Computational model of human body motion performing a complex exercise by means of a Fuzzy Finite State Machine

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Abstract

Human motion tracking and analysis is particularly useful for a wide spectrum of applications such as entertainment and gaming, surveillance, sport training, physical rehabilitation and human-computer interaction.

In this paper we focus on three major areas related to interpreting human motion: (1) human motion modeling, (2) tracking a human while performing an exercise using wireless wearable sensors, and (3) human motion analysis involving body parts. We model a series of movements which are part of the sun salutation, a flowing sequence of twelve yoga poses with physical benefits. Data is acquired by using a Wireless Body Area Network (WBAN) system for monitoring, formed by five wearable high precision tri-axial accelerometer sensors, which allows us to obtain a temporal series of numerical measurements of this exercise. Finally, we use a Fuzzy Finite State Machine (FFSM) to model the temporal evolution of this phenomenon and recognize the different poses with certain degree of membership.

1. Introduction

Human motion tracking allows to acquire an incredible amount of information regarding to the poses or movements of people while being monitored. In some fields, as physiotherapy, performance analysis is of major importance, as it could provide standardized information for evaluating patients while they are following a physical therapy. Nowadays, the development of miniaturized wearable sensors is of particular relevance in this area, as this technology allows to gather data that permit to precisely assess the impact of clinical interventions on the real life of patients and the recovery [8]. The proper interpretation of the acquired data in order to identify different poses of the body is one of the current challenges [2]. In this work, we apply Fuzzy Finite State Machines (FFSMs) to interpret the available data by using our previous experience in both recognizing and analyzing complex phenomena.

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European Centre for Soft Computing Internal Report (December 2012).

Final version published in Proceedings of the International Conference on Medical Imaging using Bio-Inspired and Soft Computing (MIBISOC), Brussels, Belgium, May 2013, Pages 245-251.

We take as an example one of the oldest yoga exercises, the *sun salutation*, which is a sequence formed by twelve postures (see Figure 1), each of them counteracting the preceding one and producing a balance between flexion and extension. Yoga postures help to increase the tone of weak muscles and the alignment of the spinal column [15], reason why it is used in physical therapies [10], where the effects of practicing yoga on motor variability, i.e. strength, steadiness and balance, are assessed.

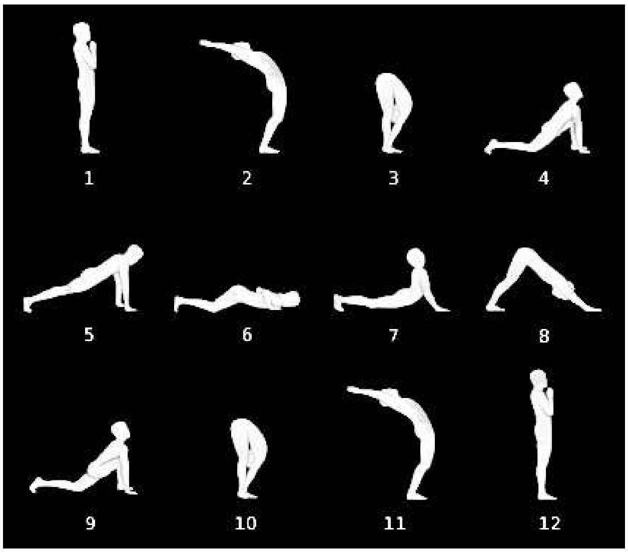


Figure 1: The twelve poses of the sun salutation sequence.

Some work has already been done regarding motion analysis of sun salutation. In particular, in [16] a study was done to analyze the transition phase during poses of such exercise in terms of grace and consistency by using one sensor attached to the lower back, but without recognizing automatically each one of the poses. This specific sequence has also been used in [12] for testing a virtual rehabilitation system which guides the user through a therapeutic exercise program. Although in this case various sensors are used for data acquisition, the system has the inconvenient that a capture suit, which includes several interconnection cables, needs to be worn by the user.

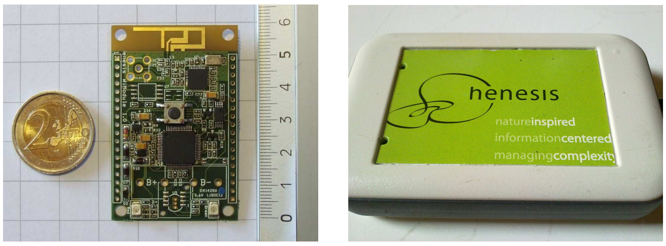
In this paper we perform human motion recognition following a bottom-up approach. We start acquiring data by monitoring a person using a previously developed WBAN system, firstly introduced in [9], formed by five wearable tri-axial accelerometer sensors which are attached to the body with thin elastic bands. We then identify the poses and motion of different body parts, based on the accelerations that are produced during the process.

The two main techniques used for human activity or behavior recognition are template matching approaches [17] and state-space models [7]. The main advantage of using the template matching technique is its low computational cost. However, it is sensitive to noise and the time interval of the movements. On the other hand, state-space approaches overcome these drawbacks by defining each static posture as a state, although involving iterative computation, to predict, estimate and detect time series over a long period of time [1]. Following this technique, we explore the application of FFSMs to model a series of poses corresponding to the sun salutation exercise. FFSMs instead of processing crisp symbols, use fuzzy values both in the input and the output. This technique was first used for the analysis of quasi-periodic signals in [4], and afterwards applied for human body posture recognition [5] and human gait modeling [6]. Here, we increase the complexity by fusing information from various sensors to model an exercise which involves the movement of several body parts.

The remainder of this paper is organized as follows. In Section 2 the system used for human motion monitoring is introduced. Section 3 presents the main concepts of FFSMs for modeling complex phenomena evolving in time and describes how to use these concepts for modeling the sun salutation sequence and recognizing each pose. In Section 4 the experimentation carried out is described, including the results discussion. Finally, Section 5 draws some conclusions and introduces future research works.

2. Human motion monitoring system

Among the many different sensors that can be used for monitoring patients during rehabilitation, MEMS (*Micro-Electro-Mechanical Systems*) inertial sensors show great potentials. This is mainly due to the progress in making them become smaller as well as cheaper, in such a way that they can be incorporated in compact, non-obtrusive continuous monitoring devices that can be easily attached to the body [14]. In particular, accelerometers can provide reliable information as well as objective and quantitative measurements when attached to different parts of the body [19]. In this work we use a low-cost and low-power wearable sensing system which allows for precise human motion acquisition [9]. It is formed by six small universal modules (a master module, and five wearable slave modules, which include high performance tri-axial accelerometers), and a software for data reception and synchronization. The main component of the architecture is the acquisition device, the Henesis WiModule [11], shown in Figure 2.



(a) Comparative size (b) Example of encapsulation

Figure 2: Details of the Henesis WiModule.

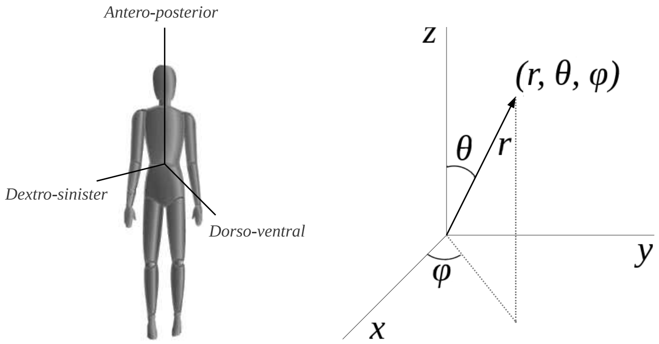
The master module acts as a receiver, and it is connected to a computer in order to save the data, while the other five modules, acting as slaves (and identified by an ID number), are attached to the body and transmit the information related to human motion to the master device using wireless communications. The transmissions follow the IEEE 802.15.4 standard for wireless communications in the 2.4GHz band, while the accelerometers provide measurements in ±6g range with a sampling frequency of 160Hz. For each instant of time, i.e., every 6.25ms, the record contains the following information: $(x_1, y_1, z_1, x_2, y_2, z_2, x_3, y_3, z_3, x_4, y_4, z_4, x_5, y_5, z_5)$, fifteen channels, which correspond to the three axes of each of the five slave modules.

In order to acquire meaningful data to model appropriately the movement, it is necessary to take into consideration the postures performed during the sun salutation. This process allows us to decide the location of the sensors as follows:

- Sensor 1: on the right forearm, above the hand.
- Sensor 2: on the left forearm, above the hand.
- Sensor 3: on the back waist, near to the center of mass of the body.
- Sensor 4: on the right lower part of the calf, over the Achilles tendon.
- Sensor 5: on the left lower part of the calf, over the Achilles tendon.

The selected locations allow, in addition, to avoid the problems related to placing the sensors, e.g., in the middle of a limb, and analyzing the influence of the height of different people in the obtained data.

During the sun salutation, the movement of the body is done along the dorso-ventral and the antero-posterior axes, as shown in Figure 3(a). Considering how the exercises are performed in this space, we realized that the movements can be modeled by considering a relevant feature, the angle of the sensors with respect to the vertical axis. Interpreting the available data from this point of view, permits us to reduce its dimensionality. Therefore, we decided to change from the Cartesian to the spherical coordinate system (see Figure 3(b)), obtaining the vector representation of each accelerometer and then extracting the angle with respect to the vertical axis, Z, i.e. the θ angle. This angle proves to be a relevant attribute with an adequate resolution degree to describe the human body movements while performing this sequence of poses. Following this approach, the record reduces to five channels related to the angles: $(\theta_1, \theta_2, \theta_3, \theta_4, \theta_5)$.



(a) Human body reference axes (b) Spherical coordinate system

Figure 3: Reference coordinate system.

In order to more accurately recognize the transitions between the different poses of the exercise, five additional channels were considered, corresponding to the derivatives of the mentioned angles.

Once the sensors are worn, it is necessary to proceed with a calibration process to align the axes of their accelerometers to the same reference coordinate system, previously shown in Figure 3. For this reason, at the beginning of the exercise it is required that the user stays in a certain position, just standing with the arms in a relaxed position next to the body and the legs closed together, for a pair of seconds. In our convention, the Z axis is aligned with the gravity, but being positive in the upper half-plane. By obtaining the corresponding rotation matrix and applying it to the following data, in this static position, all the accelerometers' vectors point to the floor, due to the gravity, having the θ angle a value of 180°. For further comprehension, these angles are referred afterwards to the horizontal plane, going from $-90°$ to $90°$ (in the calibration pose).

3. FFSM for modeling the sun salutation sequence

The concept of the traditional Finite State Machines (FSMs) can be extended using fuzzy logic [13]. FFSMs have demonstrated to be a suitable tool for modeling signals which evolve in time following a quasi-periodic repetitive pattern [4, 5, 6].

In general, a FFSM is described as a tuple $\{Q, S, U, Y, f, g\}$ where:

- $Q = \{q_0, q_1, q_2, \ldots, q_n\}$ is the set of n fuzzy states of the system.
- $S = \{s_0, s_1, s_2, \ldots, s_n\}$, with $s_i \in [0, 1]$, is the state activation vector which represents the state of the FFSM. It stores in each of its components the activation degree of the different states, considering that the system is always in a known state (see Eq. 1).

$$\sum_{i=0}^{n} s_i = 1 \tag{1}$$

- $U = \{u_0, u_1, u_2, \ldots, u_n\}$ is the input vector of the system, i.e., the set of fuzzy input variables.
- $Y = \{y_0, y_1, y_2, \ldots, y_n\}$ is the output vector. Y is a summary of the relevant characteristics of the system while remained in each state.
- f is the state transition function that calculates at each instant of time the next value of the state activation vector: $S[t+1] = f(U[t], S[t])$.
- g is the output function that calculates the set of output vectors of the system: $Y[t] = g(U[t], S[t])$.

Both the state transition function and the output function can be represented by using fuzzy rules. In the case of the state transition function, each rule can be denoted as R_{ij}, which refers to the change from the actual state, q_i, to the next one, q_j.

This section presents the design of the main elements needed to build an appropriate FFSM to model the sun salutation sequence. In order to simplify the demonstration of concept in this paper, the set of poses of the sun salutation to be considered is reduced to the first three and the last two poses shown in Figure 1, including an additional one at the beginning (and at the end, closing the circle) for the sensors calibration. Figure 4 represents the state diagram of the FFSM designed for the reduced cycle of the sun salutation which will permit to recognize this set of poses. Each of its components will be described in the next subsections.

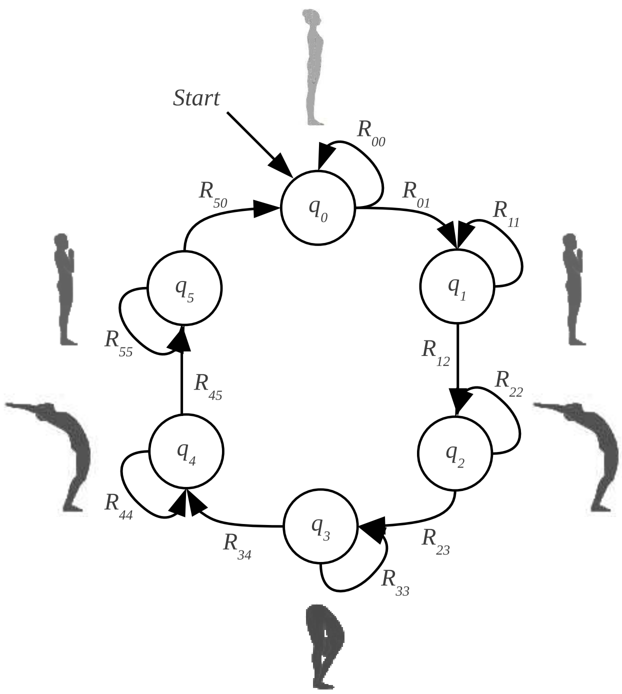


Figure 4: State diagram of the FFSM for the reduced cycle of the sun salutation.

3.1. Defining the states

According to our knowledge about the phenomenon, we can define a fuzzy state for each of the selected poses of the sun salutation sequence (see Figure 4 for the correspondences) as follows:

- q_0: *"The pose is: standing with arms falling in relaxed position (calibration pose)."* (Pose 0).
- q_1: *"The pose is: standing with hands in mountain pose (initial pose)."* (Pose 1).
- q_2: *"The pose is: standing raising hands overhead (initial pose)."* (Pose 2).
- q_3: *"The pose is: standing forward fold, hands next to feet."* (Pose 3).
- q_4: *"The pose is: standing raising hands overhead (final pose)."* (Pose 11).
- q_5: *"The pose is: standing with hands in mountain pose (final pose)."* (Pose 12).

3.2. Defining the linguistic labels of the input variables

As introduced in Section 2, the set of input variables is formed by the angles and their derivatives related to each of the sensors in the system, which are fuzzified as explained below. Therefore, U is formed by a total of ten variables:

$$U = \left(\theta_1, \theta_2, \theta_3, \theta_4, \theta_5, \frac{\mathrm{d}\theta_1}{\mathrm{dt}}, \frac{\mathrm{d}\theta_2}{\mathrm{dt}}, \frac{\mathrm{d}\theta_3}{\mathrm{dt}}, \frac{\mathrm{d}\theta_4}{\mathrm{dt}}, \frac{\mathrm{d}\theta_5}{\mathrm{dt}}\right)$$

Having two different kinds of variables, we need to associate also different sets of linguistic labels to them for a higher interpretability. The linguistic labels for each variable related to the angles of the sensors are $\{VN_{\theta_i}, N_{\theta_i}, Z_{\theta_i}, P_{\theta_i}, VP_{\theta_i}\}$, where VN, N, Z, P and VP are linguistic terms that represent *very negative*, *negative*, *zero*, *positive* and *very positive*, respectively. Figure 5 shows the trapezoidal membership functions used to calculate the membership degree of the angles to each linguistic label.

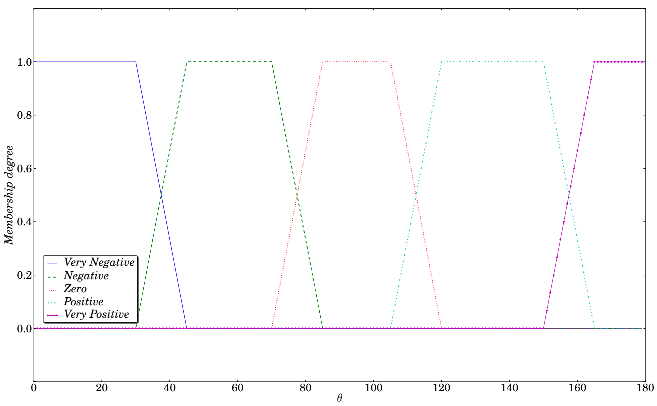


Figure 5: Trapezoidal membership functions used to calculate the membership degree of the angles.

On the other side, the linguistic labels that represent the derivatives of the angles are $\{N_{d\theta_i}, Z_{d\theta_i}, P_{d\theta_i}\}$, where N, Z, and P are linguistic terms that represent *negative (decreasing)*, *zero (keeping constant)*, and *positive (increasing)*, respectively. The trapezoidal membership functions used to calculate the membership degree of the derivative of the angles are shown in Figure 6.

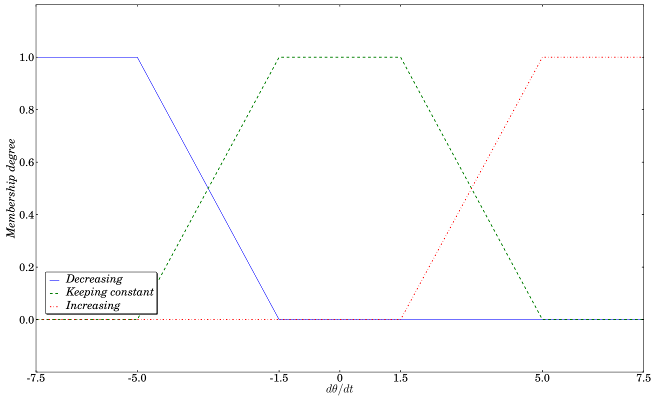


Figure 6: Trapezoidal membership functions used to calculate the membership degree of the derivative of the angles.

3.3. Defining the rules of the transition function

We decided to aggregate the information from the sensors in a way that we could describe the pose of different parts of the body (forearms, back waist and calves) and their movement. In order to simplify the expression of the poses restrictions, we define various intermediate fuzzy variables using logical expressions. The following tables show how these internal variables are specified for being used later in the definition of the rules of the FFSM, making the algorithm easier to understand.

Table 1 shows how the information corresponding to the angles of the sensors on both forearms, θ_1 and θ_2, is used to provide the description of the forearms pose. In Figure 7 it is defined the space where the forearms poses are specified considering the membership functions of the angles of sensors 1 and 2.

Table 1: Forearms poses and related variables

Forearms poses	**Intermediate variables**	
- *Straight*	$\boldsymbol{F_1}$	(θ_1 is VP) AND (θ_2 is VP)
- *Mountain*	$\boldsymbol{F_2}$	(θ_1 is N) AND (θ_2 is N)
- *Overhead*	$\boldsymbol{F_3}$	(θ_1 is VN) AND (θ_2 is VN)

In Table 2 it is shown how the information corresponding to the angle of the sensor in the back waist is used in order to indicate its pose.

Table 2: Back waist poses and related variables

Back waist poses	**Intermediate variables**	
- *Straight*	$\boldsymbol{B_1}$	θ_3 is VP
- *Bending backward*	$\boldsymbol{B_2}$	(θ_3 is P) OR (θ_3 is VP)
- *Bending forward*	$\boldsymbol{B_3}$	(θ_3 is N) OR (θ_3 is Z)

Table 3 shows the description of the calves pose and the intermediate variables defined by using the information corresponding to the angles of the sensors on both calves.

Once this set of intermediate variables has been defined to identify the poses of different parts of the body, the same methodology is applied with the derivatives of the angles of the sensors to describe the movement of these parts of the body. In Table 4 it is shown the description of the forearms movement by combining the information of the derivatives of the angles corresponding to their sensors (hereafter, for simplicity, $\frac{\mathrm{d}\theta_i}{\mathrm{d}t}$ is noted as $d\theta_i$).

Table 5 shows the description and the intermediate variables of the back waist movement by interpreting the information related to the derivative of the angle of the sensor attached to it.

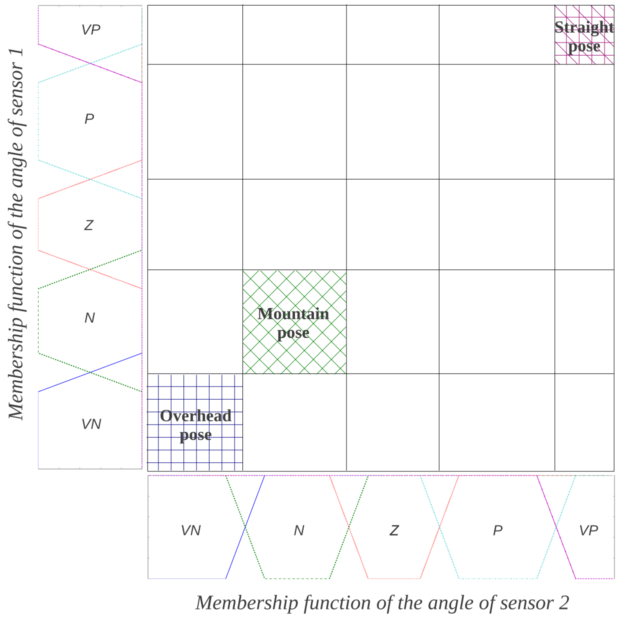


Figure 7: Input space where the forearms poses are defined

Table 3: Calves poses and related variables

Calves poses	Intermediate variables	
- *Straight*	$\boldsymbol{C_1}$	$(\theta_4$ is $VP)$ AND $(\theta_5$ is $VP)$
- *Bending backward*	$\boldsymbol{C_2}$	$((\theta_4$ is $P)$ OR $(\theta_4$ is $VP))$ AND $((\theta_5$ is $P)$ OR $(\theta_5$ is $VP))$

Finally, Table 6 shows the description of the calves movement and the related variables.

We implement the state transition function using a set of zero-order Takagi-Sugeno-Kang (TSK) inference rules [18], distinguishing between rules to remain in the state q_i $(R_{i\to i})$ and rules to change from state q_i to state q_j $(R_{i\to j})$. Due to the characteristics of the reduced sun salutation exercise and according to the state diagram previously shown in Figure 4, there are 12 fuzzy rules in total in the system, 6 rules to remain in each pose and other 6 to change between poses. We chose the pose 0 as the initial one, i.e., state q_0, *"The pose is: standing with arms falling in relaxed position (calibration pose)"*, will initially have an activation degree of 1. In this way, the FFSM will synchronize with the sun salutation exercise, without the need of doing previous segmentation of the signal, when the conditions to be in that pose are fulfilled. The rules to remain in the current state are the following ones:

$\boldsymbol{R_{0\to 0}}$: IF q_0 AND F_1 AND B_1 AND C_1 AND FM_1 AND BM_1 AND CM_1 THEN q_0

$\boldsymbol{R_{1\to 1}}$: IF q_1 AND F_2 AND B_1 AND C_1 AND FM_1 AND BM_1 AND CM_1 THEN q_1

$\boldsymbol{R_{2\to 2}}$: IF q_2 AND F_3 AND B_2 AND C_2 AND FM_1 AND BM_1 AND CM_1 THEN q_2

$\boldsymbol{R_{3\to 3}}$: IF q_3 AND F_1 AND B_3 AND C_1 AND FM_1 AND BM_1 AND CM_1 THEN q_3

$\boldsymbol{R_{4\to 4}}$: IF q_4 AND F_3 AND B_2 AND C_2 AND FM_1 AND BM_1 AND CM_1 THEN q_4

$\boldsymbol{R_{5\to 5}}$: IF q_5 AND F_2 AND B_1 AND C_1 AND FM_1 AND BM_1 AND CM_1 THEN q_5

Whereas the rules to change between states are these ones:

Table 4: Forearms movement and related variables

Forearms movement	Intermediate variables	
- *Not moving*	$\boldsymbol{FM_1}$	($d\theta_1$ is Z) AND ($d\theta_2$ is Z)
- *Moving up*	$\boldsymbol{FM_2}$	($d\theta_1$ is N) AND ($d\theta_2$ is N)
- *Moving down*	$\boldsymbol{FM_3}$	($d\theta_1$ is P) AND ($d\theta_2$ is P)

Table 5: Back waist movement and related variables

Back waist movement	Intermediate variables	
- *Not moving*	$\boldsymbol{BM_1}$	$d\theta_3$ is Z
- *Moving backwards*	$\boldsymbol{BM_2}$	($d\theta_3$ is Z) OR ($d\theta_3$ is P)
- *Moving forwards*	$\boldsymbol{BM_3}$	$d\theta_3$ is N

$\boldsymbol{R_{0\to1}}$: IF q_0 AND F_2 AND B_1 AND C_1 AND FM_2 AND BM_1 AND CM_1 THEN q_1

$\boldsymbol{R_{1\to2}}$: IF q_1 AND F_3 AND B_2 AND C_2 AND FM_2 AND BM_2 AND CM_2 THEN q_2

$\boldsymbol{R_{2\to3}}$: IF q_2 AND F_1 AND B_3 AND C_1 AND FM_3 AND BM_3 AND CM_1 THEN q_3

$\boldsymbol{R_{3\to4}}$: IF q_3 AND F_3 AND B_2 AND C_2 AND FM_2 AND BM_2 AND CM_2 THEN q_4

$\boldsymbol{R_{4\to5}}$: IF q_4 AND F_2 AND B_1 AND C_1 AND FM_3 AND BM_1 AND CM_1 THEN q_5

$\boldsymbol{R_{5\to0}}$: IF q_5 AND F_1 AND B_1 AND C_1 AND FM_3 AND BM_1 AND CM_1 THEN q_0

where:

- The first term in the antecedent computes the activation degree of state q_i, i.e., S_i. With this mechanism, we only allow the FFSM to move from the state q_i to the state q_j (or to remain in state q_i, when $i = j$). For example, in $R_{0\to0}$, it is computed the activation degree of state q_0: *"The pose is: standing with arms falling in relaxed position (calibration pose)"* (S_0).
- The second, third and fourth terms in the antecedent describe the constraints imposed on the positions of the forearms, the back and the calves, respectively. In the case of the second antecedent, related to the position of the forearms, it computes the activation degree of one of their three possible poses.
- The fifth, sixth and seventh terms in the antecedent describe the constraints imposed on the movement of the forearms, the back and the calves, respectively. In the case of the fifth antecedent, related to the movement of the forearms, it computes the activation degree of one of their three possible movements.
- Finally, the consequent of the rule defines the next pose. To calculate the activation degrees of being in each pose j (S_j), a weighted average using the firing degree of each rule R_{ij} (ϕ_{ij}) is computed as defined in Eq. 2:

$$S_j = \frac{\sum_{i=0}^{5} \phi_{ij}}{\sum_{i=0}^{5}\sum_{j=0}^{5} \phi_{ij}} \tag{2}$$

where (ϕ_{ij}) is calculated using the minimum for the AND operator and the bounded sum of Łukasiewicz [3] for the OR operator.

It is worth remarking that, in this approach, the trapezoidal membership functions, both for the angles and their derivatives, and the sets of fuzzy rules have been set up empirically. However, it is interesting

Table 6: Calves movement and related variables

Calves movement	Intermediate variables	
- *Not moving*	$\boldsymbol{CM_1}$	($d\theta_4$ is Z) AND ($d\theta_5$ is Z)
- *Moving to "bending backward pose"*	$\boldsymbol{CM_2}$	(($d\theta_4$ is N) OR ($d\theta_4$ is Z)) AND (($d\theta_5$ is N) OR ($d\theta_5$ is Z))

to mention that in [5, 6] it is presented an automatic method for learning the model parameters based on the hybridization of fuzzy finite state machines and genetic algorithms leading to genetic fuzzy finite state machines (GFFSMs). Nevertheless, in order to apply this model in practice, these parameters should be tuned in accordance with the criteria of the specific final application.

3.4. Defining the output of the FFSM

In this work, we consider $Y[t] = S[t]$, so the output of the FFSM contains the degree of activation of each state at each instant of time, which means providing the information related to the pose recognition.

4. Experimentation

In this section, we present the experimental results obtained with the proposed approach. To evaluate it, we collected the acceleration signals of two healthy participants, who voluntarily took part in the evaluation (a woman and a man with ages 27 and 30 years, respectively), while performing the sun salutation sequence. One of them had performed the exercise regularly before acquiring the data, while for the other one, it was the first time. They will be identified hereafter as subject A and B, respectively. We asked each person to perform the complete exercise four times, producing a total of four datasets for each of them.

First of all, as an example of the performance of our FFSM for the reduced sun salutation sequence, Figure 8 represents, for one of the data acquisitions, the activation degrees of each state together with the angles and their derivatives of each one of the sensors (θ_i and $\frac{\mathrm{d}\theta_i}{\mathrm{d}t}$, respectively). It shows how the set of fuzzy rules described above is able to recognize adequately the evolution through the six poses of the selected sequence of movements.

On the other side, we analyzed the data obtained for each subject, the activation degree of each of the poses at each instant of time, from two different points of view: the duration of the poses and their stability. The duration refers to the amount of time that each pose is recognized by the FFSM as the active pose, while the stability takes into account the percentage of the time that this pose is recognized as being active with the highest activation degree, 1.

Table 7 shows the results for each subject, being indicated the average values and the corresponding standard deviation over their datasets, for each of the sun salutation poses (state q_0 is not included as it is related to the calibration pose). The last column provides the average values for the whole exercise. As it can be seen, for both subjects, the duration of the states q_2 and, specially, q_4 is significantly shorter than those of the other states. These poses are considered the *most complex* ones of the sequence and, therefore, more difficult to maintain for a longer period of time. This is also reflected on the stability of subject B, who is not able to stay in this pose without moving or wobbling. Consequently, the state q_4 is not unequivocally recognized during its duration, causing the stability to be lower than in the other states (which are recognized with the highest degree of membership). This information could be used to determine that subject A, who is more experienced in practicing the exercise than subject B, is able to perform the sequence with a more uniform duration of the poses and a higher stability.

5. Concluding remarks

This paper contributes to the field of motion recognition by modeling a complex exercise using a FFSM and fusing multiple sensors information. Performing human motion analysis involving several body parts, the FFSM designed allows the proper recognition of the different poses of the sun salutation sequence.

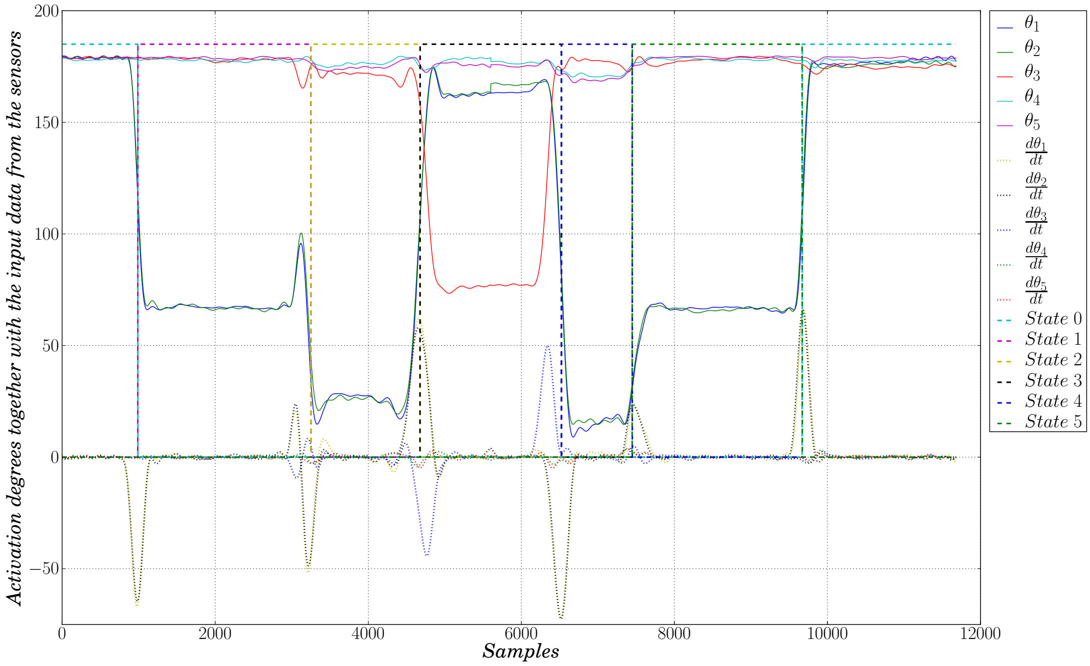


Figure 8: Graphical representation of the activation degrees of each state together with the evolution of the angles and their derivatives for each one of the sensors (θ_i and $\frac{\mathrm{d}\theta_i}{\mathrm{d}t}$, respectively).

Table 7: Results analysis about the duration and stability of the poses

Results analysis							
Subject	Feature	States statistics					
		q_1	q_2	q_3	q_4	q_5	Total average
A	Duration	13.32s (± 0.82)	8.57s (± 0.40)	11.91s (± 2.78)	6.93s (± 1.24)	13.07s (± 1.08)	**10.75s (± 1.27)**
	Stability	100% (± 0.00)	100% (± 0.00)	100% (± 0.00)	100% (± 0.00)	100% (± 0.00)	**100% (± 0.00)**
B	Duration	11.25s (± 1.38)	8.94s (± 1.62)	11.38s (± 1.18)	7.81s (± 0.82)	14.68s (± 3.95)	**10.81s (± 1.79)**
	Stability	100% (± 0.00)	100% (± 0.00)	100% (± 0.00)	72.78% (± 31.92)	100% (± 0.00)	**94.56% (± 6.38)**

In the future, along with a refinement of the rules set, this work will be integrated in a higher level model for analyzing how the exercise is being performed in order to provide a linguistic description of it and a feedback to the user. It will also be considered a comparison with other methods, such as neural gas algorithms.

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