TOWARDS PEOPLE INDOOR LOCALIZATION COMBINING WIFI AND HUMAN MOTION RECOGNITION

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Abstract

This work presents a general framework for people indoor localization. Firstly, a WiFi localization system implemented as a fuzzy rule-based classifier (FRBC) is used to deal with the intrinsic uncertainty of such environments. It consists of a set of linguistic variables and rules automatically generated from experimental data. As a result, it yields an approximate position at the level of discrete zones (room, corridor, toilet, etc). Secondly, a Fuzzy Finite State Machine (FFSM) mainly based on expert knowledge is used for human motion (activity, body posture and step length) recognition. The goal is finding out whether people is (or not) moving, in which direction, at which pace, etc. Finally, another FFSM combines both WiFi localization and human motion recognition with the aim of obtaining a robust, reliable, and easily understandable human-oriented localization system.

Keywords: WiFi localization, Human motion recognition, Fuzzy rule-based classifier, Fuzzy finite state machine.

1 INTRODUCTION

People localization systems provide interesting applications in many areas [12, 14, 16]: personal navigation assistance, medical assistance, finding and rescuing emergency first responders, personal security, etc. We are mainly interested in security applications (for instance sending warnings when someone gets into a dangerous area in order to reduce the occupational health and safety risk) and/or people assistance (for instance helping elderly or handicapped people).

There are three main types of localization systems: (1) satellite based systems, (2) local network based systems and (3) sensor based systems.

First, the satellite based systems, e.g., Global Positioning System (GPS) [9], are widely used in outdoor applications with great successful. However, they do not provide precise indoor localization (nor even in cities with high buildings), making this problem an open challenge.

Second, local network based systems use the network infrastructure to estimate user's location. There are systems based on pre-existing networks like ZigBee networks designed for home control applications [7]. However, the most used systems are based on WiFi networks. The main advantage opposite to satellite based systems is that they are able to provide indoor absolute localization. In contrast, the principal 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 Access Points (APs) in most public buildings like hospitals, libraries, universities, museums, etc. In addition, 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 [2].

Third, sensor based systems provide absolute information (e.g., magnetic compass, ultrasonic or infrared sensors) or relative information (e.g., inertial measurement units or pressure sensors). One low-cost inertial sensor is the accelerometer, based on the Micro Electro Mechanical Systems (MEMS) technology that has allowed its integration in small and low energy consumption devices. Accelerometers can be used as step length estimators; furthermore they let us to obtain some information about body posture [21]. Human activity can also be analyzed by means of combining one accelerometer with a skin conductivity meter [22].

Our localization system is mainly based on Fuzzy Logic (FL) [25] because it combines several heterogeneous sources of knowledge (mainly expert knowledge and knowledge automatically extracted from experimental data provided by sensors), dealing with vague information, and its interaction with humans demands building an easily understandable system. There are other recent works [4, 8] that show the advantages of using FL for modeling and monitoring human activity. They are mainly based on fusing video sensors what means installing additional hardware (HW) like video cameras in the environment under study. Our approach takes profit of the available HW (WiFi APs) and avoids adding new devices to the environment.

This paper contributes to the field of people indoor localization by providing a fusion framework that yields the estimated location of a person thinking on maximizing its accuracy and interpretability. We propose a general framework for people indoor localization which is made up of three main modules as illustrated in Fig. 1. Each block will be described in the following sections. Section 2 focuses on WiFi localization and how it contributes to this work. Section 3 presents some previous works related to human motion recognition. Section 4 describes the proposed fusion framework (human-oriented indoor localization), explaining how it can be applied in a real-world scenario. Finally, section 5 draws some conclusions and future works.

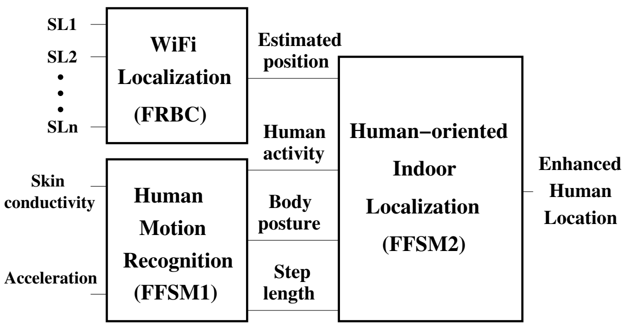

Figure 1: Scheme of the proposed fusion framework.

2 WIFI LOCALIZATION

WiFi localization systems use 802.11b/g network infrastructure to estimate a device position without using additional hardware. The received signal level (SL) from each AP depends on the distance and the obstacles between APs and the receiver. Therefore, the simplest method for estimating the device position consists of applying a triangulation algorithm [18]. Unfortunately, in indoor environments SL is strongly affected by the well-known multipath effect [17] 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.

Only approximate solutions are able to get nice results. Authors of [5] propose 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. We have previously proposed the use of fuzzy classification for WiFi robot localization, handling the signal measure uncertainty and getting small localization errors [2]. In this contribution we propose to use an enhanced version of such system devoted to people localization. It yields zone-level localization. Notice that, a zone may be only one room or a set of rooms.

A fuzzy rule-based classifier (FRBC) is designed following the Highly Interpretable Linguistic Knowledge (HILK) methodology [1]. Useful pieces of knowledge are automatically extracted from experimental data and represented by means of linguistic variables [26] and linguistic rules [15] under the fuzzy logic formalism. Rules are of form: **IF** *Condition* **THEN** *Conclusion*, where both *Condition* and *Conclusion* use linguistic terms.

For instance, **IF** *Signal received from APi is High* AND *Signal received from APj is Low* **THEN** *We are close to Position P which belongs to zone Z.* Notice that, the output of the FRBC will be one zone of the environment along with an activation degree which is understood as a degree of confidence on the system output. It is computed as the result of a fuzzy inference that takes into account all defined variables and rules. We have selected the usual fuzzy classification structure and the winner rule fuzzy reasoning mechanism. Of course, several fuzzy rules can be fired (by the same input vector) at the same time yielding several output classes (zones) with non-zero activation degree.

As an illustrative example, let us suppose that two zones A and B are one close to the other (with a common wall) and one person is inside zone A but near the wall, the FRBC may give as output an activation degree of 0.7 related to zone A and 0.3 regarding zone B. Hence, the interpolation ability of fuzzy systems makes possible to define a hierarchical localization system where the position can be refined as much as desired. In a first level it is possible to identify the floor of the building, in a second level it points out the room where the person is located, but in a third level (depending on the application) it may be interesting giving also the position inside the room. Thus, thanks to this approach, a FRBC made up of a small number of rules is used for each level, keeping a good accuracy-interpretability trade-off.

3 HUMAN MOTION RECOGNITION

The use of accelerometers in personal navigation or localization is not new. Accelerometers can be used as the basic sensors of a technique called Dead Reckoning (DR). It is the process of estimating one's current position based upon a previously determined position, and advancing that position based upon known or estimated speeds over elapsed time. Pedestrian Dead Reckoning (PDR) consists of estimating the position of a person based on his/her step length and heading [6].

In theory, the walking speed and distance could be obtained by integrating the acceleration signals once and twice respectively. However, the double integration causes an error in position which grows cubically in time [11]. For this reason, some authors [10, 23] use the accelerometer, in dead reckoning algorithms, to provide an estimation of the step length whereas the heading is obtained from gyroscopes or magnetic compass. The easiest way to get an estimation of the step length is to count the number of steps provided by the vertical axis acceleration. Then, a fix step length can be assigned to every person. The main drawback of this method is that the step length is not constant for a certain person; it varies significantly with the walking speed. There are some models that relate the step length to the vertical acceleration, like [24] that uses an empirical equation to provide step length estimation:

$$Step\ Length = \sqrt[4]{a_{max} - a_{min}} \cdot C \qquad (1)$$

where:

- a_{min} and a_{max} are the minimum and the maximum of the vertical acceleration.
- C is an experimental parameter practically invariant for a certain person. It is calculated making a person to walk a known distance.

In previous works, we have shown how a Fuzzy Finite State Machine (FFSM) can deal with signals which evolve following an approximately repetitive pattern [3]. It is able to synchronize with the acceleration signal produced during the human gait and to extract the relevant characteristics suitable for our purpose. It can provide the maximum and minimum values of the vertical acceleration in each complete gait cycle, and using Equation 1, we are able to calculate the step length in each gait cycle and therefore, the distance walked.

In our approach, not only have we used accelerometers as step length estimators, but also we have successfully used a FFSM for processing data provided by accelerometers yielding useful information about human activity [22] as well as body posture [21]. The FFSM in charge of human motion recognition (called FFSM1 in Fig. 1) was thoroughly described in [3]. The interested reader is referred to it to get further details. As an introduction to what a FFSM is and how it is used, we define a FFSM as a tuple:

$$\{Q, U, f, Y, g, Q_0\}$$

where:

- Q is a set of fuzzy states $\{q_1, ..., q_i, ..., q_{N_{states}}\}$. When the system evolves, it could stay simultaneously in several fuzzy states. The degree with which the system is in state q_i is called degree of activation of the state q_i.
- U is the input vector $(u_1, u_2, ..., u_{N_{inputs}})$.
- f is the state activation transition function defined by $Q[t+1] = f(U[t], Q[t])$, which is implemented using a set of Takagi-Sugeno-Kang (TSK) fuzzy rules [20]. 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. The allowed transitions have associated fuzzy rules and simply the forbidden ones have not associated fuzzy rules.
- Y is the output vector $(y_1, y_2, ..., y_{N_{outputs}})$. The output provided by a FFSM can be expressed as a linguistic summary of relevant characteristics of the system while it remains in q_i.
- g is the output function $Y[t] = g(U[t], Q[t])$. When a transition occurs, the values of the output variables are typically obtained applying, e.g., the average and the standard deviation of the values of the input variables while the signal remains in the considered state.
- Q_0 is the initial degree of activation of the set of states.

4 FUSION FRAMEWORK: HUMAN-ORIENTED INDOOR LOCALIZATION

The general framework illustrated on Fig. 1 suggests combining WiFi localization data and human motion data, including the distance, the human activity and the body posture. On the one hand, FRBC is in charge of estimating the user position taking as inputs the SL received from each AP in the current position. Then, FFSM1 translates data captured by one accelerometer and one skin conductivity meter into useful information summarizing the user motion such as human activity, body posture, and distance walked. Finally, FFSM2 combines all available information to obtain a robust, reliable, and easily understandable localization system. The final output is called *Enhanced human location* because it is two-fold human-oriented. First, it yields the estimated location of a person. Second, the whole system design is made thinking on maximizing its interpretability. Thus, the output explanation is based on a set of linguistic variables and rules quite close to the human natural language.

The rest of the section gives some details on how FFSM2 was designed for a specific real-world scenario. It summarizes the preliminary experiments made as part of this work, with the aim of showing how it can be applied to the chosen scenario. The test-bed was established at the European Centre for Soft Computing (ECSC) premises whose layout is shown in Fig. 2. The topological map of the whole environment is illustrated at the top picture of the figure. It has a surface of 49 x 9 meters, and it has been discretized into seven main zones as it can be appreciated at the middle picture: (1) main corridor, (2) coffee area, (3) working area A, (4) working offices, (5) working area B, (6) administration area, and (7) head unit offices.

These seven zones determine the set of fuzzy states of the FFSM2 introduced in Fig. 1. The designed diagram of states for FFSM2, with the allowed transitions rules, is shown at the bottom part of the Fig. 2. The whole design includes defining the input vector, the state activation transition function (fuzzy rules), the output vector through its output function and the initial degree of activation of the set of states. The input vector has four components related to the following variables (that take values in the interval [0,1]):

- The WiFi estimated position (WEP). It is computed as the output of the FRBC yielding a degree of membership for each of the seven zones.

- The degree of activity (A). As explained in [22], it comprises four different states (*Idle*, *Working*, *Walking*, and *Relaxing*) with their corresponding degree of activation.

- The body posture (P). As the degree of activity, it has four different states (*Seated*, *Standing up*, *Upright*, and *Sitting down*) [21] also with their degree of activation.

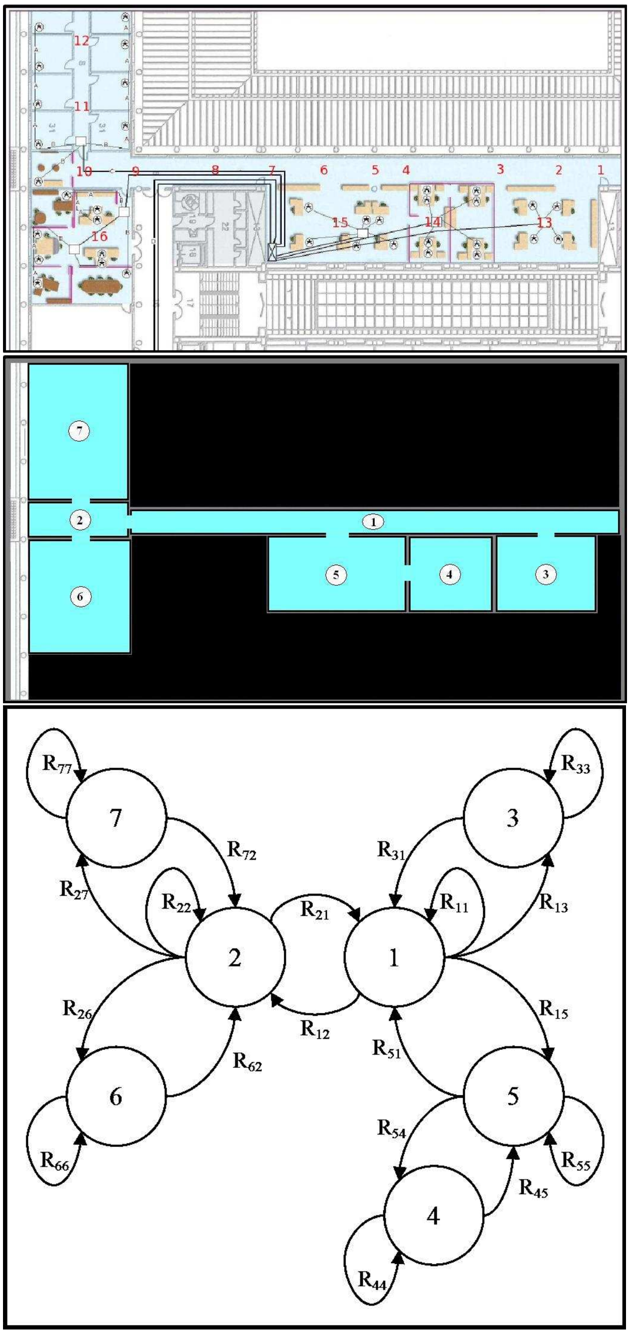

Figure 2: Discretization and diagram of states of the ECSC environment.

- The distance (D). It is calculated from the step length, and it is modeled as a linguistic variable that comprises several linguistic terms (*None*, *Short*, *Medium*, *Long*, etc.) with their attached membership functions.

The state activation function, as can be deduced from the diagram shown in Fig. 2, is made up of 19 fuzzy rules. As an example, below you can find four of them to have and idea about how they look like:

R_{11} : IF ($Q[t]$ is $Zone$ 1) AND (WEP is $Zone$ 1) AND (A is $Walking$) AND (P is $Upright$) AND (D is $Short$) THEN $Q[t+1]$ is $Zone$ 1.

R_{12} : IF ($Q[t]$ is $Zone$ 1) AND (WEP is $Zone$ 2) AND (A is $Relaxing$) AND (P is $Sittingdown$) AND (D is $Long$) THEN $Q[t+1]$ is $Zone$ 2.

R_{51} : IF ($Q[t]$ is $Zone$ 5) AND (WEP is $Zone$ 1) AND (A is $Walking$) AND (P is $Standing\ up$) AND (D is $Medium$) THEN $Q[t+1]$ is $Zone$ 1.

R_{33} : IF ($Q[t]$ is $Zone$ 3) AND (WEP is $Zone$ 3) AND (A is $Working$) AND (P is $Seated$) AND (D is $None$) THEN $Q[t+1]$ is $Zone$ 3.

Previous rules are interpreted as follows. R_{11} means that the user was (and still continues) walking through the main corridor (*Zone* 1). R_{12} is going to be fired if the user goes from the main corridor to the coffee area (*Zone* 2). R_{51} means that the user is currently walking with the aim of leaving the working area A (*Zone* 5) to pass through the main corridor. Finally, according to R_{33} the user remains working at his/her usual place (*Zone* 3). Notice that, several rules can be fired at the same time. As a result, the final output depends on the activation degree of each rule as well as on the aggregation of all the rules.

The output vector of the FFSM provides the zone where the user is. In this way, it validates (confirming and/or correcting) the WEP. One criterion could be choosing that zone corresponding with the state with the maximum degree of activation. However, this selection will make the FFSM very sensitive to noise and spurious in the signal, and that is precisely what we want to avoid. Therefore, the output is designed as the zone corresponding to the state which has had the maximum average degree of activation over the last minute. Notice that, the initial degree of activation of the set of states Q_0 is taken as the computed WEP for each zone when the application was started.

For testing our WiFi localization system in the ECSC environment, we have built a training data set (LRN) with the SL measures (from all visible APs) carried out in the center of all the 16 remarked positions at the top picture in Fig. 2. One of the main problems of WiFi localization is the SL small-scale variations that happen when moving in a small distance (under the wavelength λ) [19]. They are generated by multipath effect producing a lot of uncertainty because they may arise up to 10 dBm for positions around the same location. For the 802.11b networks working at the 2.4 GHz range, λ is 12.5 cm. Thus, with the aim of checking the robustness of our system we have generated a test data set (TST) taking measures around all the sixteen positions (always under λ distance).

Then, HILK methodology [1] has been applied on LRN in order to build a FRBC with a good accuracy-interpretability trade-off. It includes six input variables (one per each AP in the environment) which are characterized by strong fuzzy partitions of nine linguistic terms (extremely low, very low, low, etc). In addition, linguistic rules are automatically generated from data by means of the neuro-fuzzy ID3[13], a version of the popular fuzzy decision trees (FDT). Finally, the simplification procedure provided by HILK was run getting a more compact and general FRBC, keeping high accuracy while increasing even more its interpretability. Main results are presented in Table 1 considering two cases: (1) training-test with raw data and (2) training-test with averaged data in blocks of four samples. Notice that we use 4 samples per block because the maximum acquisition frequency of the WiFi interface is 4Hz, i.e., we are capturing 4 samples per second.

Table 1: Experimental results for WiFi localization.

	ROW DATA (1 sample)			AVERAGED DATA (4 samples)		
	LRN	**TST**	**RULES**	**LRN**	**TST**	**RULES**
MP	98.9	97.04	-	100	97.64	-
C45	99.74	96.59	28	100	91.61	8
FRBC	99.3	94.2	46	100	96.3	14

In addition to our solution (FRBC), for comparison purpose, the table includes results provided by other methods implemented in Weka[1]: MP (Multilayer Perceptron) which yields very accurate neural network classifiers (disregarding comprehensibility), and C45 (Quinlan's decision trees) which usually provides good interpretability-accuracy trade-offs. The most accurate solution, i.e., the highest classification rate for training and test, is provided by MP with averaged data. C45 yields the most interpretable solution with the smallest number of rules. However, FRBC achieves the best trade-off with a larger accuracy than C45 but at the cost of a larger number of rules.

5 CONCLUSIONS

So far, we have already developed separately two of the three main blocks belonging to the proposed framework: (1) the WiFi localization module and (2) the human activity recognition module. In both cases, as explained in this paper but also in cited works, achieved results are encouraging. In consequence, the integration of both modules by means of the third one, which is currently under development, should yield a really powerful global system. Of course, more experiments

[1] http://www.cs.waikato.ac.nz/ml/weka/

are needed in order to show the utility of our fusion framework because it is part of an ongoing research project.

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