WiFi Localization System Using Fuzzy Rule-Based Classification

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Abstract. The framework of this paper is robot localization inside buildings using WiFi signal strength measure. This localization is usually made up of two phases: training and estimation stages. In the former the WiFi signal strength of all visible Access Points (APs) are collected and stored in a database or Wifi map, while in the latter the signal strengths received from all APs at a certain position are compared with the WiFi map to estimate the robot location. This work proposes the use of Fuzzy Rule-based Classification in order to obtain the robot position during the estimation stage, after a short training stage where only a few significant WiFi measures are needed. As a result, the proposed method is easily adaptable to new environments where triangulation algorithms can not be applied since the AP physical location is unknown. It has been tested in a real environment using our own robotic platform. Experimental results are better than those achieved by other classical methods.

1 Introduction

WiFi localization systems take advantage of the boom in wireless networks over the last few years. The wireless networks have become a critical component of the networking infrastructure and are available in most corporate environments (universities, airports, train stations, tribunals, hospitals, etc), and in many commercial buildings (cafes, restaurants, cinemas, shopping centres, etc).

In the literature, we can find multiples systems proposed and successfully deployed to find the pose (position and orientation) of a robot from its physical sensors. These systems are based on: infrared sensors [1], computer vision [2], ultrasonic sensors [3], laser [4] or radio frequency (RF) [5] [6]. Within the last group we can find localization systems that use WiFi signal strength measure.

These WiFi systems are attractive for indoor environments where traditional techniques, such as Global Positioning System (GPS) [7], fail. One of the main advantages of these systems is that they do not need to add any extra hardware in the environment. They use the signal strength measure of the wireless communication network established by the WiFi.

The signal strength depends on the distance and obstacles between APs and the robot. Moreover, the system needs more than one base stations or AP to

R. Moreno-Díaz et al. (Eds.): EUROCAST 2009, LNCS 5717, pp. 383–390, 2009.
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measure the distance from them to the device. In [8] they use these measures to apply a triangulation algorithm to infer the estimated position.

Unfortunately, in indoor environments, the WiFi channel is very noisy and the RF signal can suffer from reflection, diffraction and multipath effect, which makes the signal strength a complex function of distance [5]. To solve this problem, it can be used a priori WiFi map, which represents the signal strength of each AP at certain points in the area of interest [9] [10] [11] [12].

These systems work in two phases: training and estimation of the position. During the first phase, a WiFi map is built while in the estimation phase, the vector of samples received from each access point is compared with the WiFi map and the "nearest" match is returned as the estimated robot location.

Fuzzy Logic (FL) introduced by Zadeh [13] is acknowledged for both its well-known ability for linguistic concept modeling and its use in system identification. The semantic expressivity of fuzzy logic, using linguistic variables [14] and linguistic rules [15], is quite close to expert natural language. In addition, being universal approximators [16], fuzzy inference systems (FIS) are able to perform non-linear mappings between inputs and output. FL is especially useful to handle problems where the available information is vague. This is the typical situation regarding WiFi localization where measures normally yield incomplete or distorted data.

In this paper we use Fuzzy Classification in the estimation stage to obtain the estimated robot position. Such classification obtains several benefits over the classical methods. The most significant advantages are: (1) The robustness of the built systems which are able to deal with the intrinsic uncertainty of indoor environments; and (2) the adaptability to new environments where AP location is indeterminate.

The rest of the paper is organized as follows: Section 2 provides a description of the proposed Fuzzy Classification system. Section 3 shows the implementation and some experimental results, as well as a description of the used test bed. Finally, the conclusions and future work are described in Section 4.

2 Description of the Fuzzy Classification System

In this section we provide a brief description of the Fuzzy Rule-based Classification system. It was designed and built using Knowledge Base Configuration Tool (KBCT) [17] a free software tool which implements the Highly Interpretable Linguistic Knowledge (HILK) methodology [18]. This new methodology focuses on building interpretable fuzzy classifiers, i.e., classifiers easily understandable by human beings. Applying machine learning techniques it is able to extract useful pieces of knowledge from data sets. In addition, knowledge automatically extracted form data is represented by means of linguistic variables and rules 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** *The robot is close to Position k*. The semantic expressivity of fuzzy logic makes easier the knowledge extraction and representation phase. In addition, it lets us combine under the same formalism knowledge extracted from data and knowledge described by an expert[1] in natural language.

In classical logic only two crisp values are admissible (0/1, false/true, negative/positive, etc). This is a strong limitation in order to deal with real-world complex problems where there are many important details which are usually vague. In the real world things are not so simple as black and white but there is a continuous scale of grays. To cope with this problem FL is a useful tool. Working with FL everything has a membership degree. For instance, the same person can be considered more or less tall or short depending on the context: 1.80 is tall in Spain but it is not so tall in Sweden.

This information is represented by membership functions like the ones in Figure 1. As it can be seen the same value *xi* is partially *Low* (0.22) and *Medium* (0.78), but the addition of both membership degrees equals one. This kind of partitions is called strong fuzzy partitions (SFPs) [19] and they are the best ones from an interpretability point of view. By default we use SFPs of seven linguistic terms.

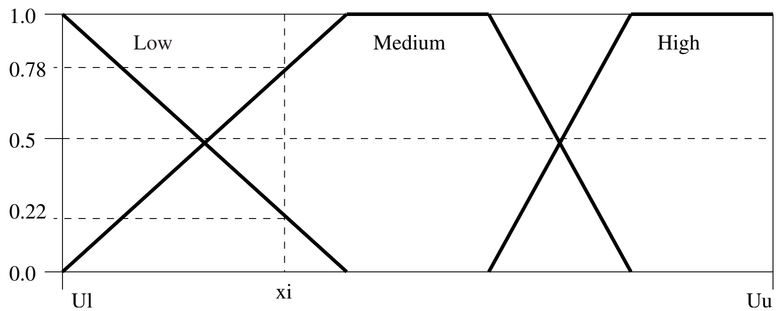

Fig. 1. A strong fuzzy partition with three linguistic terms

Once the fuzzy partitions of the input variables are defined they are used in linguistic rules of form:

$$\textbf{If} \quad \underbrace{\underbrace{X_a \text{ is } A_a^i}_{Partial\ Premise\ P_a} \quad \textbf{AND} \ \ldots \ \textbf{AND} \quad \underbrace{X_z \text{ is } A_z^j}_{Partial\ Premise\ P_z}}_{Premise} \quad \textbf{Then} \quad \underbrace{Y \text{ is } C^n}_{Conclusion}$$

On the one hand, rule premises are made up of tuples (*input variable*, *linguistic term*) where X_a is the name of the input variable a, while A_a^i represents the label i of such variable. Notice that the absence of an input variable in a rule means that the variable is not considered in the evaluation of that rule. On the other

[1] An expert is a person who has a deep knowledge about the problem under study. It is usually an expert domain but not a fuzzy expert.

hand, C^n is one of the possible output classes, i.e., one position in the case of WiFi localization.

Regarding the rule generation from data, there are lots of methods in the fuzzy literature [20]. However, keeping in mind the interpretability goal we have chosen Fuzzy Decision Tree (FDT) [21], a fuzzy version of the popular decision trees defined by Quinlan [22]. Notice that our implementation of FDT is able to build quite general rules with the interpretable partitions previously defined.

Then, a simplification procedure is carried out on the whole fuzzy knowledge base with the aim of removing redundancies and getting still more compact and understandable partitions and rules.

Finally, the output of the fuzzy classifier will be one position along with an activation degree computed as the result of a fuzzy inference that takes into account all defined inputs and rules[2]. Such activation degree can be understood as a degree of confidence on the system output. Notice that several output classes can be activated since several fuzzy rules can be fired at the same time by the same input vector. The activation degrees of the different classes can be used in order to make an interpolation among several positions. For instance, if the system output says that the robot is in position A with degree 0.2 and in position B with degree 0.8, it can be concluded that it is located someway between A and B but closer to B.

3 Implementation and Results

The robot used in the experimentation is called Sancho3. It is shown in Figure 2 and it was developed in the European Centre for Soft Computing (ECSC[3]). This robot is based on a modular architecture whose first version was designed in the Technical University of Madrid (UPM[4]). It has the following configuration: Linux Debian 5.0 Lenny operating system, Orinoco PCMCIA Silver wireless card, wireless tools v.28, two ultrasound sensors mounted over servos and one AXIS 213 pan-tilt-zoom camera.

The Test-Bed environment was established on the ECSC. The layout of this zone is shown in Figure 3. It has a surface of 60m x 20m, with 8 different rooms, including offices, labs, bathrooms, storerooms and meeting rooms. Six APs are available at the whole environment.

For simplicity, the tests were achieved in the main corridor. This was discretized into 16 nodes placed at the positions indicated in Figure 3. Sancho3 was placed at each node and 1000 signal strength samples were collected from all APs. These samples contain the signal and noise levels expressed in dBm and they have been used for both purposes, to train and to test the proposed method.

For each position, we computed the mean and the deviation of the corresponding signal and noise values for each AP. Then, we constructed two tables, one

[2] Please refer to the cited literature for a complete description.

[3] http://www.softcomputing.es

[4] http://www.upm.es

Fig. 2. Real prototype used in the experimentation

Fig. 3. Test-bed. European Centre for Soft Computing

for training and the other for testing. These tables contain tuples of the form: $(pos, \overline{S_{AP1}}, \sigma_{S_{AP1}}, \overline{N_{AP1}}, \sigma_{N_{AP1}}, ..., \overline{S_{APi}}, \sigma_{S_{APi}}, \overline{N_{APi}}, \sigma_{N_{APi}})$, where *pos* is the environment position and i is the number of APs. The training data were used to automatically generate the partitions and rules of the Fuzzy Classification system.

In addition, the same data were used to compare our method with a classical localization method called Nearest Neighbour (NN) [5]. It obtains the location by means of computing the Euclidean distance from the tuple received at a certain position and the tuples stored in the training table. The lowest distance indicates the estimated position.

The methods have been tested using different number of samples, both in training and test phase. The best classification rate was 60.16% for the NN method and 99.2% for FC, these were obtained with 60 samples in the training and test stages. The results are shown in Table 1.

Also, we have tested the classification rate when the samples taken in the training and test stage were different. It is important to note that the maximum

Table 1. Comparison of classification methods regarding training data

Samples	Data	Errors (NN)	Classification rate (NN)	Errors (FC)	Classification rate (FC)
12	1328	732	44.88	17	98.72
28	560	275	50.89	5	99.1
60	256	102	60.16	2	99.22

acquisition frequency of the WiFi interface is 4Hz, then to take 60 samples it is needed to spend 15 seconds at the same place. We have reduced the samples from 60 to 4 with the aim of checking the classification rate of both methods, Figure 4 shows these results. As it can be seen in this figure, the FC (on the right picture of the figure) maintains a good classification rate even when the samples taken are 12 and 4 in the training and test stages. As a result, the FC yields robust and simple solutions. In the worst case, the classification rate is around 70 % for a FC trained with groups of 60 samples when it is tested regarding groups made up of only 4 samples (the robot only spends 1 second to capture them). In addition, the best classification rate achieved by NN method (on the left picture of the figure) is lower than the worst one obtained by FC.

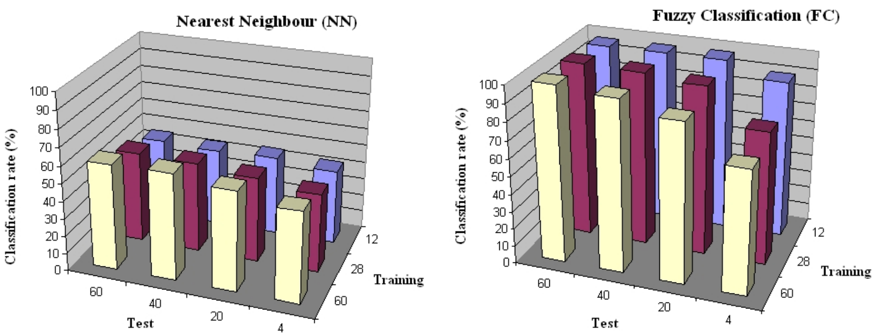

Fig. 4. Comparison of classification rates

Finally, Table 2 gives an idea on the complexity of the fuzzy classifiers built for this problem. They are more easily interpretable (because of the smaller number of rules, inputs, etc.) when the number of samples is increased. However, if the number of samples grows then the acquisition time is increased. In consequence, the system design has to be made carefully looking for a good trade-off (depending on the application) between number of samples (acquisition time), classification rate, and interpretability of the model.

Table 2. Complexity of fuzzy classifiers

Samples	Rules	Inputs	Linguistic Terms
12	77	16	91
28	35	13	57
60	25	10	42

4 Conclusions and Future Works

In this work we have presented a WiFi localization system based on Fuzzy Classification. We demonstrate that it is useful and robust to localize the robot in real conditions.

The classification rate of our method improves the ratings of other classical methods like Nearest Neighbour. This rate is maintained even when we take only a few samples.

In the near future, we have the intention of using this system in other environments to test the applicability of the method. Also we want to add new data sources provided by the robot, such as actions and ultrasound observations to improve the classification rate.

Acknowledgement. This work has been funded by grant S-0505/DPI/000176 (Robocity2030 Project) from the Science Department of Community of Madrid, TIN2008-06890-C02-01 (CWPIE Project) from the Spanish Ministry of Science and Technology (MCyT) and CCG08-UAH/DPI-3919 (SISLOPEWI Project) from the Community of Madrid and University of Alcala.

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