# Human activity recognition in indoor environments by means of fusing information extracted from intensity of WiFi signal and accelerations

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**Abstract**

In this work, we propose an activity recognition system based on the use of a topology-based WiFi localization system combined with accelerometers for body posture recognition. The WiFi localization system is developed using a fuzzy rule-based classifier while the recognition of the body posture and its integration with the WiFi localization system is developed using two fuzzy finite state machines.

These tools for modeling dynamical processes allow us to handle imprecise and uncertain data in the form of linguistic labels and fuzzy rules producing a linguistic description of the human activity.

A practical application that consists of recognizing different activities of an office worker in her/his environment is developed. It yields high accuracy (83.7 %, in average regarding all experimental trials). Interpretability and robustness of the proposal are also analyzed and alternative classifiers for the WiFi localization system are tested and compared obtaining competitive performance in terms of accuracy-interpretability trade-off.

*Key words:* Human activity recognition, Fuzzy logic, Interpretability-accuracy trade-off

## 1. Introduction

The research field of human activity recognition consists of characterizing the activities of one or more people from a series of data observations on the people's actions. This problem, which is not constrained, is very difficult due to the fact that complex activities are composed of other simpler ones [42], i.e., they can be segmented and characterized on different levels of granularity [58, 77]. The level to choose depends on the requirements of the application demanded by the specific user, however, there is an evidence that humans try to structure and name the different levels of detail in a hierarchical fashion [44].

This research field has attracted considerable attention over the last 30 years due to the vast array of possible applications that it provides in many areas. A promising application is the proactive care for the elders or people suffering degenerative dementia such as Alzheimer's disease, e.g., the detection of changes in the daily living activities can be used to produce warnings or emergency calls. Moreover, the recognition of routines can help these people to remember their daily tasks. There are also security applications that

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produce warnings in order to reduce the safety risk by detecting when someone is performing a dangerous task. Finally, the recognition of different human activities can provide context aware services, which are very demanded in human-computer interaction. For instance, by detecting office workers activities such as attending a meeting, having a coffee or working at the desk we may endow a mobile phone with an intelligent system capable of filtering the phone calls depending on these different circumstances.

In this work, we propose an activity recognition system based on acceleration data for body posture recognition combined with a topology-based WiFi localization system. On the one hand, the WiFi localization system, which yields topology-based room-level localization, was developed using a highly interpretable fuzzy rule-based classifier (FRBC) whose output is a vector containing a degree of activation for each zone in the environment. It can be interpreted as a confidence degree on the system output. On the other hand, the recognition of the body posture and its integration with the WiFi localization system was developed using fuzzy finite state machines (FFSMs). The main advantage of FFSMs is that their fuzziness allows them to handle imprecise and uncertain data, which is inherent to real-world phenomena, in the form of fuzzy states and transitions.

Hence, from the viewpoint of the techniques used, this work is mainly based on fuzzy logic (FL), which is widely recognized for its ability for linguistic concept modeling and its use in system identification. Furthermore, FL makes easier merging expert knowledge and induced knowledge, i.e., knowledge automatically extracted from data, because both kind of knowledge can be expressed under the same fuzzy formalism [1]. Moreover, the FRBC as well as FFSMs are made up of a small number of rules and linguistic variables keeping a good interpretability-accuracy trade-off [20, 21].

In the experimental phase, a practical application of our proposal is presented. It consists of recognizing different human activities performed by an office worker in her/his environment. Performance related to accuracy, interpretability and robustness of the proposal is analyzed and compared with other approaches.

This paper is organized as follows: Section 2 gives an overview on related works regarding human activity recognition, remarking their more outstanding advantages and drawbacks. It also summarizes the main contributions of our proposal. Then, Section 3 describes the fundamentals, namely, how to design an interpretable FRBC and the notion of FFSM. Afterwards, Section 4 explains in detail our proposal related to human activity recognition. It combines one FRBC and two FFSMs. Then, Section 5 shows the experimental results. And finally, Section 6 expounds the conclusions and future works.

## 2. Human activity recognition: literature review and contribution

### 2.1. Literature review

There are different human activity recognition approaches from different points of view. One possible taxonomy divides the activity recognition works into sensor-based and computer vision approaches.

The sensor-based approach consists of using small sensors (usually accelerometers) placed in the body of the person [14] or in the objects [54, 59, 66] in order to detect how people move themselves or how they move the objects. In [10], authors showed how acceleration data can aid recognition of pace and slope. Authors of [69] demonstrated that a subject's acceleration can discriminate between sedentary, moderate or vigorous activities. The principal drawback of this approach is the user's need of wearing the sensors. Fortunately, they can be embedded into clothes or electronic devices such as mobile phones due to the advances in miniaturization, the capabilities of communication between sensors through wireless connections, and the low cost and energy consumption. Moreover, the addition of sensors has demonstrated an improvement in the performance, e.g., the acceleration data of the wrist and the arm improve the recognition rates of activities which involve upper body parts [32].

The computer vision approach is based on the use of video cameras installed in the scenario under study. Here, the additional hardware must be installed in each room of the environment. This approach usually works in lab but fails in real world scenarios due to clutter, variable light intensity and contrast. Moreover, the video cameras are sometimes perceived as invasive and threatening by some people. Other important drawback is the computational cost of working with video signals. To solve this, authors of [15] proposed a method which does not require a full video sequence and only some image samples are enough to recognize activities by means of multidimensional hash tables. The interested reader is referred to [68], where a complete survey of activity recognition works based on computer vision can be found. In addition, there are some recent works [11, 22] proving the advantages of considering FL for computer vision analysis aimed to human activity modeling and monitoring.

For both approaches, the activity recognition problem is seen as a learning problem that can be supervised or unsupervised [63]. The supervised learning problem involves learning a function from supervised training data, i.e., from data where the activity is known. On the other hand, the unsupervised learning problem involves learning patterns in the output when no specific output values (activities) are supplied. Examples of supervised approaches can be found in [14] where different classifiers (decision tables, nearest neighbors, C4.5 decision trees and Naïve Bayes) are tested, and in [38], where authors propose the use of hidden Markov models (HMMs) to classify six different activities. HMMs are also used in [26] in an unsupervised fashion to detect different activities from audio and video signals.

In addition, there are several works which consider localization data as basis for human activity recognition. In [45] authors use GPS data to derive high-level activities and to identify places. The main problem is that GPS signals do not work in indoor environments and do not allow recognizing activities in an office work environment, where one person might work, hold meetings and even occasionally have lunch. To overcome this problem in indoor environments, several authors have proposed the use of the network infrastructure to estimate user's location. Notice that, local network based systems are sometimes based on pre-existing infrastructures like ZigBee networks designed for home control applications [17]. However, the most used systems are based on WiFi networks which are able to provide indoor absolute localization. Moreover, the analysis of WiFi signals, considering both time-domain and frequency-domain algorithms, is useful not only for localization purposes but also for inferring motion models [53].

The main advantage of WiFi localization systems, based on the use of 802.11b/g network infrastructure, is that they are able to estimate a device position without using additional special hardware [53]. The received signal level (SL), also known as received signal strength indicator (RSSI), from each access point (AP) depends on the distance but also on the obstacles placed between the emitter and the receiver. Therefore, the simplest method for estimating the device position consists of applying a trilateration algorithm. Unfortunately, in indoor environments SL is strongly affected by the well-known multipath effect that comprises reflection, refraction and diffraction. Thus, SL becomes a complex function of the distance that dynamically changes with time because it is affected by every modification made in the environment [49]. Anyway, the main drawback is the need of a complete network infrastructure in the whole building where we want to localize a person. Luckily, this technology is quickly growing of coverage. Currently, there are WiFi APs in most companies facilities and public buildings like hospitals, libraries, universities, museums, etc. Moreover, measuring the WiFi signal level is free even for private WiFi networks. As a result, WiFi technology is a good choice for indoor global localization systems yielding a good accuracy-cost trade-off.

Two main approaches are usually considered, namely distance-based and topology-based approaches. In the first case, localization is carried out in a low abstraction level with the aim of estimating X-Y coordinates in a two dimensional map. On the contrary, a topological approach yields a symbolic localization in a more human friendly way, i.e., in a higher abstraction level. Thus, the goal is not finding out the exact X-Y coordinates but giving an approximate position (at room level for instance) with high confidence. In consequence, the localization stage is naturally formalized in the form of a regression problem in the case of distance-based approach while it can be treated as a classification problem for the topology-based approach.

The distance-based approach is by far the most popular. Authors of [13] proposed the use of a priori radio map storing the received SL of each AP belonging to an interest region. The radio map is built during the training stage. Then, in the estimation stage, a vector with received SL of each AP is created and compared with the radio map to obtain the estimated position. This technique is commonly known as fingerprinting. Nerguizian et al. proposed the use of neural networks and fingerprinting to deal with the well-known multipath effect in indoor environments [55]. They introduced a method for mobile robot localization following a distance-based approach. Even though the learning stage is done off-line, it become computational costly (and even unfeasible) for very large environments. More recently, Outemzabet et al. presented a similar proposal whose main novelty arises from estimating X-Y coordinates that are enhanced first with Kalman filtering [57] and later with particle filtering and a low-cost sensor [56]. In addition, Wu et al. [72] advocated for extending Kalman filtering with propagation channel modeling. They compared three regression models. The first one is based on curve fitting by means of polynomial regression. The second one consists of a novel interpolation method. And the third one is based on an adaptive neural fuzzy inference system (ANFIS), a supervised learning strategy, which yields a propagation model automatically learnt from RSSI measures previously collected. The ANFIS model achieves the best results. As an alternative to fingerprinting, neural networks can also be generated from synthetic data provided by theoretical propagation models [29]. This way of doing makes easier the adaptation of localization systems to unknown environments, avoiding the tedious task of physically collecting RSSI samples for building the characteristic radio map of fingerprinting. Unfortunately, setting a good theoretical propagation model becomes almost an impossible mission in indoor environments mainly due to the multipath effect.

However, in many applications, like for instance proximity classification of mobile devices [19], the accurate positioning provided by distance-based approaches is not necessary. In those cases, following topology-based approaches is enough. Moreover, designed models become much more efficient, effective, and human-friendly. The use of FL, which is especially useful to handle problems where the available information is vague like when working with WiFi signal strength sensors, has become quite popular. FL lets us to deal with the uncertainty in the environment and makes possible to estimate the device position without a high number of samples [12]. Dharne et al. [30] proposed a fuzzy rule-based system able to get good results while reducing the computation time thanks to take into account only significant grid-points in a grid-based map describing the whole environment under consideration. Chan et al. [23] introduced a spatial analytical multi-layer fuzzy model for WiFi localization based on fingerprinting. Finally, the combination of fuzzy rule-based classifiers and fingerprinting have already been proved to be highly successful when dealing with topology-based WiFi localization [6].

### 2.2. *Contribution*

The main contributions of the paper are listed as follows:

- The development of a framework for dealing with complex systems through merging different sources of information, mainly expert and induced knowledge. They are characterized in the form of linguistic variables and rules under the fuzzy logic formalism what favors the generation of systems exhibiting good performance in terms of interpretability-accuracy trade-off.

- An example of application of this framework to the real-world problem of human activity recognition in the context of a person working in an office environment. The scheme of this example of application is represented in Figure 1. Starting from the preliminary study presented in [7], we propose the design of a human activity recognition module which arises from successfully combining a topology-based WiFi localization module with a body posture recognition module based on the data provided by accelerometers because, although location is a powerful indication of the different activities of the daily live, it is not enough. The WiFi positioning module is implemented by an interpretable FRBC while the posture recognition module and its combination together with the WiFi positioning module are developed using two FFSMs.

- A careful design process to guarantee the interpretability of the entire system along the whole designing process. Although interpretability is acknowledged as a key feature of fuzzy systems [2] and it has recovered a predominant role regarding fuzzy modeling [4, 33, 51, 61], fuzzy systems are not interpretable *per se*. Moreover, interpretability becomes mandatory for those applications exhibiting high human-machine interaction like the one tackled with in this paper.

- The introduction of the unknown state in the definition of our FFSM model with the aim of measuring the ability of the FFSM in recognizing the current state of the monitored phenomenon based on the current inputs.

- The combination of two types of FFSMs. The first one, FFSM1, is in charge of posture recognition. Its knowledge base is automatically obtained from data using a genetic learning procedure [8] which keeps its interpretability, allowing the user to understand the performance of the system. The second one, FFSM2, implements the activity recognition module. In this case, the knowledge base is defined by an expert, and it must be capable of integrating the outputs of the two first modules (FRBC and FFSM1) while keeping simple enough to be easily customized by each specific end-user in an experimental scenario.

- The adaptation to human beings indoor localization of a WiFi localization approach which was already applied successfully in the robotics field [3]. It is implemented as a fuzzy rule-based classifier for topology-based room-level WiFi localization inspired on fingerprinting.

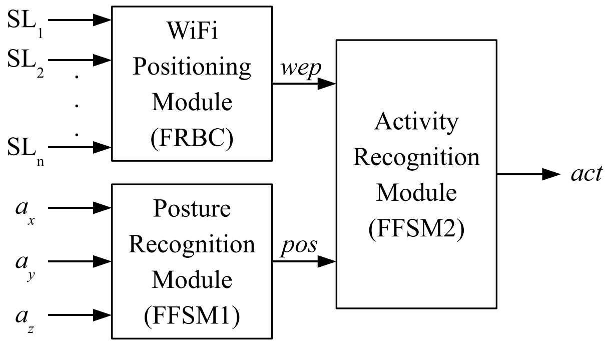


Figure 1: Scheme of the proposed example of application.

## 3. Fundamentals

### *3.1. Interpretable fuzzy rule-based classifiers*

A fuzzy rule-based classifier (FRBC) is a fuzzy rule-based system able to carry out classification tasks, i.e., a system computing the following function:

$$f_{FRBC} : \mathbf{X} \longrightarrow C$$

Given an $n$-dimensional input space where $\mathbf{X} = X_1 \times X_2 \times \cdots \times X_n \subseteq \mathbb{R}^n$ and $\mathrm{C} = \left\{C^1, C^2, \ldots, C^{n_C}\right\}$, $f_{FRBC}$ yields one output class $C^i$ from the pre-defined set of $n_C$ classes C. By means of applying a fuzzy inference mechanism $f_{FRBC}$ provides an activation degree associated to each class $C^i$. Of course, several classes can be activated at the same time with activation degree greater than zero. The usual fuzzy classification mechanism is based on the Max-Min inference scheme and the winner rule fuzzy reasoning mechanism:

$$y_{FRBC}(\mathbf{x}^p) \;=\; C^i \Leftrightarrow \mu_{C^i}(\mathbf{x}^p) \;=\; \max_{k=1,\ldots,n_C} \mu_{C^k}(\mathbf{x}^p)$$

$$\mu_{C^k}(\mathbf{x}^p) \;=\; \max_{R=1,\ldots,n_R} \mu_R(\mathbf{x}^p) \Leftrightarrow Y_R \text{ is } C^k$$

$$\mu_R(\mathbf{x}^p) \;=\; \min_{i=1,\ldots,n} \mu_{A_i^j}(x_i^p)$$

where given an input vector $\mathbf{x}^p = (x_1^p, \ldots, x_n^p)$, the output class $C^i$ is derived from the highest $\mu_{C^i}(\mathbf{x}^p)$ which is the membership degree of $\mathbf{x}^p$ to the class $C^i$. It is computed as the maximum firing degree of all rules yielding $C^i$ as output class. For each rule, the firing degree is computed as the minimum membership degree of each component $(x_i^p)$ to its related fuzzy set $A_i^j$, for all the $n$ inputs.

With the aim of preserving interpretability [2], our FRBC is designed following the fuzzy modeling methodology called HILK (Highly Interpretable Linguistic Knowledge) [3, 5]. It focuses on building comprehensible fuzzy classifiers, i.e., classifiers easily understandable by human beings. Useful pieces of knowledge can be directly provided by an expert or automatically extracted from experimental data and they are represented by means of linguistic variables [74, 75, 76] and linguistic rules [48, 73] under the FL formalism.

HILK enables the user to follow a step-by-step procedure in the generation of all elements involved in a FRBC: starting from the design of fuzzy partitions, going through the rule base learning and ending up with a linguistic simplification stage which iteratively refines both partitions and rules.

Thus, the first step is setting global semantics, i.e., defining all significant variables for a FRBC. They will be shared by all the rules. Thus, a linguistic variable $V$ is defined by a quintuple $\{N, G, T, UD, S\}$ [18] where $N$ is the name of the variable, $G$ is a grammar, $T$ is a set of linguistic terms, $UD$ represents the universe of discourse of $V$, and $S$ defines a fuzzy partition in such a way that the semantics of each linguistic term is given by a fuzzy set. Notice that, interpretable fuzzy partitions must be readable and fully meaningful to the user. Fortunately, the use of strong fuzzy partitions (SFPs) [62] satisfies semantic constraints (distinguishability, normalization, coverage, overlapping, etc.) [52] demanded to get comprehensible partitions. SFPs satisfy the following equation:

$$\forall x \in UD, \ \sum_{i=1}^{|T|} \mu_{A_i}(x) = 1$$

where $|T|$ is the number of linguistic terms in $T$, and $\mu_{A_i}(x)$ is the membership degree of $x$ to the fuzzy set $A_i$. Of course, SFPs are not necessarily uniform, they can be directly defined by an expert or automatically generated from experimental data (in case they are available) by means of applying clustering algorithms in order to fit the data distribution. When there is not any reliable expert able to provide a good expert partition, HILK suggests making a comparison between uniform partitions and those partitions derived from data by the well-known k-means clustering algorithm [39] and the hierarchical fuzzy partitioning method [36]. Quality of partitions is computed by three indexes: the partition entropy (PE) and the partition coefficient (PC) defined by Bezdek [16], and the Chen index (ChI) introduced by Chen [25]. A good partition should minimize PE while maximizing PC and ChI. Then, the selection of the best partition is based on an absolute majority voting process. Thus, the partition winning at least two out of the three quality criteria is chosen.

Once all involved linguistic variables have been defined, their related linguistic terms can be used to express linguistic propositions. Then, several propositions may be combined to form fuzzy rules describing the classifier behavior. Linguistic rules can be directly given by an expert or automatically extracted from experimental data. Rules are of form **IF** *Premise* **THEN** *Conclusion*, where both *Premise* and *Conclusion* make use of the linguistic terms previously defined:

$$R\text{: } \mathbf{IF} \ \underbrace{\underbrace{I_1 \text{ is } A_1^i}_{Premise\ P_1} \ \mathbf{AND} \ldots \mathbf{AND} \ \underbrace{I_n \text{ is } A_n^j}_{Premise\ P_n}}_{Premise} \ \mathbf{THEN} \ \underbrace{Y_R \text{ is } C^i}_{Conclusion}$$

where given a rule $R$, rule premises are made up of tuples (*input variable*, *linguistic term*) where $I_a$ is the name of the input variable $a$, while $A_a^i$ represents the label $i$ of such variable, with $a$ belonging to $\{1, ..., n\}$ and being $n$ the number of inputs. In the conclusion part, $C^i$ represents one of the possible output classes.

Keeping in mind the comprehensibility goal, we have chosen Fuzzy Decision Tree (FDT) [43] as basic rule induction method among those suggested by HILK. It can be seen as a fuzzy version of the popular decision trees defined by Quinlan [60]. In more detail, FDT generates a neuro-fuzzy decision tree which is easily translated into quite general incomplete rules where only a subset of input variables is considered. Starting from a root node, FDT uses a recursive procedure to split each parent node into several child nodes, so many nodes as fuzzy sets were previously defined for the related variable. In addition, input variables are sorted according to their importance (minimizing the entropy). In consequence, for each node, the algorithm selects the variable which maximizes the gain criterion. Notice that, we use the implementation of FDT provided by FisPro, so the interested reader is referred to [37] for additional details.

The last step, linguistic simplification, is aimed at solving inconsistencies and removing redundancies. As a side effect, it increases even more interpretability without jeopardizing accuracy. Namely, as it is detailed in [5], the simplification procedure is an iterative refinement process that comprises two main steps in each cycle: rule base simplification and data base reduction. Depending on the complexity of the initial FRBC, the whole process could involve several iterations as data base reduction affects to rule base simplification and vice versa. In short, simplification starts with finding out those redundant elements (linguistic terms, variables, rules, etc.) whose removal does not modify the accuracy of the designed FRBC. Then, the procedure tries to merge elements (regarding linguistic terms) that are always used together in all rules. Finally, the simplification procedure forces removing elements apparently needed but not contributing too much to the final accuracy. It becomes a trial and error task. If accuracy does not decrease, then the element is removed forever, otherwise it is restored.

*3.2. Fuzzy finite state machines*

Here, we briefly introduce the main concepts and elements of our paradigm for system modeling allowing experts to build comprehensible linguistic fuzzy models, in the form of FFSMs, in an easier way. The interested reader is referred to [7, 9, 67] for a more detailed description. A FFSM is a tuple $\{Q, U, f, Y, g\}$, where:

- $Q$ is the set of states of the system, which is defined as a linguistic variable [74, 75, 76] that takes its values in the set of linguistic labels $\{q_0, q_1, q_2, \ldots, q_n\}$, with $n$ being the number of fuzzy states and $q_0$ the unknown state. Numerically, the state of the FFSM is represented by a state activation vector: $S[t] = (s_0[t], s_1[t], s_2[t], \ldots, s_n[t])$, where $s_i[t] \in [0, 1]$. The FFSM implementation verifies $\sum_{i=0}^{n} s_i[t] = 1$ in such way that we maintain compatibility with classical finite state machines where only one state can be activated with degree 1 at each time instant.

- $U = (u_1, u_2, ..., u_{n_u})$ is the set of input vectors, with $n_u$ being the number of input variables. It is a set of linguistic variables obtained after fuzzification of numerical data where each input variable $u_i$ can take $A_{u_i} = \{A^1_{u_i}, A^2_{u_i}, \ldots, A^{n_i}_{u_i}\}$, with $n_i$ being the number of linguistic labels of the linguistic variable $u_i$.

- $f$ is the transition function which calculates, at each time instant, the next value of the state activation vector: $S[t+1] = f(U[t], S[t])$. This function is implemented by means of a fuzzy rule-based system. We distinguish between rules $R_{ii}$ to remain in a state $q_i$, and rules $R_{ij}$ to change from the state $q_i$ to the state $q_j$ in such a way that fuzzy rules will only be associated to allowed transitions. Moreover, there are not any fuzzy rules explicitly associated to the unknown state ($q_0$), because it only activates when no rule is fired.

- $Y$=$(y_1, y_2, ..., y_{n_y})$ is the set of output vectors, with $n_y$ being the number of output variables. It summarizes the characteristics of the system evolution that are relevant for the application.

- $g$ is the output function which calculates the set of output vectors of the system: $Y[t] = g(U[t], S[t])$.

The introduction of $q_0$ in the definition of our FFSM is one of the novelties of this paper, whose goal is to represent ignorance when the total firing degree of the rules is less than one. Therefore, a poor firing degree of the rules, i.e., the sum of firing degrees less than 1, is interpreted as a fault of the system to recognize the current state of the monitored phenomenon. On the other hand, if the sum of firing degrees is greater than 1 due to an excess of random (usefulness) information, this information will be equally distributed among the states indicating uncertainty. E.g., a state activation vector $S[t] = (0, 0.25, 0.25, 0.25, 0.25)$ in a FFSM with five states (including the default one, which is not activated) represents total uncertainty about the current state that might be produced by an excess of information.

Moreover, thanks to the introduction of the default state $q_0$ , we can define the Confidence Degree (CD) of our system based on its activation degree ($s_0[t]$). Such CD is defined as one minus $s_0[t]$. Thus, CD takes values in the range $[0, 1]$ being equal to one when the unknown state is not activated ($s_0[t] = 0$), zero when the unknown state is fully activated ($s_0[t] = 1$), and a real value between zero and one otherwise.

The introduction of $q_0$ made us change the fuzzy reasoning mechanism of our FFSM. The next value of the state activation vector is still calculated as a weighted average of the individual rules, where the weight of each rule $R_{ij}$ corresponds to its firing degree $\omega_{ij}$. The main difference arises in the calculation of the next value of the activation degree of $q_0$, which is calculated by means of Equation 1. This equation has two different possibilities based on the sum of the firing degrees of the whole rule set. If this quantity is less than one, the unknown state will have the rest up to one. On the other hand, if the rule set's sum of firing degrees is greater than one, the activation degree of the unknown state will be zero.

$$s_0[t+1] = \begin{cases} 1 - \sum_{i=1}^{n} \sum_{j=1}^{n} \omega_{ij} & \text{if } \sum_{i=1}^{n} \sum_{j=1}^{n} \omega_{ij} \leq 1 \\ 0 & \text{if } 1 < \sum_{i=1}^{n} \sum_{j=1}^{n} \omega_{ij} \end{cases} \tag{1}$$

The activation degree of the rest of states is calculated by means of Equation 2. The activation degree of each state $q_j$ ($s_j$) will be the sum of the firing degrees of the rules predicting that state ($\omega_{ij}$). If the rule set's sum of firing degrees is less than one, the relation $\sum_{i=0}^{n} s_i = 1$ is fulfilled and there is no need of normalizing the values. This is not the case when the rule set's sum of firing degrees is greater than one and the value must be normalized.

$$s_j[t+1] = \begin{cases} \sum_{i=1}^{n} \omega_{ij} & \text{if } \sum_{i=1}^{n} \sum_{j=1}^{n} \omega_{ij} \leq 1 \\ \frac{\sum_{i=1}^{n} \omega_{ij}}{\sum_{i=1}^{n} \sum_{j=1}^{n} \omega_{ij}} & \text{if } 1 < \sum_{i=1}^{n} \sum_{j=1}^{n} \omega_{ij} \end{cases} \tag{2}$$

The computation of the next state for the FFSM may be seen as a classification problem where the set of possible fuzzy states are taken as the classes and the fuzzy system provides a membership degree to each of them by means of the aggregation of the firing degree of the fuzzy rules matching the class and the input pattern. Nevertheless, the main difference between both fuzzy reasoning mechanisms is that, while the membership degree to all the possible fuzzy states must sum up to 1 in a FFSM, there is no such restriction for the existing class labels in a FRBC. Moreover, although there is a clear similarity between the fuzzy rule structure of FFSMs and the rule structure for FRBCs, there is a subtle but significant difference: while all the rule antecedents in a FRBC belong to the input space, in the rule antecedent of a FFSM the current state (seen as the output class in a FRBC) is also considered to predict the next state, what means that the output class of a FRBC computed in an instant time $t$ is considered as a member of the input space in the next computation step $t + 1$.

## 4. Combining FRBCs and FFSMs for human activity recognition

This section explains the proposed fusion framework for human activity recognition. It is made up of three main modules as it was illustrated in Figure 1 (page 5). Each block will be described in the following subsections. First, Subsection 4.1 focuses on building a FRBC devoted to estimate the location of a person in an indoor environment by means of processing WiFi SLs. Then, Subsection 4.2 describes the FFSM1 in charge of human body posture recognition. Finally, Subsection 4.3 gives the details related to the FFSM2 that combines both WiFi positioning and posture recognition yielding the desired human activity recognition.

### *4.1. WiFi Positioning Module (FRBC)*

First of all, we created an experimental training data set that represents the fingerprint (radio map) of the test-bed environment which will be thoroughly detailed later in Section 5. Thus, we collected training samples made up of SL measures (taken from all APs that are visible in the surrounding environment) in several reference locations for each of the zones of interest. In consequence, the training data set is very imbalanced, since we consider a real-world environment containing zones of very different size. Therefore, We have used the Synthetic Minority Oversampling Technique (SMOTE) [24] in a pre-processing stage because it has been proved as a very useful tool to deal properly with imbalance datasets [46]. As a result, training data corresponding to the smaller zones, where fewer data were collected, are oversampled by taking each experimental sample and introducing synthetic ones along the line segments joining any or all of sample's nearest neighbors with the aim of having a uniform coverage of the whole environment. Once we have built a balanced training dataset, then it is time to generate a FRBC for WiFi localization according to HILK, the fuzzy modeling methodology presented in Section 3.1.

We start with the partition design. As a first step, we identify the zones of interest in a map of the environment under analysis. The number of zones determines the number of classes of the FRBC. As it will be thoroughly explained later (in Section 5) there are six zones in our experimental scenario. Second, we have to find out the visible APs in such environment. The number of APs determines the number of input variables of the FRBC (four in our experiments). Then, all input variables (one per each AP visible in the environment) are characterized by SFPs of nine linguistic terms (*Extremely Low* (EL), *Very Low* (VL), *Low* (L), etc.). Taking advantage from those conclusions drawn from our preliminary works [6, 7], in this work we advocate for the generation and selection of fuzzy partitions automatically derived from experimental data so that fitting better the data distribution. Hence, they are not necessarily uniform partitions. Notice that, we have set nine as number of terms because we want to get high accuracy while keeping a reasonable level of interpretability.

Since it is not straightforward defining universal expert rules for WiFi localization, we have opted for linguistic rules automatically generated from experimental data by means of the FDT algorithm. It is run with the training dataset and the fuzzy partitions previously described. Since we have set nine terms per input and given the complexity and large size of experimental data, the number of generated rules is likely to be huge and simplification becomes necessary to keep interpretability. The goal of the simplification procedure is getting a more compact and general FRBC, increasing interpretability while preserving the high accuracy achieved before. It is worth noting that linguistic simplification not only reduces the number of rules but also the number of premises per rule and moreover the number of linguistic terms per input. In consequence, the final FRBC is made up of only 11 rules with a total of 26 premises.

It is important to remark that in case of considering the WiFi Positioning Module (FRBC) as an isolated module, then the output (zone) is determined by the majority class since it is computed with the usual Max-Min inference scheme and the winner rule fuzzy reasoning mechanism. Maximizing interpretability is the reason why we consider Max-Min and majority class which are acknowledged as the preferred methods by the specialized literature related to interpretable fuzzy systems. Notwithstanding, we would like to clarify how is made the connection (and the propagation of uncertainty) between the WiFi Positioning Module (FRBC) and the Activity Recognition Module (FFSM2). Of course, the WiFi estimated position (*wep*) is inferred by the FRBC and taken as input of the FFSM2. However, *wep* is not just the majority class but an array made up of as many real values (fuzzy membership degrees) as zones of interest identified in the experimental scenario. Hence, FFSM2 is fed with all the available information provided by FRBC that is the entire array representing *wep* instead of considering only the value related to the majority class.

### *4.2. Posture Recognition Module (FFSM1)*

This section presents the design of the main elements needed to build a FFSM (in accordance with Section 3) for body posture recognition.

#### *4.2.1. Fuzzy States (Q)*

Here, the fuzzy states are defined based on our own necessities related to the body posture. So, we have considered four fuzzy states: $\{q_0$: Unknown, $q_1$: Seated, $q_2$: Upright, $q_3$: Walking$\}$.

*4.2.2. Input variables (U)*

The set of linguistic variables $U$, as stated in the definition of the FFSM, can be directly obtained from sensors. In our experiments, we have used a three-axial accelerometer tight with a belt in the middle of the back, therefore, the numerical values that we obtain from the sensor are: the dorso-ventral acceleration ($a_x$), the medio-lateral acceleration ($a_y$) and the antero-posterior acceleration ($a_z$). With these numerical values, and in order to distinguish between the three different states, we have created three linguistic variables $\{a_x, mov, tilt\}$:

- $a_x$ is the dorso-ventral acceleration as it was obtained from the sensor.
- *mov* measures the movement. It is the sum of the difference between the maximum and minimum values of $a_x$, $a_y$ and $a_z$ respectively contained in a interval of one second.
- *tilt* is a variable that measures the tilt of the body. It is calculated as the sum of the absolute value of the medio-lateral acceleration ($a_y$) and the absolute value of the antero-posterior acceleration ($a_z$), i.e., $tilt = |a_y| + |a_z|$.

The linguistic labels for each linguistic variable are: $\{S_{a_x}, M_{a_x}, B_{a_x}\}$, $\{S_{mov}, M_{mov}, B_{mov}\}$, and $\{S_{tilt}, M_{tilt}, B_{tilt}\}$, where $S$, $M$, and $B$ are linguistic terms representing small, medium, and big, respectively. These linguistic labels, that summarize the domain of each linguistic variable, are SFPs based on trapezoidal MFs in order to achieve a good interpretability, satisfying semantic constraints on MFs in order to respect semantic integrity within the partitions.

*4.2.3. Transition function (f)*

The definition of which transitions are allowed and which are not can be easily represented by means of a state diagram. Figure 2 shows how we use the FFSM to define constraints on the possibilities to change of state. More specifically, we force the model to pass by the state *Upright* ($q_2$) when the subject passes from *Seated* ($q_1$) to *Walking* ($q_3$). This restriction makes the system more robust. Please, notice that state $q_0$ (Unknown) is not displayed in the diagram because it does not represent any body posture but it has to be interpreted as a measure giving our confidence degree (CD) about the rest of states.

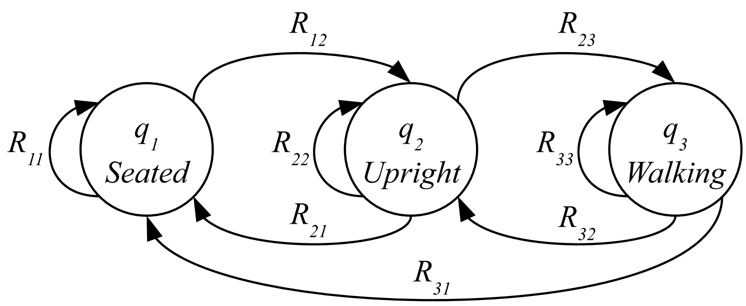


Figure 2: Diagram of states of the FFSM1 (Posture Recognition Module).

From the state diagram plotted in Figure 2, it can be recognized that the rule base (RB) is made up of eight fuzzy rules (three rules $R_{ii}$ to remain in each state $i$; and five rules $R_{ij}$ to change from state $i$ to state $j$):

$R_{11}$: **IF** ($S[t]$ is $q_0$ **OR** $q_1$) **AND** $C_{11}$ **THEN** $S[t+1]$ is $q_1$
$R_{22}$: **IF** ($S[t]$ is $q_0$ **OR** $q_2$) **AND** $C_{22}$ **THEN** $S[t+1]$ is $q_2$
$R_{33}$: **IF** ($S[t]$ is $q_0$ **OR** $q_3$) **AND** $C_{33}$ **THEN** $S[t+1]$ is $q_3$
$R_{12}$: **IF** ($S[t]$ is $q_0$ **OR** $q_1$) **AND** $C_{12}$ **THEN** $S[t+1]$ is $q_2$
$R_{21}$: **IF** ($S[t]$ is $q_0$ **OR** $q_2$) **AND** $C_{21}$ **THEN** $S[t+1]$ is $q_1$
$R_{23}$: **IF** ($S[t]$ is $q_0$ **OR** $q_2$) **AND** $C_{23}$ **THEN** $S[t+1]$ is $q_3$

$R_{32}$: **IF** ($S[t]$ is $q_0$ **OR** $q_3$) **AND** $C_{32}$ **THEN** $S[t+1]$ is $q_2$
$R_{31}$: **IF** ($S[t]$ is $q_0$ **OR** $q_3$) **AND** $C_{31}$ **THEN** $S[t+1]$ is $q_1$

Notice that both the MFs parameters and conditions over the input variables ($C_{ij}$) in the RB are automatically determined from experimental data using a genetic learning procedure. In the following paragraphs, a brief description about the learning method is presented. Anyway, the interested reader is invited to go to [8] for a deeper description of the procedure.

Due to the fact that the MFs are SFPs, we only need to code the two modal points of each MF in a real-coded representation. The conditions over the input variables ($C_{ij}$) of the RB are expressed in in Disjunctive Normal Form (DNF) [27, 40, 47] encoded in a single chromosome following the Pittsburgh approach [28].

Then, a binary tournament selection and a generational replacement with elitism are considered. The classical two-point crossover has been used for the RB (binary-coded) part of the chromosome and BLX-$\alpha$ crossover [31] for the data base (DB) (real-coded) part. The BLX-$\alpha$ crossover is applied twice over a pair of parents in order to obtain a new pair of chromosomes. The classical bitwise mutation has been selected for the binary-coded RB part, while uniform mutation has been chosen for the real-coded DB part. Three different termination conditions have been considered. First, the search is stopped when the algorithm has obtained a fitness value equal to zero, which is the best value that the fitness function can take. Moreover, we have decided to set a maximum number of generations and also to stop the search when, for a certain number of generations, the fitness value of the best individual is not improved.

Since the computation of the next state is based on the previous state, we need to evaluate the tentative FFSM definition encoded in each chromosome over the whole data set. We have chosen as fitness function the mean absolute error (MAE) measure, defined by Equation 3:

$$\text{MAE} = \frac{1}{n} \cdot \frac{1}{T} \cdot \sum_{i=0}^{n} \sum_{j=0}^{T} |s_i[j] - s_i^*[j]| \tag{3}$$

where $n$ is the number of states ($n = 3$ for this module), $T$ is the dataset size (i.e., the considered time interval duration), $s_i[j]$ is the degree of activation of state $q_i$ at time $t = j$, and $s_i^*[j]$ is the expected degree of activation of state $q_i$ at the same time instant.

The MAE directly measures the difference between the actual state activation vector ($S^*[t]$) and the obtained one ($S[t]$). However, we need to define $S^*[t]$ for each input data set that we want to learn. This definition could be problematic and must be done carefully because, more than one state can be defined at each time instant, each of those states activated with certain degree in the interval $[0, 1]$. We have to create a training vector which consists of $a_x[t]$, $a_y[t]$, $a_z[t]$ and $S^*[t]$, i.e., $(a_x[t], a_y[t], a_z[t], s_1^*[t], s_2^*[t], s_3^*[t])$ (we expect that the actual state unknown ($q_0$) is never activated, considering its activation as an error). To define it, we have developed a user-friendly graphical interface that allows the expert to select manually the relevant points where each state starts and ends using her/his knowledge about body posture and the duration of each part of the experiment. The fuzzy definition of the states is based on the imprecision of the expert when defining those relevant points. The interested reader is referred to [9] for a deeper description on the human definition of the activation degrees for the fuzzy states in FFSMs.

#### *4.2.4. Output vector ($Y$) and output function ($g$)*

The output of FFSM1 is going to be taken as one of the inputs of FFSM2. Therefore, we have set as output variable the state activation vector, i.e., $Y[t] = S[t]$. Hence, the output vector is a linguistic variable representing the user's posture (*pos*) whose four different states (*Unknown*, *Seated*, *Upright* or *Walking*) always sum up to one and are easily interpretable. For example, the output of the system may be $(0.2, 0.1, 0.7, 0)$ indicating that the user is *Seated* with a degree 0.1 and *Upright* with a degree 0.7, while we have 0.2 degree of ignorance (or in other words, a CD of 0.8) derived from the state *Unknown*.

### *4.3. Activity Recognition Module (FFSM2)*

In the following, we explain how to design a FFSM for combining the WiFi Positioning Module and the Posture Recognition Module with the aim of achieving a Human Activity Recognition system.

*4.3.1. Fuzzy States (Q)*

We assume that this system should be easily customized for each specific end-user. Therefore, we manage linguistic descriptions of the different activities daily performed by a user. As we will show in the experimental phase (Section 5), we will distinguish among the following fuzzy states (plus the *Unknown* state) related to the activities in an office :

- $q_0$: Unknown.
- $q_1$: Walking. Typical body movement detected by accelerometers.
- $q_2$: Working at her/his desk. Usually, the user is seated, in a specific WiFi position.
- $q_3$: Visiting a colleague. Seated or standing upright, in several possible zones identified by WiFi coordinates.
- $q_4$: Having coffee. Seated or standing upright, in a specific WiFi position (the coffee area).
- $q_5$: Having a meeting. Seated in specific zones recognized by WiFi coordinates.

*4.3.2. Input variables (U)*

In order to distinguish among the different states, we will make use of the two linguistic variables $\{wep, pos\}$ in charge of characterizing the outputs of the two previous modules (FRBC and FFSM1) which are taken as inputs of FFSM2 as shown in Figure 1 (page 5):

- *wep* is the WiFi estimated position provided by the WiFi positioning module (the FRBC designed in Subsection 4.1).
- *pos* is the posture estimation obtained from the posture recognition module (the FFSM1 described in Subsection 4.2).

These variables are characterized by the following linguistic labels which are singletons defined in the interval $[0, 1]$:

- *wep* = {*WAA*, *MC*, *WAB*, *WO*, *CA*, *MR*}, which are the zones of interest in our experimental scenario (see later Section 5).
- *pos* = $\{Seated, Upright, Walking\}$ which corresponds to three outputs of the four different states of the FFSM1. Note that we do not include the state *Unknown* as input for FFSM2, because it does not provide us with any information about the current posture of the person. Of course, since all the four states sum up to one, the state *Unknown* implicitly expresses our confidence regarding the activation degree of the other states.

*4.3.3. Transition function (f)*

As in the FFSM1, we will obtain the next value of the activation vector using the transition function $S[t+1] = f(U[t], S[t])$. Since the input variables are singletons with concrete values obtained from the FFSM1 and the FRBC, and in order to allow the final user to introduce her/his own prior knowledge about the specific application, the RB for the FFSM2 will be manually designed by the expert instead of being automatically derived from experimental data like in the cases of FRBC and FFSM1.

Therefore, once we have identified the relevant states in the FFSM2, we can represent the fuzzy rules that govern the temporal evolution of the system among these states. Figure 3 shows the transition diagram of the FFSM specific for the experimental scenario explained in Section 5. There are five rules to remain in a state ($R_{ii}$) and eight rules to change of state ($R_{ij}$). Notice that, in this application not all the possible transitions are allowed, and the majority of the states are connected to the state $q_1$ ($Walking$).

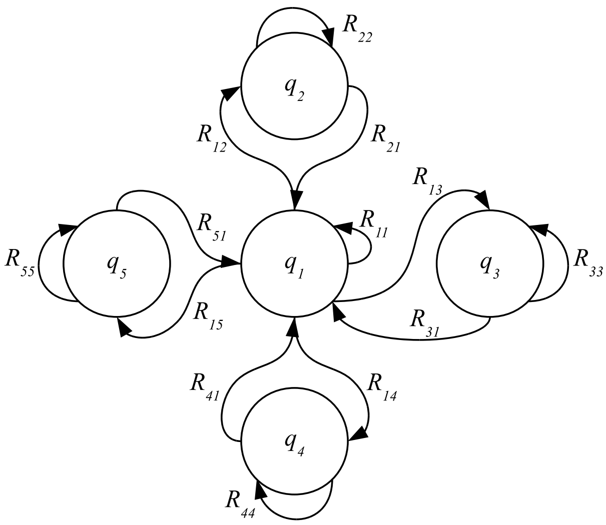


Figure 3: Diagram of states of the FFSM2 (Activity Recognition Module).

### *4.3.4. Output vector ($Y$) and output function ($g$)*

Similarly to the FFSM1, we might use as output variable the state activation vector, i.e., $Y[t] = S[t]$. However, we have to give a crisp description of the activity of the person. Therefore, it would be better considering as output the state with the maximum degree of activation at each instant of time $t$. However, such selection will make the FFSM very sensitive to noise and spurious in the signal, and that is precisely something we want to avoid. Thus, the output is computed taking into account only the state which has exhibited the maximum average degree of activation over the last second.

In consequence, the output function $g(U[t], S[t])$ calculates the value of the output variables as follows (being $h$ the number of delayed samples within the last second):

$$Y[t] = g(U[t], S[t]) = \underset{i \in \{0,1,2,3,4,5\}}{\arg\max} \left( \sum_{j=t-h}^{t} s_i[j] \right)$$

As we have stated above, the "arg max" stands for the argument of the maximum. It calculates the set of points (in this case, the set of fuzzy states) of the given argument for which the value of the given expression (which is the average value of the activation degree of each state in the last second) attains its maximum value.

## 5. Experimentation

This section presents the experimentation carried out. First, the experimental setup is explained, describing the experimental scenario and the data acquisition process. Second, the results obtained for each module are reported. Then, the third part yields a critical discussion regarding both accuracy and interpretability of the entire proposed system. Finally, a discussion about the main strengths and weaknesses of our proposal against other alternative approaches is presented.

### *5.1. Experimental setup*

Table 1 gives the description of our experimental scenario that tries to summarize the most common activities carried out by a user during a normal day at his/her work. Of course, this is a simplified scenario where we only consider five basic activities (*Working at the desk*, *Walking*, etc.), however, it is an application of our proposal in a real world working environment, in contrast with other works which are only based on simulated data. Moreover, the extension of this real experimental scenario, which poses difficulties from the technical point of view (new hardware devices in more zones of interest), does not mean a conceptual challenge due to the fact that our proposed system can be applied at different levels of granularity, e.g., by designing a FFSM capable of recognizing different human activities for each zone of interest.

We have set a reduced time for the different tasks with the aim of making feasible several repetitions of the whole experiment in a reasonable period of time. For example, *Having a meeting* lasts less than 2 minutes. Notice that we wanted to test how our system is able to recognize all defined states of activity. The whole experiment takes about 9 minutes because the time walking is approximated. Furthermore, the same user has repeated ten times the same experiment yielding more than one hour and a half of experimentation. Of course, there may be a slight time delay between different repetitions of the experiment when the user is walking.

Table 1: Description of the experimental scenario.

| **Duration ($s$)** | **Description** | **Activity** |
|---|---|---|
| 60 | Seated and typing | Working at the desk |
| 30 | Standing up and walking towards the coffee area | Walking |
| 75 | Staying up in front of the coffee machine. Sitting and having the coffee | Having a coffee |
| 25 | Standing up and walking until the office of a colleague | Walking |
| 50 | Staying up and waiting for a colleague | Visiting a colleague |
| 30 | Walking towards the meeting room | Walking |
| 100 | Seated in the meeting room | Having a meeting |
| 40 | Standing up and walking back to the work-desk | Walking |
| 100 | Seated and typing | Working at the desk |

We have used a PDA to collect all the information that our system requires for inferring the activities identified above. The user carried a HP iPAQ hw6915 PDA. It has a WiFi interface with a maximum acquisition frequency of 4 Hz, i.e., it is able to capture up to four samples per second. In addition, an external three-axial accelerometer (WiTilt v2.5) with acquisition frequency of 100 Hz was connected to our PDA through Bluetooth. Although we are aware that measuring acceleration on the subjects thigh is the most powerful [14], in our experiments the user wore the accelerometer with a belt in the middle of her/his back to maintain the ergonomics of the application. Our program measures both WiFi signal and accelerations in the same cycle with the aim of keeping synchronization. Notice that, each 25 measures provided by the accelerometer correspond to only one WiFi SL measure.

The experimentation took place at the premises of the European Centre for Soft Computing (ECSC). The ECSC layout environment has a surface of 440 m$^2$ and it is shown in Figure 4. The experimental environment (look at the top picture) has been discretized into six zones of interest (look at the bottom picture): *WAA* (working area A), *MC* (main corridor), *WAB* (working area B), *WO* (working office), *CA* (coffee area), and *MR* (meeting room). Such zones are covered by four APs. Inside each zone, we have set several training fixed positions for the WiFi Positioning Module. They are represented by gray circles at the bottom picture in Figure 4. In each position, we collected 100 samples coming from all the four APs.

Moreover, for comparison purposes, we have substituted our interpretable FRBC by other different alternative classifiers that were trained exactly with the same available experimental data. These alternative classifiers are implemented in Weka [71] (default parameters suggested by Weka were considered). Namely they are C4.5, FURIA, NB, MP and SVM. C4.5 stands for the well-known Quinlan's decision trees which provide good interpretability-accuracy trade-offs. FURIA means Fuzzy Unordered Rule Induction Algorithm and it is a fuzzy modeling method developed by [41] and only guided by accuracy. NB is Naïve Bayes, a classifier which provides accuracy keeping good interpretability. MP means Multilayer Perceptron and it

http://www.cs.waikato.ac.nz/ml/weka/

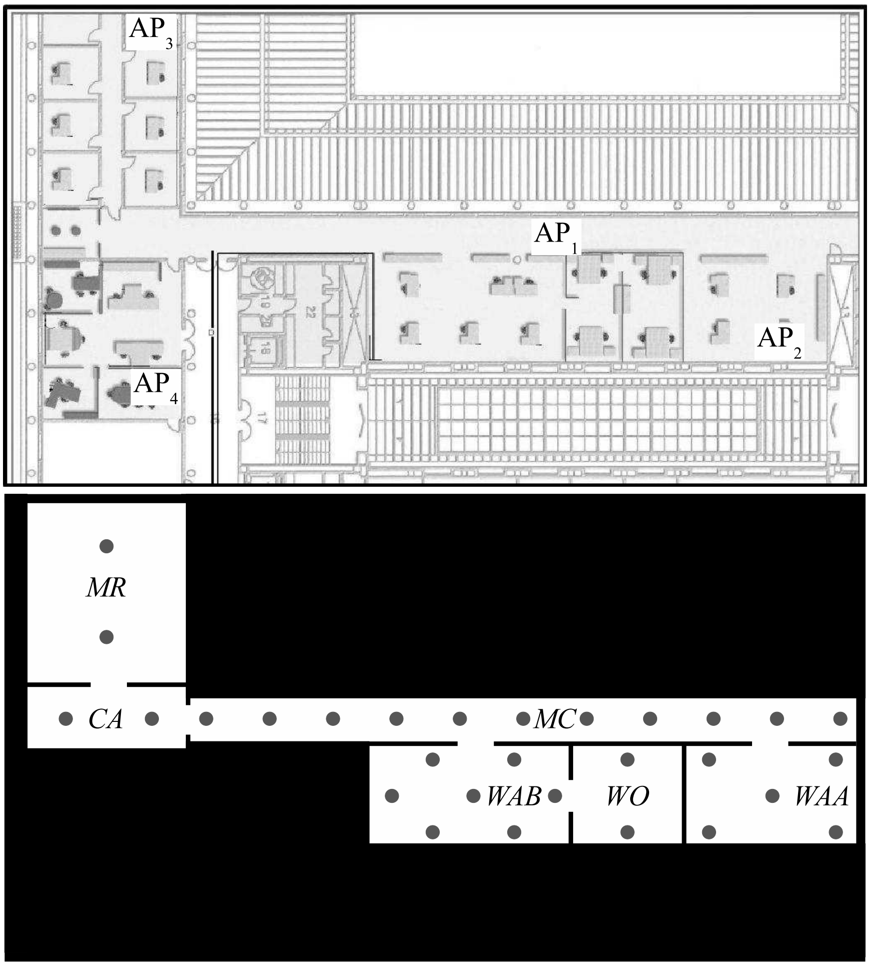


Figure 4: Experimental environment and discretized zones.

yields very accurate neural network classifiers but disregarding comprehensibility. Finally, SVM stands for Support Vector Machine and it is based on the John Platt's sequential minimal optimization algorithm.

Finally, in order to test the ability of the overall proposed system to tackle with larger error rates of our FRBC, for instance derived from failures of APs, we have simulated that one AP was not working during the trials. To do so, all measures coming from the selected AP are set to "-99", which is the default value given by the WiFi interface when one AP is not visible. Of course, the fact that one $AP_i$ is not working properly affects directly to the WiFi Positioning module jeopardizing its good classification behavior. Obviously, the robustness against APs failures depends on the relative importance given to each removed $AP_i$ by the specific classifier integrated in the WiFi Positioning module, along the ten experimental trials. Moreover, decreasing the classification ratio of the WiFi Positioning module is expected to produce a negative effect in the ratio of misclassified samples by the Human Activity Recognition module.

*5.2. Results*

The following subsections present the results obtained by each of the three modules in our experimental scenario. In the case of the WiFi Positioning Module and the Activity Recognition Module, we also report the results obtained by alternative classifiers for comparison purpose. Moreover, the results achieved when any of the APs is dysfunctional are included too.

### 5.2.1. *WiFi Positioning Module*

Before showing the results obtained by our interpretable FRBC compared to the alternative ones, it is worth to remark the importance of SMOTE for balancing the training dataset. Table 2 shows the ratio of misclassified samples obtained by our interpretable FRBC when considering the original imbalanced training dataset (HILK WITHOUT SMOTE) and when it has been previously balanced (HILK WITH SMOTE). Obviously, results achieved by HILK after applying SMOTE are by far the best. Therefore, we can conclude that from now on all the classifiers used in the WiFi Positioning Module must be trained using the dataset previously balanced with SMOTE.

Table 3 shows achieved results in terms of the ratio of misclassified samples reported for each one of the ten repetitions of our experimental scenario. It includes the results obtained by our interpretable FRBC (HILK) but also the alternative classifiers introduced in Section 5.1 for comparison purposes. As a summary, we have computed the average value (AVG) along with the standard deviation (STD) with respect to all the ten experiments (EXP). Moreover, the training error (TRAIN) is also shown at the bottom line. C4.5 and FURIA produce the most accurate classifiers only regarding TRAIN. However, they suffer somehow of overfitting and SVM arises as the most accurate classifier with respect to AVG and STD over all the ten experimental trials. Notice that, HILK provides a highly interpretable FRBC with accuracy comparable to the other alternative classifiers. Of course, it is not the most accurate classifier regarding neither training nor test data sets. This fact is mainly due to the huge number of interpretability constraints imposed by HILK which are slightly penalizing accuracy.

Table 2: Ratio of misclassified samples regarding the ten trials carried out in our experimental scenario for evaluating our interpretable FRBC using balanced (HILK WITH SMOTE) and imbalanced (HILK WITHOUT SMOTE) training data.

| **EXP** | **HILK WITH SMOTE** | **HILK WITHOUT SMOTE** |
|---|---|---|
| 1 | 0.122 | 0.370 |
| 2 | 0.255 | 0.484 |
| 3 | 0.166 | 0.362 |
| 4 | 0.163 | 0.376 |
| 5 | 0.200 | 0.368 |
| 6 | 0.170 | 0.366 |
| 7 | 0.166 | 0.348 |
| 8 | 0.152 | 0.376 |
| 9 | 0.190 | 0.388 |
| 10 | 0.150 | 0.331 |

Table 3: Ratio of misclassified samples regarding the ten trials carried out in our experimental scenario for evaluating the WiFi positioning module.

| **EXP** | **HILK** | **C4.5** | **FURIA** | **NB** | **MP** | **SVM** |
|---|---|---|---|---|---|---|
| 1 | 0.122 | 0.127 | 0.111 | 0.140 | 0.322 | 0.103 |
| 2 | 0.255 | 0.256 | 0.181 | 0.166 | 0.422 | 0.154 |
| 3 | 0.166 | 0.186 | 0.158 | 0.206 | 0.380 | 0.143 |
| 4 | 0.163 | 0.173 | 0.160 | 0.202 | 0.417 | 0.157 |
| 5 | 0.200 | 0.254 | 0.193 | 0.210 | 0.340 | 0.160 |
| 6 | 0.170 | 0.203 | 0.145 | 0.197 | 0.400 | 0.139 |
| 7 | 0.166 | 0.166 | 0.141 | 0.181 | 0.367 | 0.139 |
| 8 | 0.152 | 0.150 | 0.123 | 0.157 | 0.352 | 0.109 |
| 9 | 0.190 | 0.199 | 0.151 | 0.192 | 0.376 | 0.142 |
| 10 | 0.150 | 0.145 | 0.143 | 0.173 | 0.361 | 0.142 |
| **AVG** | 0.173 | 0.186 | 0.151 | 0.182 | 0.374 | 0.139 |
| **STD** | 0.036 | 0.044 | 0.024 | 0.023 | 0.032 | 0.019 |
| **TRAIN** | 0.017 | 0.001 | 0.001 | 0.028 | 0.008 | 0.014 |

#### 5.2.2. Posture Recognition Module

With the aim of assessing the performance of the FFSM designed for the posture recognition module, we have done a leave-one-out cross validation [65] considering all the ten repeated trials carried out in our experimental scenario. Notice that, the same procedure is repeated ten times, taking nine trials for training and the remaining one for test. Hence, we will have ten different FFSMs which calculate the value of the posture that will feed the Activity Recognition Module without using this trial of the experiment as training data. Table 4 shows the MAE and the confidence degree (CD) obtained for each fold of the leave-one-out in training and test. It also depicts average values (AVG) and standard deviations (STD) for the ten results of the procedure. It is worthy of highlighting the goodness of achieved results with extremely low MAE and high CD.

Table 4: Performance of the FFSM in charge of recognizing body posture. MAE and CD obtained for each fold of the leave-one-out cross validation procedure in training and test.

| **EXP** | **TRAIN** | | **TEST** | |
|---|---|---|---|---|
| | **MAE** | **CD** | **MAE** | **CD** |
| 1 | 0.011 | 0.999 | 0.010 | 0.999 |
| 2 | 0.011 | 1.000 | 0.012 | 1.000 |
| 3 | 0.010 | 1.000 | 0.011 | 1.000 |
| 4 | 0.011 | 0.996 | 0.013 | 0.995 |
| 5 | 0.011 | 0.991 | 0.014 | 0.989 |
| 6 | 0.010 | 1.000 | 0.012 | 1.000 |
| 7 | 0.011 | 1.000 | 0.012 | 1.000 |
| 8 | 0.010 | 1.000 | 0.011 | 1.000 |
| 9 | 0.011 | 0.994 | 0.012 | 0.995 |
| 10 | 0.011 | 0.994 | 0.012 | 0.994 |
| **AVG** | 0.011 | 0.997 | 0.012 | 0.997 |
| **STD** | 0.001 | 0.003 | 0.001 | 0.004 |

#### 5.2.3. Activity Recognition Module

Table 5 shows the results in terms of ratio of misclassified samples (ERROR) and the confidence degree (CD) obtained for each trial of the experiments using our interpretable FRBC (HILK). For comparison purpose, the alternative classifiers introduced in Section 5.1 are also considered. We report average values (AVG) and standard deviations (STD) for all the ten trials. Please, notice that after combining FRBC (WiFi Positioning) and FFSM1 (Posture Recognition) by means of FFSM2 (Activity Recognition), the use of HILK (in the generation of FRBC) yields the lowest ERROR (0.023) along with the second highest CD (0.965), even though HILK was not producing the most accurate solution when only considering WiFi Positioning. As a result, we can point out HILK as the most suitable classifier in combination with FFSMs. Moreover, FFSM2 yields a drastically low ratio of misclassified samples (no matter the specific classifier used by the WiFi positioning module) thanks to the effective combination of the two first modules.

#### 5.2.4. APs Failures

We report the results provided by the WiFi Positioning Module and the Activity Recognition Module under simulated APs failures. This process, equivalent to remove or switch off the selected $AP_i$, has been repeated for each AP resulting in four sets of results which are the rows corresponding to "$AP_i$ Removed" in Table 6. This table also includes the results of the misclassification ratio for both WiFi Positioning and Activity Recognition Modules when no APs failures are considered in the first two rows ("All APs Working"). Notice that, we do not show results for Posture Recognition Module because they are not affected by APs failures.

### 5.3. Discussion

This section aims to present a constructive discussion regarding the goodness of the results reported by the proposed model paying attention to two key issues: accuracy and interpretability.

Table 5: Overall ratio of misclassified samples by the Activity Recognition Module when comparing different classifiers for the WiFi Positioning Module.

| EXP | HILK | | C4.5 | | FURIA | | NB | | MP | | SVM | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | ERROR | CD | ERROR | CD | ERROR | CD | ERROR | CD | ERROR | CD | ERROR | CD |
| 1 | 0.016 | 0.969 | 0.021 | 0.985 | 0.021 | 0.980 | 0.023 | 0.952 | 0.187 | 0.984 | 0.020 | 0.872 |
| 2 | 0.018 | 0.940 | 0.024 | 0.933 | 0.032 | 0.959 | 0.015 | 0.977 | 0.210 | 0.993 | 0.021 | 0.871 |
| 3 | 0.022 | 0.966 | 0.042 | 0.955 | 0.039 | 0.950 | 0.053 | 0.912 | 0.223 | 0.967 | 0.031 | 0.863 |
| 4 | 0.041 | 0.969 | 0.045 | 0.985 | 0.041 | 0.971 | 0.051 | 0.935 | 0.241 | 0.977 | 0.040 | 0.864 |
| 5 | 0.023 | 0.957 | 0.054 | 0.915 | 0.056 | 0.924 | 0.063 | 0.911 | 0.138 | 0.945 | 0.028 | 0.862 |
| 6 | 0.027 | 0.957 | 0.027 | 0.927 | 0.034 | 0.954 | 0.069 | 0.904 | 0.220 | 0.957 | 0.031 | 0.866 |
| 7 | 0.013 | 0.977 | 0.012 | 0.992 | 0.012 | 0.981 | 0.012 | 0.942 | 0.219 | 0.993 | 0.017 | 0.868 |
| 8 | 0.038 | 0.970 | 0.031 | 0.983 | 0.027 | 0.975 | 0.026 | 0.939 | 0.219 | 0.989 | 0.031 | 0.868 |
| 9 | 0.018 | 0.963 | 0.017 | 0.976 | 0.014 | 0.968 | 0.019 | 0.929 | 0.207 | 0.984 | 0.017 | 0.868 |
| 10 | 0.018 | 0.978 | 0.016 | 0.991 | 0.017 | 0.976 | 0.017 | 0.948 | 0.219 | 0.988 | 0.023 | 0.864 |
| **AVG** | 0.023 | 0.965 | 0.029 | 0.964 | 0.029 | 0.964 | 0.035 | 0.935 | 0.208 | 0.978 | 0.026 | 0.867 |
| **STD** | 0.009 | 0.011 | 0.014 | 0.029 | 0.014 | 0.018 | 0.022 | 0.022 | 0.028 | 0.016 | 0.008 | 0.003 |

Table 6: Average Value (AVG) and Standard Deviation (STD) of the ratio of misclassified samples by the WiFi Positioning Module and the Activity Recognition Module with different Classifiers (under AP failures).

| APs Status | Module | HILK | | C4.5 | | FURIA | | NB | | MP | | SVM | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | AVG | STD | AVG | STD | AVG | STD | AVG | STD | AVG | STD | AVG | STD |
| All APs Working | WiFi Positioning | 0.173 | 0.036 | 0.186 | 0.044 | 0.151 | 0.024 | 0.182 | 0.023 | 0.374 | 0.032 | 0.139 | 0.019 |
| | Activity Recognition | 0.023 | 0.009 | 0.029 | 0.014 | 0.029 | 0.014 | 0.035 | 0.022 | 0.208 | 0.028 | 0.026 | 0.008 |
| $AP_1$ Removed | WiFi Positioning | 0.181 | 0.032 | 0.172 | 0.021 | 0.174 | 0.031 | 0.587 | 0.030 | 0.455 | 0.040 | 0.330 | 0.039 |
| | Activity Recognition | 0.026 | 0.009 | 0.035 | 0.013 | 0.032 | 0.012 | 0.103 | 0.029 | 0.192 | 0.041 | 0.071 | 0.028 |
| $AP_2$ Removed | WiFi Positioning | 0.448 | 0.033 | 0.489 | 0.041 | 0.451 | 0.030 | 0.506 | 0.014 | 0.666 | 0.038 | 0.452 | 0.024 |
| | Activity Recognition | 0.221 | 0.006 | 0.328 | 0.010 | 0.327 | 0.011 | 0.422 | 0.010 | 0.509 | 0.030 | 0.328 | 0.009 |
| $AP_3$ Removed | WiFi Positioning | 0.583 | 0.012 | 0.589 | 0.016 | 0.519 | 0.020 | 0.499 | 0.029 | 0.564 | 0.026 | 0.417 | 0.030 |
| | Activity Recognition | 0.367 | 0.010 | 0.372 | 0.013 | 0.375 | 0.016 | 0.380 | 0.022 | 0.342 | 0.022 | 0.226 | 0.008 |
| $AP_4$ Removed | WiFi Positioning | 0.359 | 0.014 | 0.383 | 0.015 | 0.386 | 0.017 | 0.432 | 0.057 | 0.605 | 0.022 | 0.375 | 0.012 |
| | Activity Recognition | 0.154 | 0.011 | 0.171 | 0.015 | 0.173 | 0.017 | 0.196 | 0.023 | 0.364 | 0.008 | 0.165 | 0.008 |

#### *5.3.1. Accuracy analysis*

As it was shown in Section 5.2, the ratio of misclassified samples for the WiFi Positioning Module is dramatically reduced by the Activity Recognition Module for all compared classifiers. This significant improvement is due to the characteristic memory effect of FFSMs which define the new state taking into account the transition conditions but also the previous state. In addition, the output of the Activity Recognition Module (FFSM2) is averaged in an interval of time ($\Delta$). Notwithstanding, $\Delta$ only lasts one second what makes feasible the use of our system in real-time applications. In consequence, FFSM2 is able to absorb and correct most of the errors produced by the FRBC due to the high variability in the WiFi signal, mainly thanks to both memory effect and output averaging but also integrating information provided by FFSM1.

From Table 6, the importance of each AP can be seen. When $AP_1$ is removed, the results are not getting too much worse, which indicates that this AP is not very relevant because it is placed close to a great number of zones (*MC*, *WAB*, *WO* and *WAA* in Figure 4) and none of the evaluated classifiers is able to distinguish among those zones only regarding to $SL_1$. This is not the case with $AP_2$, $AP_3$, and $AP_4$ because they allow to recognize the zones $WAA$, $MR$, and $CA$ respectively. Moreover, although the effect of removing APs strongly affects to the WiFi Positioning Module, it is softened in relation with the Activity Recognition Module. This fact shows the robustness of the proposed system against APs failures thanks to the stability of FFSMs.

With the aim of assessing whether significant differences exist among results produced by our interpretable FRBC for the WiFi Positioning Module (HILK) and results provided by the five alternative Classifiers (C4.5, FURIA, NB, MP and SVM), we have used the Wilcoxon signed-rank test [70]. We chose this test for pairwise comparison among all analyzed classifiers because it does not assume normal distributions. Furthermore, it has been commonly used to compare the performance of alternative methods in computational intelligence [34, 35]. To perform the test, we used a confidence level $\alpha = 0.05$. The null hypothesis is that the average results obtained by HILK are the same as the ones obtained by the alternative classifiers regarding both WiFi Positioning and Activity Recognition Modules.

Table 7 shows the p-values obtained for the Wilcoxon signed-rank test considering the five different status of APs ("All APs Working", "$AP_1$ Removed", "$AP_2$ Removed", "$AP_3$ Removed", and "$AP_4$ Removed"). In the case of using C4.5, our proposal gets better results in 7 of the 10 cases (being non significant in the other 3 cases). Moreover, although in the rest of the alternative classifiers we cannot conclude that our proposal is more accurate in all the cases, it is easy to check that it is competitive: compared to FURIA, our proposal is worse in 2 cases and better in 3 (being non significant in the remaining 5 cases); it is worse than NB in 1 case and better in 6 cases (being non significant in the remaining 3 cases); it outperforms MP in eight cases and it is worse in the 2 remaining ones; and it is worse than SVM in 3 cases while being better for 5 cases of 10 (being non significant in the remaining 2 cases). However, the main goal of the paper is not only to offer the most accurate model. The goal is to provide a highly understandable linguistic model that can not only provide the precise position of the final user or its activity but it can also provide a linguistic explanation of why the user is located in that position doing that activity as it is explained in the following subsection. Of course, if we want a very accurate localization system and we do not care about the interpretability of our WiFi Positioning Module we could use FURIA or other non-interpretable classifier to obtain the user's position. In consequence, we still have a somehow partly interpretable model for human activity recognition based on the integration of information related to the body posture (that is expressed in terms of the linguistic model describing the FFSM) and the estimated user's location (that could not be described linguistically).

Table 7: p-values obtained in the Wilcoxon signed-rank test. The symbols [+],[-],[=] denote respectively that results provided by the proposed FRBC (HILK) are significantly better [+], worse [-] or non significant [=] in terms of accuracy than those results obtained when considering the alternative classifiers.

| **APs Status** | **Module** | **C4.5** | **FURIA** | **NB** | **MP** | **SVM** |
|---|---|---|---|---|---|---|
| All APs Working | WiFi Positioning | 0.0438 [+] | 0.0050 [-] | 0.0840 [=] | 0.0020 [+] | 0.0020 [-] |
| | Activity Recognition | 0.2604 [=] | 0.2135 [=] | 0.1934 [=] | 0.0050 [+] | 0.1137 [=] |
| $AP_1$ Removed | WiFi Positioning | 0.3850 [=] | 0.1055 [=] | 0.0020 [+] | 0.0020 [+] | 0.0020 [+] |
| | Activity Recognition | 0.0020 [+] | 0.1384 [=] | 0.0020 [+] | 0.0020 [+] | 0.0020 [+] |
| $AP_2$ Removed | WiFi Positioning | 0.0050 [+] | 0.3857 [=] | 0.0069 [+] | 0.0020 [+] | 0.5566 [=] |
| | Activity Recognition | 0.0050 [+] | 0.0050 [+] | 0.0050 [+] | 0.0050 [+] | 0.0049 [+] |
| $AP_3$ Removed | WiFi Positioning | 0.0743 [=] | 0.0050 [-] | 0.0020 [-] | 0.0488 [-] | 0.0050 [-] |
| | Activity Recognition | 0.0498 [+] | 0.0753 [=] | 0.0592 [=] | 0.0050 [-] | 0.0050 [-] |
| $AP_4$ Removed | WiFi Positioning | 0.0020 [+] | 0.0050 [+] | 0.0039 [+] | 0.0020 [+] | 0.0080 [+] |
| | Activity Recognition | 0.0020 [+] | 0.0050 [+] | 0.0050 [+] | 0.0050 [+] | 0.0050 [+] |

*5.3.2. Interpretability analysis*

On the light of reported results in previous sections, our proposal is proved to be accurate enough for solving the faced application problem, namely human activity recognition in indoor environments. However, our proposal is not only accurate but also interpretable. Moreover, interpretability can be deemed as one of the main advantages of the proposed system.

The whole system (FRBC + FFSM1 + FFSM2) is quite interpretable because it comprises several sets of linguistic variables and rules, all carefully designed under the FL formalism with the aim of maximizing interpretability. It is important to remark that using FL favors the interpretability of the model and makes easier knowledge extraction and representation but also the maintenance of the global system and verbalization of achieved results. However, fuzzy systems are not interpretable *per se*. Hence, it is necessary to impose several constraints all along the design process in order to guarantee the interpretability of the final fuzzy models.

According to the taxonomy presented in [33], there are two main approaches to take into account the interpretability of linguistic fuzzy rule-based systems: (1) complexity-based interpretability, and (2) semantics-based interpretability. Of course, these approaches consider all components of a fuzzy knowledge base, namely fuzzy partitions (data base) and fuzzy rules (rule base).

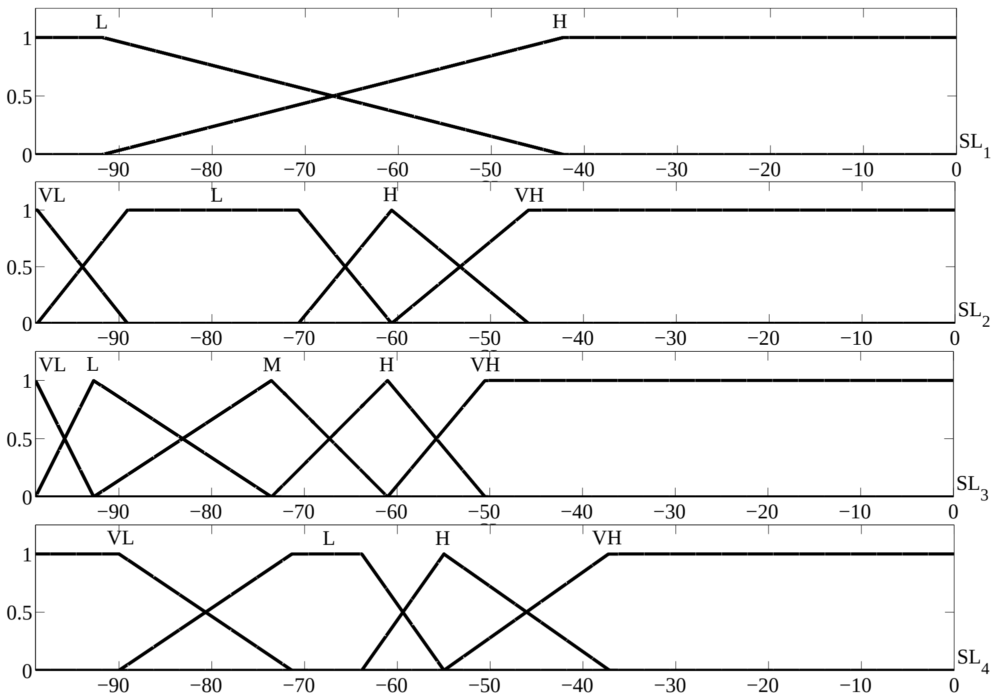


Figure 5: Final partitions used by our interpretable FRBC for the WiFi Positioning Module.

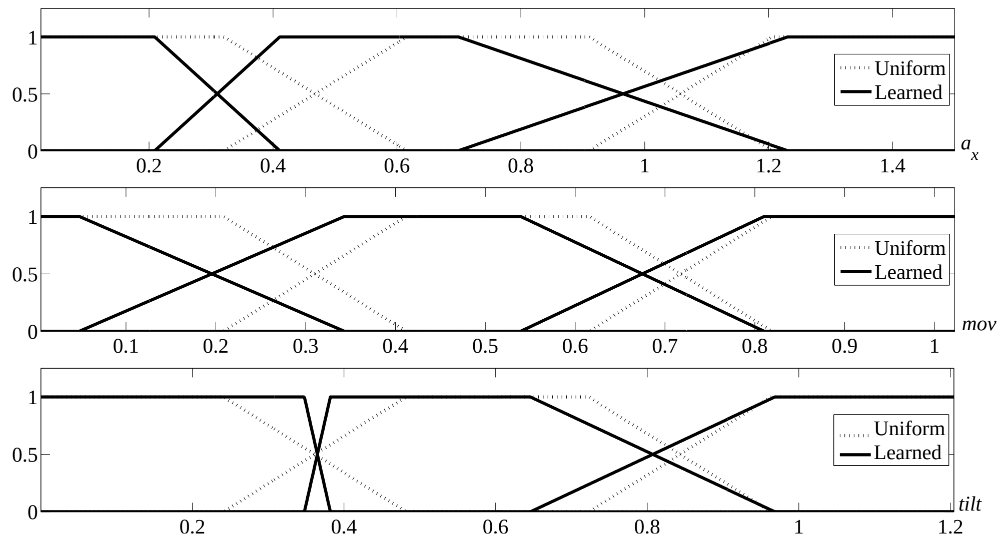


Figure 6: Example of trapezoidal MFs used by the FFSM of the Posture Recognition Module, in one of the experimental trials. For comparison purpose, the final learned MFs and the initial uniformly distributed ones are displayed in the same picture.

At the level of fuzzy partitions, we have adopted the use of SFPs with the aim of satisfying all demanded properties to guarantee semantics-based interpretability at the level of fuzzy partitions. Moreover, we have considered a small (justifiable) number of linguistic terms per input what yields a good complexity-based interpretability regarding fuzzy partition level. In the case of FRBC (WiFi Positioning Module), Figure 5 illustrates how initial partitions of nine terms are transformed along the simplification procedure yielding final partitions which are interpretable (with a smaller number of terms than initial partitions) but also well suited to the experimental training data set. For FFSM1 (Posture Recognition Module), Figure 6 shows the designed MFs. It is easy to appreciate how the initial trapezoidal MFs that were uniformly distributed have been tuned by means of the genetic learning procedure yielding final non-uniform but highly interpretable SFPs. Lastly, in the case of FFSM2 (Activity Recognition Module), all MFs are singletons obtained from the outputs of previous (FRBC and FFSM1) modules.

Moreover, in order to check the variations in the fuzzy partitions automatically generated from data in the FFSM1, we have measured the similarity between each of the ten fuzzy sets generated in the ten trials. The similarity between two fuzzy partitions $A$ and $B$ is defined in [50, 64] and it is computed by Equation 4, where the intersection and union between two fuzzy sets are calculated using the minimum and the maximum of their membership functions respectively:

$$S(A,B) = \frac{|A \cap B|}{|A \cup B|} = \frac{\sum \min\left(\mu_A(x), \mu_B(x)\right)}{\sum \max\left(\mu_A(x), \mu_(x)\right)}, \forall x \text{ discretized over } \mathbb{R} \tag{4}$$

The average similarity between all the fuzzy sets of each linguistic variable is shown in Table 8. The values obtained show that the interpretability of the FFSM1 is kept for each of the ten trials.

Table 8: Average similarity between all the fuzzy sets small ($S$), medium ($M$), and big ($B$) obtained for each linguistic variable of the FFSM1.

| Linguistic variable | $S$ | $M$ | $B$ |
|---|---|---|---|
| $a_x$ | 0.65 | 0.61 | 0.60 |
| $mov$ | 0.82 | 0.66 | 0.67 |
| $tilt$ | 0.80 | 0.55 | 0.73 |

At the level of fuzzy rules, we are also concerned about complexity-based and semantics-based interpretability. Therefore, we used compact and comprehensible rule bases. For each module, all linguistic rules use the same linguistic terms defined by the same fuzzy partitions previously described, i.e., we impose global semantics that becomes essential to guarantee not only transparency of the rule structure (DNF format) but also consistency of the rules. The rule base (RB) of the WiFi Positioning module is listed below. As it was already outlined in the previous section, it is easy to appreciate the prominent role of $AP_3$ which arises as the most discriminative access point since $SL_3$ turns out in all the rules.

$R_1$: **IF** ($SL_2$ is *High*) **AND** ($SL_3$ is *Very low*) **THEN** Zone is *WO*
$R_2$: **IF** ($SL_1$ is *High*) **AND** ($SL_2$ is *Very Low*) **AND** ($SL_3$ is *High*) **AND** ($SL_4$ is *High*) **THEN** Zone is *CA*
$R_3$: **IF** ($SL_1$ is *Low*) **AND** ($SL_2$ is *Very Low*) **AND** ($SL_3$ is *High*) **AND** ($SL_4$ is *High*) **THEN** Zone is *MR*
$R_4$: **IF** ($SL_3$ is *Very High*) **THEN** Zone is *MR*
$R_5$: **IF** ($SL_2$ is *Low*) **AND** ($SL_3$ is *High*) **THEN** Zone is *CA*
$R_6$: **IF** ($SL_3$ is *Medium*) **AND** ($SL_4$ is *High* **OR** *VeryHigh*) **THEN** Zone is *CA*
$R_7$: **IF** ($SL_3$ is *Medium*) **AND** ($SL_4$ is *Low*) **THEN** Zone is *MC*
$R_8$: **IF** ($SL_2$ is *Very Low*) **AND** ($SL_3$ is *High*) **AND** ($SL_4$ is *Low*) **THEN** Zone is *MR*
$R_9$: **IF** ($SL_3$ is *Low* **OR** *Medium*) **AND** ($SL_4$ is *Very Low*) **THEN** Zone is *WAB*
$R_{10}$:**IF** ($SL_3$ is *Low*) **AND** ($SL_4$ is *Low* **OR** *High*) **THEN** Zone is *MC*
$R_{11}$:**IF** ($SL_2$ is *Very High*) **AND** ($SL_3$ is *Very Low*) **THEN** Zone is *WAA*

It is important to remark that rules listed above must be interpreted at symbolic level in terms of prototype values like the centroids of each zone where the rules should be fired with maximum activation degree. Of course, in practice the user can be located at whatever physical points inside the environment that yielding to fuzzy degrees of activation related to each zone of interest. For instance, the premises of rules $R_2$ and $R_3$ only differ regarding $SL_1$ (received signal strength from AP1) but both rules point out different zones ($CA$ and $MR$). This is because $CA$ is located at the end of the main corridor ($MC$) while AP1 is placed in the middle of such corridor (look at Figure 4). As a result, the centroid of $CA$ is within direct sight from AP1. Unfortunately, even though $MR$ is located at side by side with $CA$, its centroid is out of direct sight from AP1. Thus, it is natural to expect that $SL_1$ is higher in $CA$ than in $MR$. Imagine the situation in which two different users are located almost in the same place. For instance, one being located inside MR but very close to CA, while the other is located inside CA but very close to MR. Obviously, since both users are almost in the same location, we should expect very close values of the received signal strength SL1 measured with the PDAs carried by the two users. Moreover, such values are expected to be somehow in the middle between the labels *Low* and *High* (look at Figure 5) yielding a membership degree close to 0.5 for each label. In consequence, rules $R_2$ and $R_3$ would be fired almost with the same activation degree.

Regarding the posture recognition module, as an illustrative example, one RB automatically generated for the FFSM1, the one obtained when taking the first trial of the ten experiments for test while using as training dataset the remaining nine trials, is depicted below:

$R_{11}$: **IF** ($pos[t]$ is $q_0$ **OR** $q_1$) **AND** ($mov$ is $S_{mov}$ **OR** $M_{mov}$) **AND** ($tilt$ is $M_{tilt}$ **OR** $B_{tilt}$) **THEN** $pos[t+1]$ is $q_1$
$R_{22}$: **IF** ($pos[t]$ is $q_0$ **OR** $q_2$) **AND** ($a_x$ is $M_{a_x}$ **OR** $B_{a_x}$) **AND** ($mov$ is $S_{mov}$) **AND** ($tilt$ is $S_{tilt}$) **THEN** $pos[t+1]$ is $q_2$
$R_{33}$: **IF** ($pos[t]$ is $q_0$ **OR** $q_3$) **AND** ($a_x$ is $M_{a_x}$ **OR** $B_{a_x}$) **AND** ($mov$ is $M_{mov}$ **OR** $B_{mov}$) **THEN** $pos[t+1]$ is $q_3$
$R_{12}$: **IF** ($pos[t]$ is $q_0$ **OR** $q_1$) **AND** ($a_x$ is $M_{a_x}$ **OR** $B_{a_x}$) **AND** ($mov$ is $M_{mov}$ **OR** $B_{mov}$) **THEN** $pos[t+1]$ is $q_2$
$R_{21}$: **IF** ($pos[t]$ is $q_0$ **OR** $q_2$) **AND** ($a_x$ is $S_{a_x}$ **OR** $B_{a_x}$) **AND** ($mov$ is $B_{mov}$) **AND** ($tilt$ is $M_{tilt}$) **THEN** $pos[t+1]$ is $q_1$
$R_{23}$: **IF** ($pos[t]$ is $q_0$ **OR** $q_2$) **AND** ($a_x$ is $B_{a_x}$) **AND** ($mov$ is $B_{mov}$) **AND** ($tilt$ is $S_{tilt}$) **THEN** $pos[t+1]$ is $q_3$
$R_{32}$: **IF** ($pos[t]$ is $q_0$ **OR** $q_3$) **AND** ($a_x$ is $S_{a_x}$) **AND** ($mov$ is $S_{mov}$ **OR** $B_{mov}$) **AND** ($tilt$ is $S_{tilt}$ **OR** $B_{tilt}$) **THEN** $pos[t+1]$ is $q_2$
$R_{31}$: **IF** ($pos[t]$ is $q_0$ **OR** $q_3$) **AND** ($a_x$ is $S_{a_x}$) **THEN** $pos[t+1]$ is $q_1$

Since rule bases for FFSM1 are generated in a leave-one-out cross-validation process, it makes sense to wonder about the similarity between the ten rule bases automatically generated from data. Thanks to the fixed size and structure of the rules (where the consequent and the first term of the antecedent are known) described in Section 3.2, we only need to compare the constraints imposed on the input variables. Due to the fact that these constraints are defined in DNF, which means that each rule is represented by a set of bits where one (zero) denotes the presence (absence) of each linguistic term in the rule, we can easily calculate the similarity between two rules as the number of common bits that both rules have divided by the total number of bits that each rule has. The similarity between two complete rule bases will thus be the average value of the similarities between each pair of rules. In our experiments, we have got an average similarity between all the rule bases of 0.65, which indicates that interpretability of the FFSM1 is also kept for each of the ten trials at the rule base level.

In the case of FFSM2, we opted for an expert RB, the same for all the trials, which is manually defined. It formalizes our own expert knowledge about human activity recognition based on the combination of outputs provided by the two previous modules (FRBC and FFSM1):

$R_{11}$: **IF** ($S[t]$ is $q_0$ **OR** $q_1$) **AND** ($pos$ is $Walking$) **THEN** $S[t+1]$ is $q_1$
$R_{22}$: **IF** ($S[t]$ is $q_0$ **OR** $q_2$) **AND** ($pos$ is $Seated$) **AND** ($wep$ is $WAA$) **THEN** $S[t+1]$ is $q_2$
$R_{33}$: **IF** ($S[t]$ is $q_0$ **OR** $q_3$) **AND** ($pos$ is $Seated$ **OR** $Upright$) **AND** ($wep$ is $WO$ **OR** $WAB$) **THEN** $S[t+1]$ is $q_3$
$R_{44}$: **IF** ($S[t]$ is $q_0$ **OR** $q_4$) **AND** ($pos$ is $Seated$ **OR** $Upright$) **AND** ($wep$ is $CA$) **THEN** $S[t+1]$ is $q_4$
$R_{55}$: **IF** ($S[t]$ is $q_0$ **OR** $q_5$) **AND** ($pos$ is $Seated$) **AND** ($wep$ is $MR$) **THEN** $S[t+1]$ is $q_5$
$R_{12}$: **IF** ($S[t]$ is $q_0$ **OR** $q_1$) **AND** ($pos$ is $Seated$) **AND** ($wep$ is $WAA$) **THEN** $S[t+1]$ is $q_2$
$R_{13}$: **IF** ($S[t]$ is $q_0$ **OR** $q_1$) **AND** ($pos$ is $Seated$ **OR** $Upright$) **AND** ($wep$ is $WO$ **OR** $WAB$) **THEN** $S[t+1]$ is $q_3$
$R_{14}$: **IF** ($S[t]$ is $q_0$ **OR** $q_1$) **AND** ($pos$ is $Seated$ **OR** $Upright$) **AND** ($wep$ is $CA$) **THEN** $S[t+1]$ is $q_4$
$R_{15}$: **IF** ($S[t]$ is $q_0$ **OR** $q_1$) **AND** ($pos$ is $Seated$) **AND** ($wep$ is $MR$) **THEN** $S[t+1]$ is $q_5$
$R_{21}$: **IF** ($S[t]$ is $q_0$ **OR** $q_2$) **AND** ($pos$ is $Walking$) **AND** ($wep$ is $WAA$ **OR** $MC$) **THEN** $S[t+1]$ is $q_1$
$R_{31}$: **IF** ($S[t]$ is $q_0$ **OR** $q_3$) **AND** ($pos$ is $Walking$) **AND** ($wep$ is $WAB$) **THEN** $S[t+1]$ is $q_1$
$R_{41}$: **IF** ($S[t]$ is $q_0$ **OR** $q_4$) **AND** ($pos$ is $Walking$) **AND** ($wep$ is $MC$) **THEN** $S[t+1]$ is $q_1$
$R_{51}$: **IF** ($S[t]$ is $q_0$ **OR** $q_5$) **AND** ($pos$ is $Walking$) **AND** ($wep$ is $MR$) **THEN** $S[t+1]$ is $q_1$

It is clear that the complexity of the FFSM2 increases with the number of activities that we want to recognize. Just in case we want to recognize a bigger number of activities, in order to deal with the problem of combinatorial explosion of FFSMs, we may use different FFSMs in each zone of interest in a hierarchical fashion thanks to the scalability of the WiFi Positioning system, e.g., to recognize the activities inside a whole building, different Activity Recognition systems like the one developed in this work could be deployed in each floor or region of interest.

### *5.4. Main strengths and weaknesses of our application*

Table 9 summarizes the strongest points along with the weakest points that characterize our proposal against other alternative approaches found in the specialized literature. Each row corresponds to one work. The first three columns give details like Authors, Reference numbers (Refs.), and Year. They are aimed to identify each citation. The next three columns show information about the main issues treated by each work in accordance with the three main modules included in our application example. Namely, they are activity recognition (ACT REC), posture recognition (POS REC) and WiFi positioning (WiFi POS). Notice that, we have taken into account papers dealing with either one or more of those related topics. The rest of columns are devoted to yield an evaluation of each cited paper regarding three main aspects. First, the performance of the proposal is assessed in terms of accuracy (ACC) and interpretability (INT). Second, the knowledge embedded in the designed system regarding its nature, i.e., expert knowledge (EXP) or knowledge automatically extracted from experimental DATA. Third, a rough estimation about the complexity (COMP) of the experimental test-bed environment is also included. Those aspects corresponding to yes/no questions are directly marked with a tick (yes) or a cross (no). On the contrary, aspects demanding qualitative evaluation are assessed by means of a four stars scale: *Bad* (★☆☆☆), *Good* (★★☆☆), *Very Good* (★★★☆), and *Excellent* (★★★★).

Table 9: Summary of the main strengths and weaknesses of our proposal against alternative approaches.

| | | | ACT | POS | WiFi | Performance | | Knowledge | | Test-bed |
|---|---|---|---|---|---|---|---|---|---|---|
| **Authors** | **Refs.** | **Year** | **REC** | **REC** | **POS** | **ACC** | **INT** | **EXP** | **DATA** | **COMP** |
| K. Aminian et al. | [10] | 1995 | ✔ | ✘ | ✘ | ★★★★ | ★☆☆☆ | ✘ | ✔ | ★★☆☆ |
| J. Ben-Arie et al. | [15] | 2002 | ✔ | ✘ | ✘ | ★★★★ | ★☆☆☆ | ✘ | ✔ | ★★★☆ |
| L. Bao and S. S. Intille | [14] | 2004 | ✔ | ✔ | ✘ | ★★★★ | ★★☆☆ | ✘ | ✔ | ★★☆☆ |
| C. Nerguizian et al. | [55] | 2004 | ✘ | ✘ | ✔ | ★★★☆ | ★☆☆☆ | ✘ | ✔ | ★★☆☆ |
| E. M. Tapia et al. | [66] | 2004 | ✔ | ✘ | ✘ | ★★★★ | ★★☆☆ | ✘ | ✔ | ★★☆☆ |
| A. G. Dharne | [30] | 2006 | ✘ | ✘ | ✔ | ★★☆☆ | ★★☆☆ | ✔ | ✘ | ★☆☆☆ |
| V. Matellán | [49] | 2006 | ✘ | ✘ | ✔ | ★★★★ | ★☆☆☆ | ✘ | ✔ | ★★☆☆ |
| L. Liao et al. | [45] | 2007 | ✔ | ✘ | ✘ | ★★★★ | ★☆☆☆ | ✘ | ✔ | ★★★☆ |
| A. Carlotto et al. | [19] | 2008 | ✘ | ✘ | ✔ | ★★★★ | ★★☆☆ | ✘ | ✔ | ★★★☆ |
| E. Chan et al. | [23] | 2008 | ✘ | ✘ | ✔ | ★★★☆ | ★★☆☆ | ✔ | ✘ | ★★★★ |
| K. Derr and M. Manic | [29] | 2008 | ✘ | ✘ | ✔ | ★★★★ | ★☆☆☆ | ✘ | ✔ | ★☆☆☆ |
| S. Outemzabet and C. Nerguizian | [56, 57] | 2008 | ✘ | ✘ | ✔ | ★★★★ | ★☆☆☆ | ✘ | ✔ | ★★★☆ |
| K. Muthukrishnan et al. | [53] | 2009 | ✔ | ✘ | ✔ | ★★★★ | ★☆☆☆ | ✘ | ✔ | ★★★☆ |
| C. W. Han et al. | [38] | 2010 | ✔ | ✔ | ✘ | ★★★☆ | ★☆☆☆ | ✘ | ✔ | ★☆☆☆ |
| B. F. Wu et al. | [72] | 2010 | ✘ | ✘ | ✔ | ★★★★ | ★☆☆☆ | ✘ | ✔ | ★★☆☆ |
| J. M. Alonso et al. | [6] | 2011 | ✘ | ✘ | ✔ | ★★★☆ | ★★★★ | ✘ | ✔ | ★★★☆ |
| A. Alvarez-Alvarez et al. | [9] | 2012 | ✘ | ✔ | ✘ | ★★★☆ | ★★★☆ | ✘ | ✔ | ★★☆☆ |
| A. Alvarez-Alvarez et al. | This paper | 2012 | ✔ | ✔ | ✔ | ★★★☆ | ★★★★ | ✔ | ✔ | ★★☆☆ |

Papers listed in the table above are ranked by publication date, from the oldest work which is included at the top of the table to the present work appearing at the bottom. Notice that, papers published in the same year are sorted alphabetically.

Only a subset of all papers under study is directly related to the main target of our application example, i.e., activity recognition (look at column ACT REC). Furthermore, only few of them are based on approaches which are explicitly taking into account posture recognition (look at column POS REC). In addition, even though we have considered several works related to WiFi positioning, please notice that only two of them ([53] and this paper) take into account both ACT REC and WiFi POS at the same time. On the one hand, in the case of [53], authors focus on WiFi POS. They show how a localization system can be improved thanks to the addition of a motion model. On the contrary, this paper is mainly focused on ACT REC. We have shown how a system for activity recognition can be enhanced with the integration of information provided by a WiFi localization system.

With respect to the interpretability-accuracy trade-off, most papers take care of accuracy but they disregard interpretability. Moreover, this work is the only one proposing a careful design methodology which remarks the need of considering interpretability as a main concern all along the design process, without jeopardizing accuracy. Our proposal is not the most accurate one. However, it yields the best balance between interpretability and accuracy.

Regarding the considered knowledge sources, most works deal only with knowledge automatically extracted from data. Please, notice that this paper is the only one setting a framework for activity recognition supported by the combination of both expert and induced knowledge.

Finally, looking at the complexity of the test-bed environment, we have made a simple but intuitive evaluation based on counting the size, shape and complexity of the environment, along with the kind of activities to be recognized for ACT REC. We are aware this evaluation is very subjective. Anyway, it is aimed to provide only a global comparative overview but not an exhaustive one. In short, we can conclude that our experimental scenario is not the most complex one but this is because it was designed for illustrative purpose as a proof of concept of the whole application framework. Anyway, it is worthy to remark that the proposal is flexible enough to be easily extended to more complex test-bed environments in future works.

## 6. Conclusions and future works

This paper provides a framework for dealing with complex systems by merging different sources of information, characterized for having linguistic variables and rules that maximize its performance in terms of accuracy-interpretability tradeoff. We apply this framework by developing a robust, easy to understand, and efficient system to recognize the activity of a person working in an office environment. This work is part of a long term project aimed to recognize human activities by aggregating imprecise data. More specifically, we deal with achieving these results using low cost computational devices as they are the current smartphones. In the field of applications of these new mobile devices, there is a growing demand of new techniques that will be used to improve the quality of life of all types of people in different circumstances. In this motivating field of work there are many challenges to address.

The main contribution of this paper resides in the proposal of a global framework for human activity recognition that is based on combining effectively information coming from different sources of knowledge, namely posture recognition and WiFi positioning are taken into account. Moreover, the whole system is designed to be highly interpretable, i.e., easily understandable by human beings. To do so, we bet for two different linguistic models based on the formalism of fuzzy IF-THEN rules, namely fuzzy finite state machines (FFSM) and fuzzy rule-based classifiers (FRBC). We have detailed how to carefully design both of them in order to guarantee the interpretability of the entire system. The WiFi positioning module is implemented as a FRBC (we chose the HILK methodology for building such rules when interpretability is the prime concern, but we may opt for FURIA in case of focusing on accuracy). The other two modules, posture recognition module and human activity recognition module, are implemented as FFSMs.

We have analyzed the accuracy, interpretability, and robustness of our activity recognizer. The proposed system exhibits an effective and successful fusion of expert knowledge along with knowledge automatically derived from experimental data. In the context of FRBCs, we have incorporated into the HILK methodology the use of SMOTE with the aim of balancing the available experimental data. We have also introduced an automatic genetic learning procedure for FFSMs. In addition, as a more theoretical contribution, we have improved the expressiveness power of FFSMs incorporating the concept of unknown state. This concept provides a new dimension to the application of FFSMs to model imprecise phenomena. We have demonstrated that it provides a convenient resource to guess the confidence degree with which phenomena are truthfully represented by the model at each time instant.

Regarding the experimental analysis, the entire proposed system has been validated with real-world experimental data yielding results that let us thinking about future commercial applications. Taking advantage of the proximity of the developed model with a natural language description, in future works, we plan to develop a system able to generate linguistic reports of human activities, e.g., in the context of monitoring patients in medical applications where the fusion of information provided by several heterogeneous sensors is important and interpretability is highly demanded. Moreover, we are also interested on incorporating additional input data to our approach, e.g., GPS data, environmental sounds, etc.


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