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Mobile and Autonomous Systems: Robots and Cars

WiFi Localization System based on Fuzzy 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 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

In the literature, we can find multiples systems proposed and successfully deployed to find the pose of a robot from its physical sensors. These systems are based on: infrared sensors, computer vision, ultrasonic sensors, laser or radio frequency (RF) [1]. 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) [2], fail. One of the main advantages of these systems is that they do not need to add any extra hardware in the environment.

The signal strength depends on the distance and obstacles between APs and the robot. 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 [1]. 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 [3] [4].

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

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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 [5] 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 [6] and linguistic rules [7], is quite close to expert natural language. In addition, being universal approximators [8], 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 Classification system. It was designed and built using KBCT (Knowledge Base Configuration Tool) a free software tool which implements the HILK methodology [9]. This new methodology focuses on building interpretable fuzzy classifiers, i.e., classifiers easily understandable by human beings.

In classical logic only two crisp values are admissible (0/1, false/true, 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. Working with FL everything has a membership degree. 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*.

Regarding the rule generation from data, we have chosen Fuzzy Decision Tree (FDT) [10], a fuzzy version of the popular decision trees defined by Quinlan [11]. Notice that our implementation of FDT is able to build quite general rules with the partitions previously defined. Then, a simplification procedure is carried out on the whole fuzzy knowledge base with the aim of removing redundancies and even getting more compact and understandable systems.

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. Such activation degree can be understood as a degree of confidence on the system output.

3 Implementation and Results

The robot used in the experimentation (Sancho3) was developed in the European Centre for Soft Computing (ECSC) and it is based on a modular architecture whose first version was designed in the Technical University of Madrid (UPM). The Test-Bed environment was established in the main corridor of the ECSC premises. It was discretized into 16 nodes, and Sancho3 was placed at each node collecting 1000 signal strength samples from each AP (six APs are available at the whole environment).

For each position, we computed the mean and the deviation of the corresponding signal (S) and noise (N) values for each AP. Then, we constructed two tables, one for training and the other for testing. These tables contain tuples of the form: $(\overline{S_{AP1}}, \sigma_{S_{AP1}}, \overline{N_{AP1}}, \sigma_{N_{AP1}}, ..., \overline{S_{APi}}, \sigma_{S_{APi}}, \overline{N_{APi}}, \sigma_{N_{APi}}, pos)$, where pos is the environment position and i is the number of APs. The training data were used to automatically generate the Fuzzy Classification system (FC). In addition, the same data were used to compare our method with the classical localization method called Nearest Neighbour (NN) [1]. Both methods have been tested using different number of samples. 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.

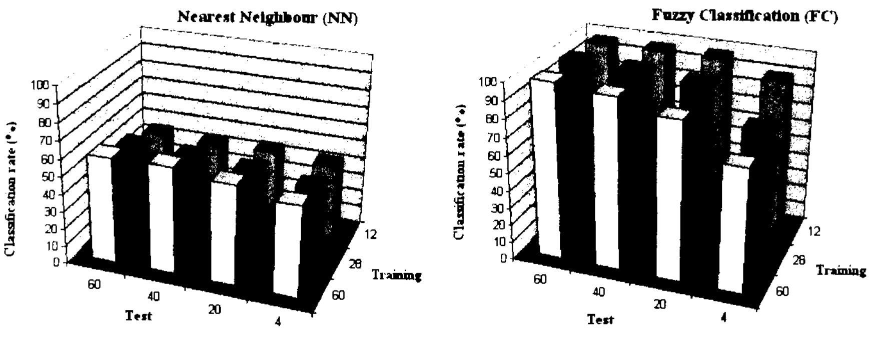

Fig. 1. Comparison of classification rates

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 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 1 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

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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.

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. In the near future, we have the intention of using this system in other environments to test the applicability of the method.

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