(\mathbf{m}^{DS}\right) \in [0,1], \qquad SS = mean\left(\mathbf{m}^{S}\right) \in [0,1]$$

4.2 Homogeneity

Homogeneity focuses on the similarity of sets of acceleration samples that are not successive —specifically, that have another set of the same state between them— (Figure 5), and therefore represent the same leg.

Again, $\bar{\rho}_k$, Δt_k and $max(\rho_k)$ —or $min(\rho_k)$— are considered, so a vector for each parameter, leg and state is built. These vectors are computed through a function that produces a value between 0 and 1 for each state and leg: DSH_A, DSH_B, SH_A and SH_B. It is not possible for the method to tell if the leg is the right or the left one, so the notation of A/B is used to refer to each leg.

Finally, homogeneity's parameters, DSH and SH, are calculated as:

$$DSH = \frac{DSH_A + DSH_B}{2} \in [0,1], \qquad SH = \frac{SH_A + SH_B}{2} \in [0,1]$$

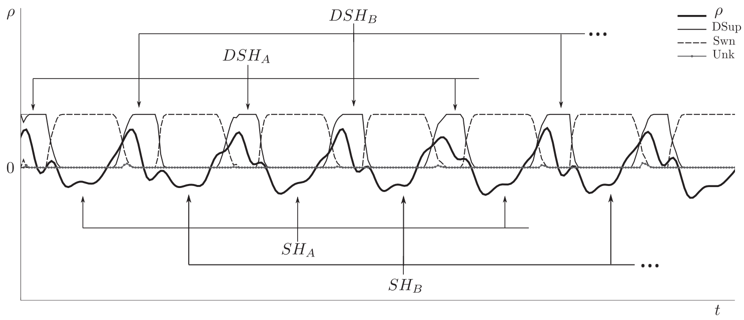

Fig. 5. Homogeneity

Table 1. Tests performed

Measure	DSS	DSH	SS	SH
1	0.86	0.76	0.90	.80
2	0.88	0.80	0.87	0.76
3	0.85	0.75	0.82	0.81
4	0.85	0.72	0.86	0.76
5	0.84	0.75	0.87	0.80
6	0.63	0.62	0.71	0.71

5 Experimentation

The experimentation process has been carried out with an Android smartphone running a custom application to gather the gait signals from the built-in triple-axis accelerometer. This simple program can perform measures for several hours while being executed in the background. The user assigns a name and starts the measure. When he/she decides to stop it, the application produces a *.csv* file in the local storage media —e.g. the SD Card— with all the data recorded.

The device can be arbitrarily oriented, but it has to be placed attached to the trunk of the person. Placing it on a limb —e.g. in a trouser's pocket— may produce different accelerations for opposite steps and therefore inaccurate symmetry scores. In this case, the phone was introduced in a backpack in order to be completely orientation-free, but it can be carried, for instance, in a shirt's pocket.

In order to easily test the proposed method, five measures were taken for a healthy young male walking under normal conditions, namely, flat surface, normal footwear and medium speed. Additionally, another measure was taken for the same person, but this time, while carrying a weight in one of his hands with the purpose of introduce some degree of dissymmetry.

As expected, the quality parameters have decreased for the sixth measure (Table 1) proving that the method properly acknowledge the lack of symmetry —and potentially the lack of homogeneity— in human gait. By contrast, the parameters for the rest of the measures show a remarkable similarity, indicating that the system is also consistent.

6 Conclusions and Future Work

We have described a solution to model human gait quality from the accelerations registered by an arbitrarily oriented smartphone. It successfully tracks the different states of walking and produces consistent quality measures under different conditions.

Further and intensive experimentation has to be done to fully test the system for longer periods of time, specially on ill patients. However, as shown, the method is already a considerable step forward regarding other methods that cope with gait quality by means of accelerometers, as it overcomes the drawback of having to place the device under a given orientation.

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