Automatic linguistic report on the quality of the gait of a person

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Abstract

Gait analysis has been explored thoroughly during the last decade as a behavioral biometric measurement. Some areas of application include: access control, surveillance, activity monitoring and clinical analysis. Our work aims to contribute to the field of human gait modeling by providing a solution based on the computational theory of perceptions. Our model differs significantly from others, e.g., based on machine learning techniques, because we use a linguistic model to represent the subjective designers perceptions of the human gait process. This model is easily understood and provides good results. Using accelerometers included in a smart phone, we propose a method for producing a linguistic report about the quality of the gait in terms of homogeneity and symmetry. This type of reports could be used to analyze the evolution of the human gait after a recovery treatment and also for preventing falls in elderly people.

1. Introduction

Human gait is a quasi-periodic phenomenon which is defined as the interval between two successive events of the same foot. Its analysis has been explored thoroughly during the last decade as a behavioral biometric measurement. Some areas of application include: access control, surveillance, activity monitoring and clinical analysis. Moreover, since the gait is a complex integrated task which requires precise coordination of the mental and musculoskeletal system, its analysis can help in the diagnosis and treatment of walking and moving disorders, identification of balance factors and assessment of clinical gait interventions and rehabilitation programs.

Our work aims to contribute to the field of human gait modeling by providing a solution based on the computational theory of perceptions. Our model differs significantly from others, e.g., based on machine learning techniques, because we use a linguistic model to represent the subjective designers perceptions of the human gait process. This model is easily understood and provides good results. Using accelerometers included in a smart phone, we propose a method for producing a linguistic report about the quality of the gait in terms of homogeneity and symmetry. This type of reports could be used to analyze the evolution of the human gait after a recovery treatment and also for preventing falls in elderly people.

The remainder of this work is organized as follows. Section 2 presents the human gait modeling problem and our proposal for tackle it. Section 3 describes how to automatically generate a linguistic report on the quality of the gait based on the features obtained by our modeling system. Finally, Section 4 draws some conclusions and introduces some future directions in this research line.

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2. Gait modeling

2.1. Proposal

Human gait modeling consists of studying the biomechanics of this human movement aimed at quantifying factors governing the functionality of the lower extremities. Gait is a complex integrated task which requires precise coordination of the neural and musculoskeletal system to ensure correct skeletal dynamics [14]. Therefore, its analysis can help in the diagnosis and treatment of walking and movement disorders, identification of balance factors, and assessment of clinical gait interventions and rehabilitation programs [7, 10].

The gait cycle is a periodical phenomenon which is defined as the interval between two successive events (usually heel contact) of the same foot [4]. It is characterized by a stance phase (60% of the total gait cycle), where at least one foot is in contact with the ground, and a swing phase (40% of the total gait cycle), during which one limb swings through the next heel contact (see Fig. 1). These phases can be quite different between individuals but when normalized to a percentage of the gait cycle they maintain close similarity, indicating the absence of disorders [11].

We base on the accelerations produced during the human gait cycle. We use a expert knowledge based fuzzy finite state machine (FFSM) as a modeling tool, which has also been used to extract relevant features for the authentication purpose [13]. The main advantage of using this tool is its flexibility when dealing with the variations in both amplitude and states time span. The fuzziness of the model allows us to handle imprecise and uncertain data which is inherent to real world phenomena in the form of fuzzy if-then rules. Moreover, the use of linguistic terms makes easier its interpretation and does not require high computational cost thanks to the lack of a learning process. Nevertheless, there exists the possibility of making use of an automatic machine learning technique to design the main elements of the FFSM as explained in [3].

We attached a smartphone equipped with a three-axial accelerometer to a belt, centered in the back of the subject. The smartphone executes an application which provide us with the dorso-ventral acceleration (a_x), the medio-lateral acceleration (a_y), and the antero-posterior acceleration (a_z) at each instant of time. In this contribution, we only use a_x and a_y because a_z has to do with the walking speed and this speed can vary for the same person. Therefore, every record contained the three accelerations and a timestamp. Fig. 1 shows three different synchronized pictures. The first one (at the top) illustrates the dorso-ventral acceleration (a_x) and the medio-lateral acceleration (a_y) obtained from the three-axial accelerometer. The middle picture plots a sketch of a person representing the different phases of the gait with the right limb boldfaced. Finally, the picture at the bottom represents the time period from one event (usually initial contact) of one foot to the subsequent occurrence of initial contact of the same foot.

2.2. Fuzzy finite state machines

As said, we will consider a FFSM to deal with the human gait modeling problem. The theoretical basics of FFSMs were established by [12] and later developed by [9, 17, 5]. The model of FFSM presented is inspired by the concepts of fuzzy state and fuzzy system developed by Zadeh [18, 21]. More specifically, it can be considered an implementation of the input-output fuzzy models of dynamic systems proposed by Yager [16].

Here, we introduce the main concepts and elements of our paradigm for system modeling allowing experts to build comprehensible fuzzy linguistic models in an easier way. In our framework, a FFSM is a tuple $\{Q, U, f, Y, g\}$, where:

- Q is the state of the system.
- U is the input vector of the system.
- f is the transition function which calculates the state of the system.
- Y is the output vector of the system.
- g is the output function which calculates the output vector.

Each of these components is described in the following subsections. Furthermore, the interested reader can refer to [2, 13, 3, 1] for additional information and applications.

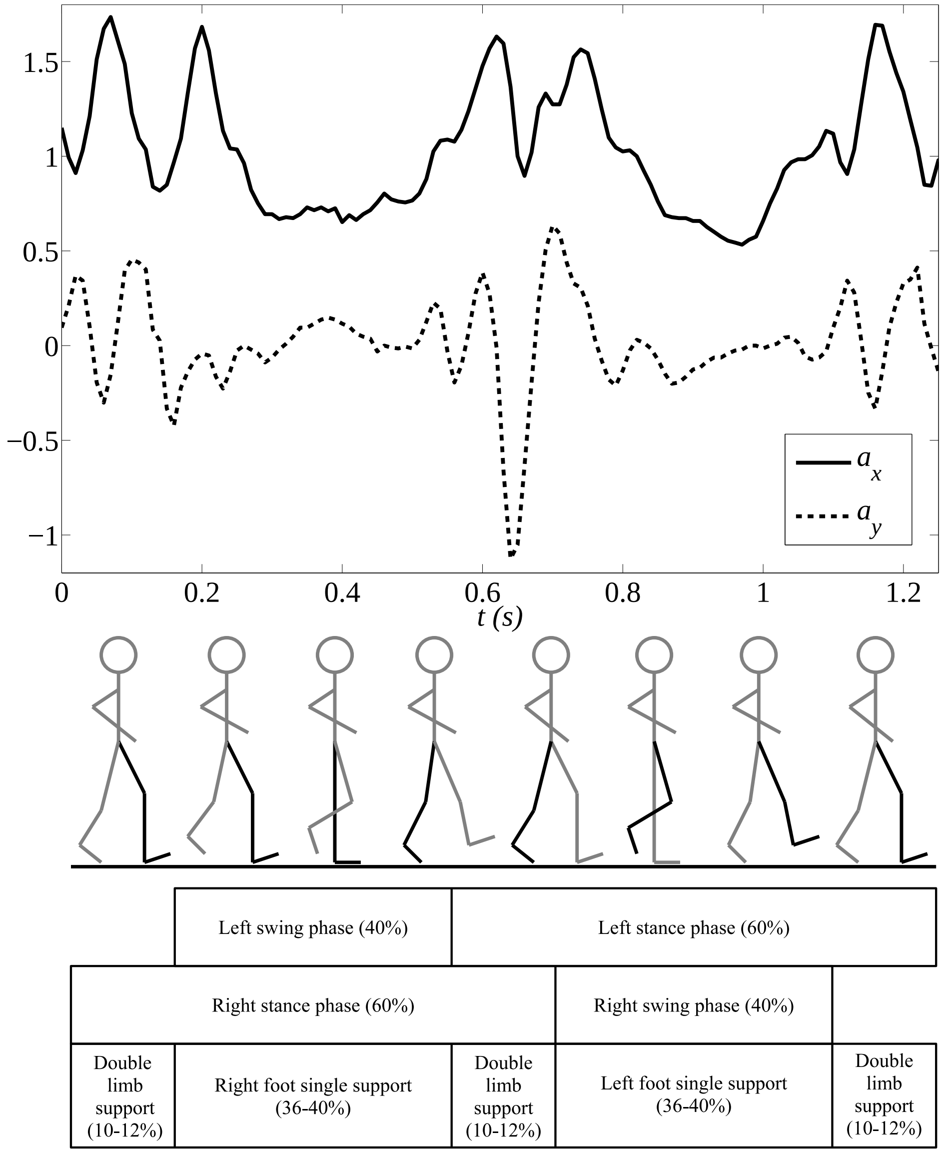

Figure 1: One gait cycle illustrating the various phases and events and the dorso-ventral (a_x) and medio-lateral (a_y) accelerations.

2.2.1. Fuzzy States (Q)

The state of the system (Q) is defined as a linguistic variable [19] that takes its values in the set of linguistic labels $\{q_1, q_2, \ldots, q_n\}$, with n being the number of fuzzy states. Every fuzzy state represents the pattern of a repetitive situation and it is represented numerically by a state activation vector $S[t] = (s_1[t], s_2[t], \ldots, s_n[t])$, where $s_i[t] \in [0, 1]$ and $\sum_{i=1}^{n} s_i[t] = 1$. S_0 is defined as the initial value of the state activation vector, i.e., $S_0 = S[t = 0]$.

2.2.2. Input Vector (U)

U is the input vector $(u_1, u_2, ..., u_{n_u})$, with n_u being the number of input variables. U is a set of linguistic variables obtained after fuzzification of numerical data. Typically, u_i can be directly obtained from sensor data or by applying some calculations to the raw measures, e.g., the derivative or integral of the signal, or the combination of several signals. The domain of numerical values that u_i can take is represented by a set of linguistic labels, $A_{u_i} = \{A^1_{u_i}, A^2_{u_i}, \ldots, A^{n_i}_{u_i}\}$, with n_i being the number of linguistic labels of the linguistic variable u_i.

2.2.3. Transition Function (f)

The transition function (f) calculates, at each time instant, the next value of the state activation vector: $S[t+1] = f(U[t], S[t])$. It is implemented by means of a fuzzy rule-based system (FRBS). Once the expert has identified the relevant states in the model, she/he must define the allowed transitions among states. There are rules R_{ii} to remain in a state q_i, and rules R_{ij} to change from state q_i to state q_j. If a transition is forbidden in the FFSM, it will have no fuzzy rules associated.

The generic expression of a rule to remain in a state q_i (R_{ii}) is formulated as follows: IF ($S[t]$ is q_i) $\vee$ (u_1 is $\widetilde{A}_{u_1}$) $\vee \ldots \vee$ (u_{n_u} is $\widetilde{A}_{u_{n_u}}$) $\vee$ (d_i is T_{stay_i}) THEN $S[t+1]$ is q_i, where:

- The antecedent ($S[t]$ is q_i) calculates the degree of activation of the state q_i in the instant of time t, i.e., $s_i(t)$. Note that the FFSM cannot remain in the state q_i if it is not in this state previously.
- The antecedents (u_1 is $\widetilde{A}_{u_1}$) , . . . , (u_{n_u} is $\widetilde{A}_{u_{n_u}}$) are the constraints over the input variables to remain in the state q_i. Each $\widetilde{A}_{u_i}$ is a set of linguistic terms whose members are joined by a disjunctive operator, e.g., $\widetilde{A}_{u_1} = A^2_{u_1} \vee A^3_{u_1}$.
- The antecedent (d_i is T_{stay_i}) is a temporal constraint that calculates the membership degree of the duration of the state q_i (d_i, which is defined as the time that $s_i > 0$) to the linguistic label T_{stay_i}, which is the maximum time that the system is expected to remain in state q_i. In Fig. 2, can be seen an example of this linguistic label.
- Finally, the consequent of the rule is the next value of the state activation vector $S[t+1]$. It consists of a vector with a zero in all of its components except in s_i, where it has a one.

The generic expression of a rule to change form state q_i to the state q_j (R_{ij}) is formulated as follows: IF ($S[t]$ is q_i) $\wedge$ (u_1 is $\widetilde{A}_{u_1}$) $\wedge \ldots \wedge$ (u_{n_u} is $\widetilde{A}_{u_{n_u}}$) $\wedge$ (d_i is T_{change_i}) THEN $S[t+1]$ is q_j, where:

- The antecedent ($S[t]$ is q_i) calculates the degree of activation of the state q_i in the instant of time t, i.e., $s_i(t)$. Note that the FFSM cannot change from the state q_i to the state q_j if it is not in this state previously.
- The antecedents (u_1 is $\widetilde{A}_{u_1}$) , . . . , (u_{n_u} is $\widetilde{A}_{u_{n_u}}$) are the constraints over the input variables to change from state q_i to the state q_j. Each $\widetilde{A}_{u_i}$ is a set of linguistic terms whose members are joined by a disjunctive operator, e.g., $\widetilde{A}_{u_1} = A^1_{u_1} \vee A^2_{u_1}$.
- The antecedent (d_i is T_{change_i}) is a the temporal constraint which calculates the membership degree of the duration of the state q_i (d_i, which is defined as the time that $s_i > 0$) to the linguistic label T_{change_i}, which is the minimum time that the signal is expected to remain in the state q_i before changing to the state q_j. In Fig. 2, can be seen an example of this linguistic label.
- Finally, the consequent of the rule is the next value of the state activation vector $S[t+1]$. It consists of a vector with a zero in all of its components except in s_j, where it has a one.

To calculate the next value of the state activation vector ($S[t+1]$), a weighted average using the firing degree of each rule k (ω_k) is computed as defined in Eq. 1:

$$S[t+1] = \begin{cases} \dfrac{\sum_{k=1}^{\#Rules} \omega_k \cdot (s_1, \ldots, s_n)_k}{\sum_{k=1}^{\#Rules} \omega_k} & \text{if} \quad \sum_{k=1}^{\#Rules} \omega_k \neq 0 \\ S[t] & \text{if} \quad \sum_{k=1}^{\#Rules} \omega_k = 0 \end{cases} \tag{1}$$

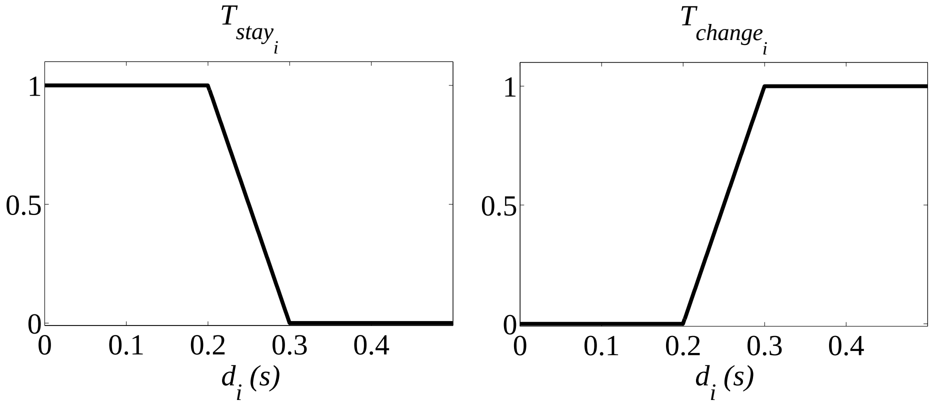

Figure 2: Temporal conditions for the state q_i.

where (ω_k) is calculated using the minimum for the AND operator ($\wedge$) and the maximum for the OR operator ($\vee$). We used $\vee$ in R_{ii} to make more difficult the change of state, which makes the FFSM more robust against spurious in the input. Moreover, we used $\wedge$ in R_{ij} to define the conditions to change more sharply.

2.2.4. Output Vector (Y)
Y is the output vector: $(y_1, y_2, ..., y_{n_y})$, with n_y being the number of output variables. Y is a summary of the characteristics of the system evolution that are relevant for the application.

2.2.5. Output Function (g)
The output function (g) calculates, at each time instant, the next value of the output vector: $Y[t] = f(U[t], S[t])$.

2.3. Fuzzy finite state machine for gait modeling

This section presents the design of the main elements needed to build a FFSM to model the human gait.

2.3.1. Fuzzy States (Q)
As stated in Section 2.2.1, every state represents the pattern of a repetitive situation. According to the diagram at the bottom of Fig. 1 and using our own knowledge about the process, we define four different fuzzy states which explain when double limb support, right limb single support, or left limb single support are produced. Therefore, we easily define the possible set of fuzzy states as follows:

- $q_1 \rightarrow$ The right foot is in stance phase and the left foot is in stance phase (double limb support).
- $q_2 \rightarrow$ The right foot is in stance phase and the left foot is in swing phase (right limb single support).
- $q_3 \rightarrow$ The right foot is in stance phase and the left foot is in stance phase (double limb support but different of q_1 because the feet position).
- $q_4 \rightarrow$ The right foot is in swing phase and the left foot is in stance phase (left limb single support).

2.3.2. Input Vector (U)

As we have explained, we only use two of the three available accelerations, which are a_x and a_y. Therefore, the set of input variables is: $U = \{a_x, a_y\}$. Each of these input variables will have only three associated linguistic labels because, as we will show in the experimental results, they are enough to achieve a good accuracy keeping a high interpretability of the model. The linguistic labels for each linguistic variable are: $\{S_{a_x}, M_{a_x}, B_{a_x}\}$ and $\{S_{a_y}, M_{a_y}, B_{a_y}\}$, where S, M and B are linguistic terms representing small, medium, and big, respectively.

As an initial step, we normalized the signals. First, we subtracted the average making them to be centered on zero. Then, we rescaled them in the range given by their standard deviations. This allowed us to perform the analysis at the scale that gives us more information about the signal changes.

2.3.3. Transition Function (f)

As showed in Section 2.2.3, the only thing required to determine the structure of the FRBS is the definition of which transitions are allowed and which are not. This is easily represented by means of a state diagram. Fig. 3 shows the proposed state diagram of the FFSM for the human gait cycle. This state diagram is very simple because the accelerations produced during the human gait are quasi-periodic, i.e., they are repeated with approximately similar values and periods. Moreover, all the states are correlative, i.e., they always follow the same activation order. Therefore, it is rather easy to define the allowed transitions and the forbidden ones.

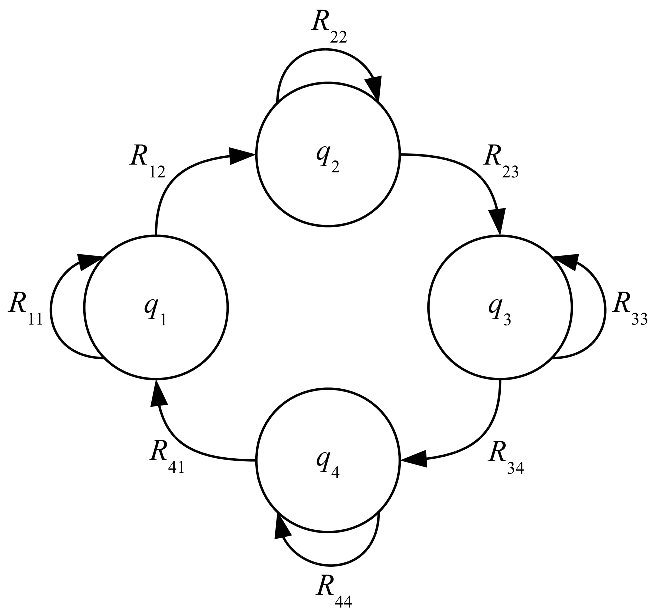

Figure 3: State diagram of the FFSM for the human gait cycle.

From the state diagram represented in Fig. 3 it can be recognized that there are 8 fuzzy rules in total in the system, 4 rules to remain in each state and other 4 to change between states. In contrast to machine learning techniques, we derived the rules from the designer's perceptions about the human gait acceleration signals. We chose q_1 as the initial state, i.e., $S_0 = (1, 0, 0, 0)$. The FFSM is able to synchronize without the need of doing previous segmentation of the signal when the conditions of q_1 are fulfilled. We defined the conditions of amplitude to remain in a state or to change between states by combining the information obtained from the sensors and the available expert knowledge about the human gait. We applied self-correlation analysis to the vertical acceleration to obtain an approximation of the signal period T. In agreement with our knowledge about the typical human gait cycle, we assigned to each state a duration according to its percentage of the period T. Fig. 2 shows a generic example of the linguistic labels T_{stay} and T_{change} used to define the temporal constraints.

R_{11}: IF ($S[t]$ is q_1) $\vee$ (a_x is B_{a_x}) $\vee$ (a_y is B_{a_y}) $\vee$ (d_1 is T_{stay_1}) THEN $S[t+1]$ is q_1
R_{22}: IF ($S[t]$ is q_2) $\vee$ (a_x is S_{a_x}) $\vee$ (a_y is M_{a_y})$\vee$ (d_2 is T_{stay_2}) THEN $S[t+1]$ is q_2
R_{33}: IF ($S[t]$ is q_3) $\vee$ (a_x is B_{a_x}) $\vee$ (a_y is S_{a_y}) $\vee$ (d_3 is T_{stay_3}) THEN $S[t+1]$ is q_3
R_{44}: IF ($S[t]$ is q_4) $\vee$ (a_x is S_{a_x}) $\vee$ (a_y is M_{a_y})$\vee$ (d_4 is T_{stay_4}) THEN $S[t+1]$ is q_4
R_{12}: IF ($S[t]$ is q_1) $\vee$ (a_x is S_{a_x}) $\vee$ (a_y is M_{a_y})$\vee$ (d_1 is T_{change_1}) THEN $S[t+1]$ is q_2
R_{23}: IF ($S[t]$ is q_2) $\vee$ (a_x is B_{a_x}) $\vee$ (a_y is S_{a_y}) $\vee$ (d_2 is T_{change_2}) THEN $S[t+1]$ is q_3
R_{34}: IF ($S[t]$ is q_3) $\vee$ (a_x is S_{a_x}) $\vee$ (a_y is M_{a_y})$\vee$ (d_3 is T_{change_3}) THEN $S[t+1]$ is q_4
R_{41}: IF ($S[t]$ is q_4) $\vee$ (a_x is B_{a_x}) $\vee$ (a_y is B_{a_y}) $\vee$ (d_4 is T_{change_4}) THEN $S[t+1]$ is q_1

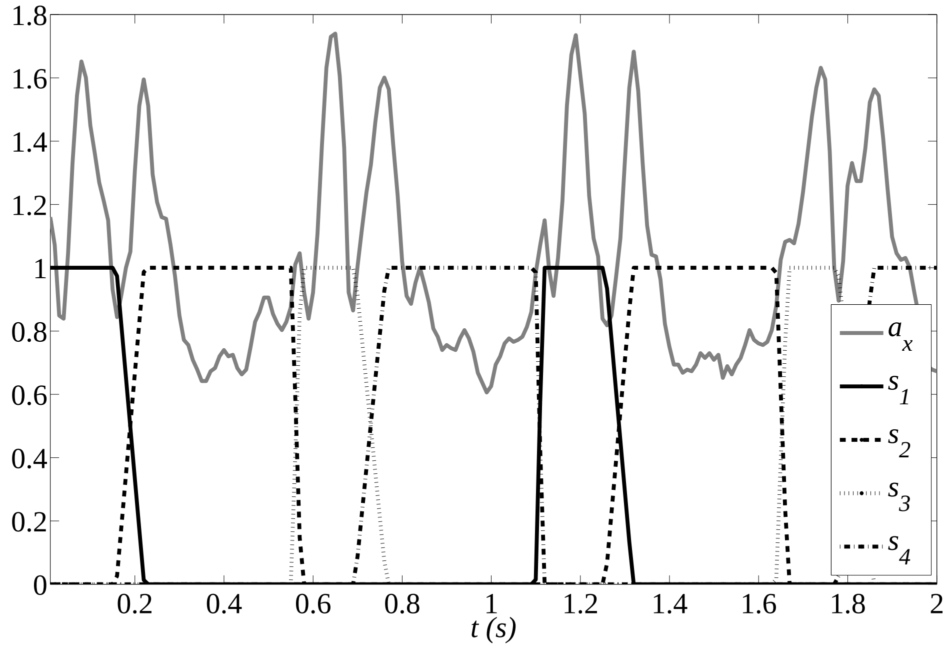

Figure 4: Graphical representation of the state activation vector ($S[t]$) of the four states together with the evolution of dorso-ventral acceleration (a_x).

As an example of the performance of our proposal for human gait modeling, Fig. 4 represents the state activation vector ($S[t]$) of the four states together with the evolution of dorso-ventral acceleration (a_x). It shows how this set of fuzzy rules is able to model the four phases of the human gait.

2.3.4. Output vector (Y) and output function (g)

Once identified the four phases in the signal, we focused on the characteristics of the vertical acceleration a_x, which provides sufficient information for our purpose. Fig. 5 shows the evolution of a_x along the four phases. The rectangles are the output of the FFSM and are calculated for each state within a complete gait cycle of duration T. Therefore, the output vector of the FFSM will be $Y = (y_1, y_2, y_3, y_4)$.

The dimensions of every rectangle summarize the values of the dorso-ventral acceleration (a_x) while staying in each state. The horizontal coordinate of the center of each rectangle ($\overline{t_i}$) is the temporal "center of mass" of a_x in the state q_i. Note that the "mass" in every instant t is calculated as the value of $a_x[t]$ weighted by the degree of activation $s_i[t]$ of the state q_i as shown in Eq. 2. The vertical coordinate of the center of each rectangle ($\overline{a_i}$) is the average of the dorso-ventral acceleration during the state q_i, which is calculated using Eq. 3. The width of each rectangle ($\sigma^2_{t_i}$) is the standard deviation of the temporal distribution of the dorso-ventral acceleration weighted by the degree of activation $s_i[t]$ of the state q_i as shown in Eq. 4. The

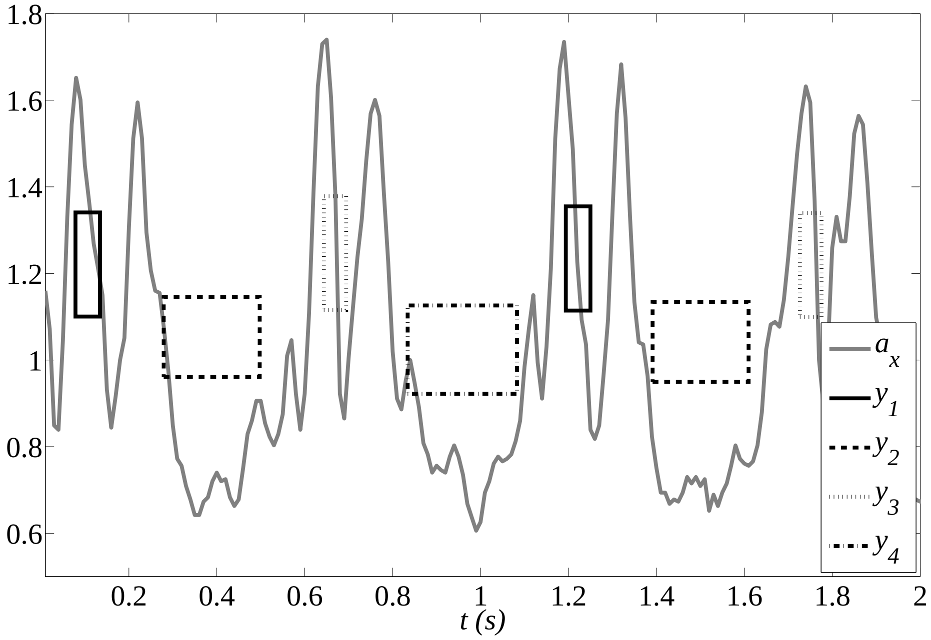

Figure 5: Graphical representation of the dorso-ventral acceleration (a_x) and the rectangles that form the output of the FFSM.

height of each rectangle ($\sigma^2_{a_i}$) is the standard deviation of the dorso-ventral acceleration during the state q_i calculated using Eq. 5.

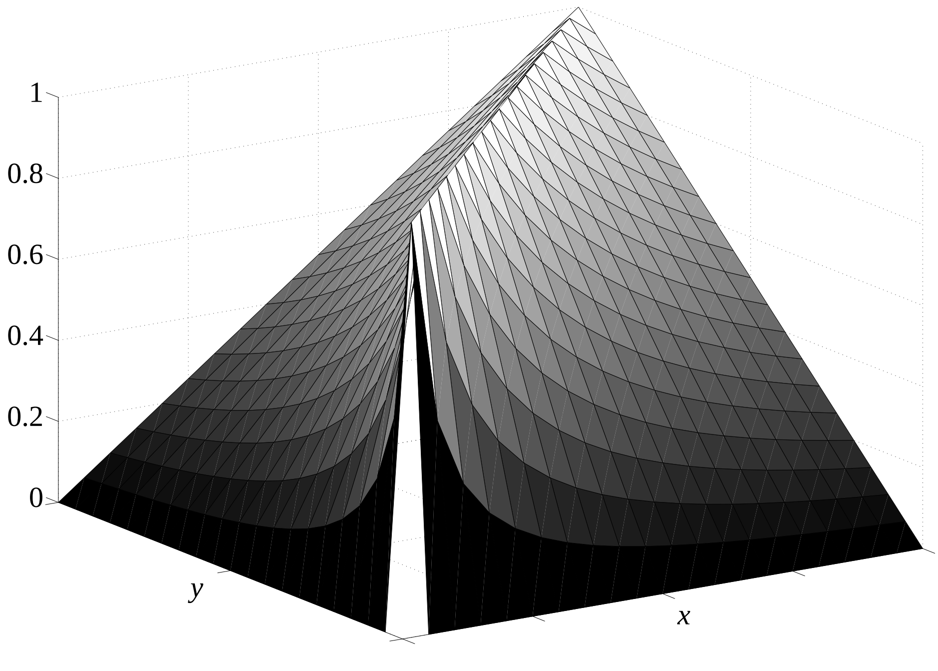

Figure 6: Graphical representation of the similarity function $F(x, y)$.

$$\overline{t_i} = \frac{\sum\limits_{t=0}^{T} t \cdot a_x[t] \cdot s_i[t]}{\sum\limits_{t=0}^{T} a_x[t] \cdot s_i[t]} \tag{2}$$

$$\overline{a_i} = \frac{\sum\limits_{t=0}^{T} a_x[t] \cdot s_i[t]}{\sum\limits_{t=0}^{T} s_i[t]} \tag{3}$$

$$\sigma_{t_i}^2 = \frac{\sum\limits_{t=0}^{T} (t - \overline{t_i})^2 \cdot a_x[t] \cdot s_i[t]}{\sum\limits_{t=0}^{T} a_x[t] \cdot s_i[t]} \tag{4}$$

$$\sigma_{a_i}^2 = \frac{\sum\limits_{t=0}^{T} (a_x[t] - \overline{a_i})^2 \cdot s_i[t]}{\sum\limits_{t=0}^{T} s_i[t]} \tag{5}$$

3. Quality of the gait

Based on the areas of the rectangles (A^1, A^2, A^3, A^4) which summarize the values of the dorso-ventral acceleration (a_x), we have defined two parameters to measure the quality of a human gait, namely homogeneity $(\mathcal{H})$ and symmetry $(\mathcal{S})$.

Both homogeneity and symmetry are calculated using a similarity function $F(x, y)$, which is defined using Eq. 6 and provide values in the interval $(0, 1]$. In Fig. 6, can be seen the shape of this function.

$$F(x,y) = \begin{cases} \frac{y}{x} & \text{if } \ x \geq y > 0 \\ \frac{x}{y} & \text{if } \ 0 < x < y \end{cases} \tag{6}$$

3.1. Homogeneity ($\mathcal{H}$)

The homogeneity $(\mathcal{H})$ is obtained by comparing a gait with itself and it is calculated for every state using two cycles. Therefore, a gait will be homogeneous for a state q_i in the cycle j if the area of its rectangle in this cycle (A_j^i) is similar to the area of its rectangle in the next cycle $j+1$ (A_{j+1}^i) as shown in Eq. 7. The total homogeneity for each cycle j $(\mathcal{H}_|)$ is calculated as the average value of the homogeneities of the four states as shown in Eq. 8.

$$\mathcal{H}_j^i = F(A_j^i, A_{j+1}^i) \tag{7}$$

$$\mathcal{H}_j = \frac{1}{4} \sum_{i=1}^{4} \mathcal{H}_j^i \tag{8}$$

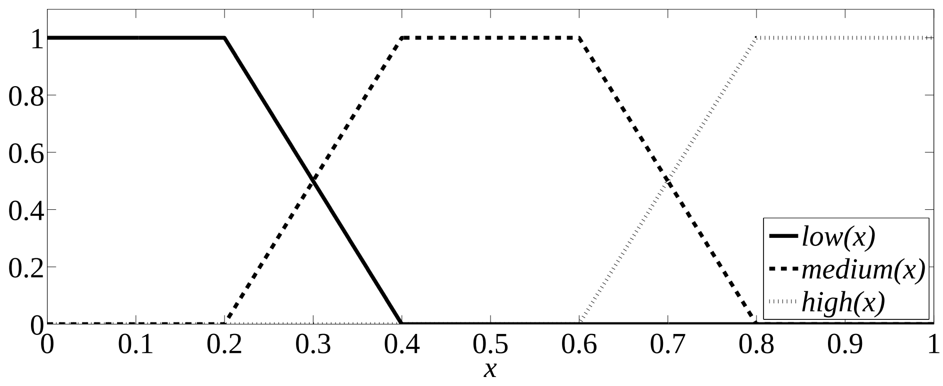

Figure 7: Trapezoidal linguistic labels which fuzzify the values of the homogeneity and the symmetry.

3.2. Symmetry ($\mathcal{S}$)

The symmetry ($\mathcal{S}$) is obtained by comparing the movement of both legs. Symmetry is based on comparing the areas of the rectangles which summarize the states q_1 and q_2 (stance and swing phase of the reference foot) versus the areas of the rectangles which summarize the states q_3 and q_4 (stance and swing phase of the opposite foot). A gait will be symmetric if the areas of the states q_1 and q_2 are similar to the areas of the states q_3 and q_4. The Symmetry in a cycle j ($\mathcal{S}_j$) is calculated using the similarity function $F(x, y)$ as can be seen in Eq. 9, where A_j^1, A_j^2, A_j^3, A_j^4 are the areas of the rectangles corresponding to states q_1, q_2, q_3, and q_4 in the cycle j.

$$\mathcal{S}_j = F(A_j^1 + A_j^2, A_j^3 + A_j^4) \tag{9}$$

3.3. Linguistic report

To automatically generate a linguistic report on the quality of the gait of a person, we will use the methodology proposed by Yager [15] and developed also by Kacprzyk [6], which is based in the concept of fuzzy cardinalities introduced by Zadeh [20].

The idea is to produce a set of natural language (NL) sentences of the type: "Most times the homogeneity is low" or "Few times the symmetry is high". First of all, we have to fuzzify the values of the homogeneity and the symmetry within the set of linguistic labels represented in Fig. 7. Therefore, for each cycle, we will have the following set of possible NL sentences:

- "The homogeneity in the cycle j is { low — medium — high }", with validity degrees $low(\mathcal{H}_j)$, $medium(\mathcal{H}_j)$, and $high(\mathcal{H}_j)$ respectively.
- "The symmetry in the cycle j is { low — medium — high }", with validity degrees $low(\mathcal{S}_j)$, $medium(\mathcal{S}_j)$, and $high(\mathcal{S}_j)$ respectively.

Once we have fuzzified the homogeneity and the symmetry for each cycle j, we can calculate the frequency of the linguistic variables that describe the homogeneity and the symmetry along a complete gait of J cycles using the general expression of cardinality (Card) defined in Eq. 10. The cardinality of a fuzzy set provides us with a value in the interval $[0, 1]$ than indicates how frequent is this fuzzy set. We can associate a new set of linguistic terms, which are represented in Fig. 8, to these values that lead us to the desired expressions such as "Most times the homogeneity is low" or "Few times the symmetry is high" whose validity degrees are $most\,[\mathrm{Card}\,(low(\mathcal{H}))]$ and $few\,[\mathrm{Card}\,(high(\mathcal{S}))]$ respectively.

$$\mathrm{Card}(x) = \frac{1}{J} \cdot \sum_{j=1}^{J} x_j \tag{10}$$

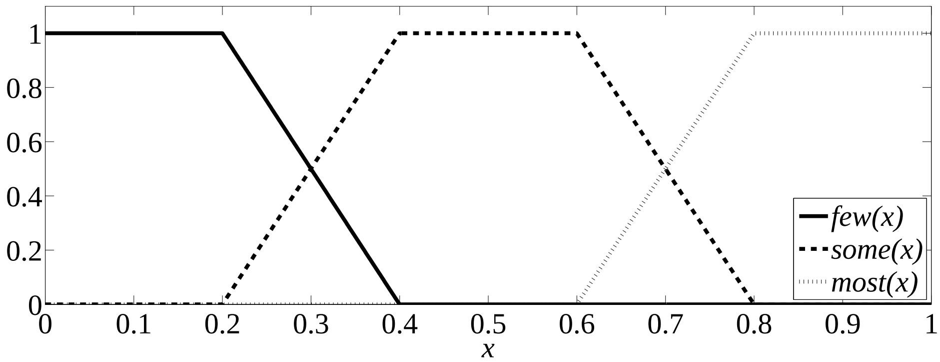

Figure 8: Trapezoidal linguistic labels which fuzzify the values of the cardinality.

	few times	some times	most times
homogeneity is low	1	0	0
homogeneity is medium	0.62	0.38	0
homogeneity is high	0	0.38	0.62
symmetry is low	1	0	0
symmetry is medium	0.06	0.94	0
symmetry is high	0	0.94	0.06

Table 1: Example of the validity degrees of the set of NL propositions.

In order to define the quality of a gait based on the validity of the NL propositions calculated previously, we have designed a FRBS which captures the expert knowledge thanks to its semantic expressiveness, using linguistic variables [19] and rules [8]. Thanks this FL formalism, when designing the fuzzy rules and linguistic labels, we can deal with isolated events of lack of symmetry or homogeneity due to turns, steps or stumbles. However, the existence of repetitive lacks of symmetry and homogeneity represents the presence of gait disorders that must be identified by the system. Therefore, the following set of fuzzy rules is aimed at qualifying the gait of a person by taking into account these issues:
R_1: If most times the homogeneity is low and most times the symmetry is low, then the quality is low.
R_2: If most times the homogeneity is medium and most times the symmetry is medium, then the quality is medium.
R_3: If most times the homogeneity is high and most times the symmetry is high, then the quality is high.
R_4: If few times the homogeneity is high and few times the symmetry is high, then the quality is low.
R_5: If few times the homogeneity is low and few times the symmetry is low, then the quality is high.
R_6: If some times the homogeneity is low and some times the symmetry is low, then the quality is medium.
R_7: If some times the homogeneity is high and some times the symmetry is high, then the quality is medium.

The output of the FRBS is calculated as a weighted average of the individual rules. The weight of each rule is calculated from its firing degree. To calculate this firing degree, we use the minimum for the *and* between the two antecedents, e.g., if the NL propositions "most times the homogeneity is low" and "most times the symmetry is low" have a validity degrees of 0.75 and 0.5 respectively, the firing degree of R_1 will be 0.5. Therefore, thanks to use of the FL formalism, we can express together with the total output the reasons of why this output is obtained.

As a practical example, consider the validity degrees of the NL propositions displayed in Table 1 which were obtained during 20 complete cycles for a certain person. With these values, only rules R_3, R_5, and R_7 are fired with firing degrees of 0.06, 1 and 0.38 respectively. Therefore, the FRBS will conclude that the quality of the gait is medium with a validity degree of 0.26 and high with a validity degree of 0.74.

Moreover, thanks to the hierarchical design of our system, we can pick up the rule with the maximum firing degree (R_5) to build the linguistic report as follows: "The quality of the gait during these 20 cycles is high because few times the homogeneity is low and few times the symmetry is low".

4. Concluding remarks

This work is part of our research in the field of human gait modeling. Using accelerometers, we can obtain many information that must be interpreted in order to obtain useful conclusions about gait characteristics.

Here, we describe a quite simple and intuitive model that allows us to extract relevant features about the gait of a person. We show how the homogeneity and the symmetry of the human gait can be used to create a simple but useful model capable of describing the quality of the gait.

In collaboration with orthopedics and physiotherapist, we believe that this work opens possibilities of exploring relevant features of human gait, by combining relevant variables within the FL formalism. Moreover, the help of these specialists will allow us to refine our proposed system with the incorporation of their useful knowledge.

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