WiFi Localization System based on Fuzzy Logic to deal with Signal Variations

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Abstract— **The goal of this paper is to study some of the most important WiFi signal variations, large and small scale variations and how they affect to WiFi localization systems. Moreover, the paper shows how to use Soft Computing techniques to deal with these uncertainties in WiFi localization systems. This work describes how to reduce uncertainty produced by small scale variations in indoor environments using fuzzy techniques. Some experimental results and conclusions are presented.**

I. Introduction

Several applications, i.e. surveillance tasks, require knowing the user location. This position can be determined by the user's device or by the environment. By knowing the user position it is possible to interact with the user, guiding it through the environment and implementing some tasks depending on the area of interest.

During last years localization applications are growing using different technologies. A great example is GPS (Global Positioning System) [1], which is the most used technology for this purpose, car drivers usually use it to be guided through cities. But this is only an example of the localization importance.

Actually, localization is applied at several areas. In fact, there are projects that use localization systems in hospitals which can locate doctors and equipment. Other systems are used for medical assistance [2], inventory control at warehouses, robotics [3], etc.

As mentioned above, nowadays GPS is the most extended technology for devices localization [1]. This technology can locate devices with an error that varies from centimetres to 100 metres, but it does not work properly in an indoor environment, or even in cities with high buildings.

So, it is necessary to find a complementary system for such environments. There are some proposals for indoor localization using infrared [4], computer vision [5], ultrasound [6], laser [7] or radio frequency (RF) [8] based systems. Moreover, there is an increasing interest in WiFi localization for these environments using different algorithms.

One of the main advantages of this technology is its quickly growing of coverage. 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. Consequently, WiFi technology is a good choice for indoor global localization systems.

WiFi localization systems use 802.11b/g network infrastructure to estimate a device position without using additional hardware. This fact makes WiFi localization systems appropriate to be used in indoor environments where traditional techniques do not work properly. To estimate a device position the system measures the received signal level (SL) from each AP by mean of a WiFi interface. SL depends on the distance and the obstacles between APs and the receiver.

In work [9] the authors show a system that calculates the distance to each AP using the received SL and then infers the position by a triangulation algorithm. Unfortunately, RF signal is affected by reflection, refraction and diffraction in indoor environments. This effect, known as multipath effect, turns the SL into a complex function of the distance.

To solve this problem, authors of [8] propose a WiFi localization system based on a priori radio map, that stores the received SL of each AP belonging to an interest region. This system has two stages: training and estimation stages. In the first one, a manual radio map is built. While 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.

There are two main techniques to estimate the position: deterministic and probabilistic. Usually, in the first one, the environment is divided in cells and the position is obtained in the estimation stage comparing the measures with the stored pattern [8] [10]. In the other hand, probabilistic techniques keep a probabilistic distribution over all positions [11]. The last technique gets a better precision but with a high computational cost.

Deterministic way is a common choice for these systems. The Nearest Neighbor algorithm is used to classify the device position as it is shown in [8]. Usually, this algorithm is used as baseline to compare the new methods.

With the aim of solving the WiFi SL measure problems in indoor environments, we propose to use a WiFi localization system based on fuzzy techniques to get a lower localization error and to handle the signal measure uncertainty.

In this paper we use Fuzzy Classification to obtain the estimated position. Fuzzy Logic (FL) is especially useful to handle problems where the available information is vague,

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which is the typical situation in WiFi localization. There are several advantages of using this kind of techniques instead of classical methods. The most important are: the robustness of FL which is able to deal with the uncertainty in the environment and makes possible to infer the device position without a high number of samples [12] [13] [14].

The rest of the paper is organized as follows: section 2 shows WiFi SL measure process and WiFi signal variations; section 3 shows the developed fuzzy localization system; section 4 describes the results obtained by our WiFi localization system using fuzzy logic; and finally, section 5 shows some conclusions and future works.

II. WiFi Signal Level Measure

In this section, the WiFi SL measuring process is described. It is important to remark that WiFi technology works at a 2.4 GHz frequency, which is very close to the water resonant frequency, therefore SL is affected by several variations. To develop a WiFi localization system is important to consider such variations which can affect to the system behaviour. Work [15] studies the main variations that affect to WiFi signal.

- Temporal variations: when the user is standing at a fixed position, the signal strength measure varies over time. SL variations can be upper to 10 dBm. These variations are usually due to changes in the physical environment such as people in movement.
- Large-scale variations: signal strength varies over a long distance due to attenuation of the RF signal. Large-scale variations can be used by WiFi localization systems to estimate the device position. In addition, propagation models can make use of such variations to estimate the distance between transmitter and receiver. Figure 1 shows an example of APs signal level for different distances.
- Small-scale variations: these variations happen when the user moves over a small distance (in the range of wavelength). This fact leads to changes in the average received signal strength. For the 802.11b networks working at the 2.4 GHz range, the wavelength is 12.5 cm. These kinds of variations are generated by multipath effect. Small-scale variations introduce a lot of uncertainty in the system. These variations make difficult to estimate the device position due to they can be up to 10 dBm for positions around the same location. Figure 2 shows small scale variations for several positions around wavelength (these positions will be explained later in section IV-C).

III. Fuzzy localization system

A Fuzzy localization system has been developed to deal with the uncertainty derived from small scale variations. In classical logic only two crisp values are admissible (0/1, false/true, negative/positive, etc), what is a strong limitation when dealing with real-world complex problems where there are many important details which are usually vague. FL is a useful tool to deal with these problems, because working with FL everything is a matter of degree. The semantic expressivity of FL makes easier the knowledge extraction and representation

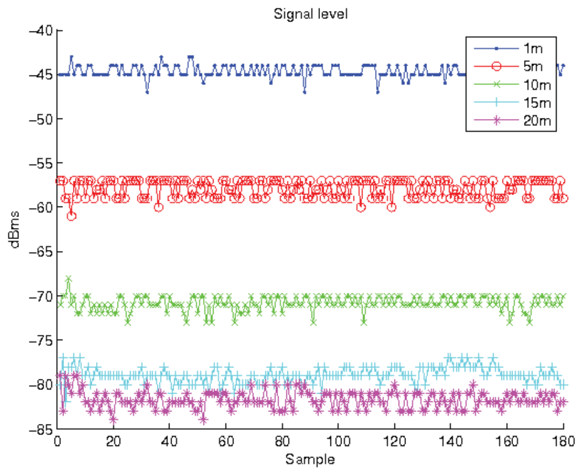

Fig. 1. Signal Level at different distances

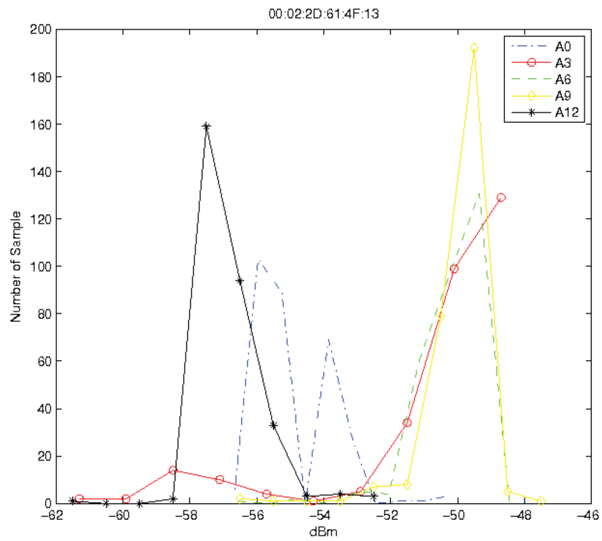

Fig. 2. SL Histogram for small scale variations

phase. In addition, it lets us combine under the same formalism knowledge extracted from data and knowledge described by an expert in natural language.

As shown in Figure 3, the developed system has three inputs (SL measured from three different APs) and one output (the position where the device is located). The three APs can be selected automatically and it is not necessary to know their position. The selection has been made looking for the APs, in the samples group, with the best SL which are visible from all the positions. The fuzzy inference system has been implemented by means of the Mamdani's method provided by the Matlab Fuzzy Toolbox.

In addition, the SL input information has been represented by Membership Functions (MFs) like the ones shown in Figure 4. We have designed Strong Fuzzy Partitions (SFPs) for

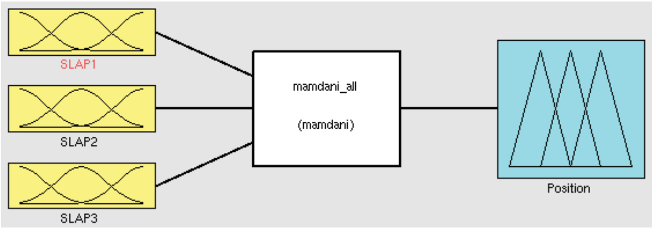

Fig. 3. Mamdani Fuzzy System

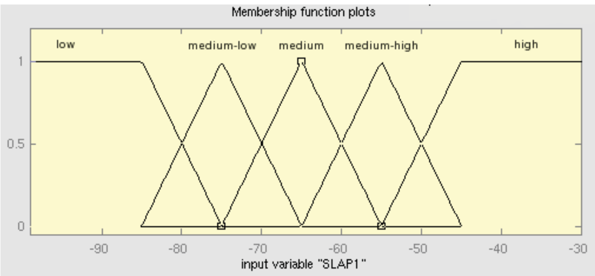

Fig. 4. Designed membership function with SFPs and five linguistic terms

interpretability purpose. Moreover, each SFP has five linguistic terms in order to obtain a good resolution to discriminate every position from each other.

The limits of the MFs ared determined by the usual range of the WiFi signal measure which normally varies from -99 to -30 dBm. Then, the partitions are made up of five uniformly distributed MFs with the attached linguistic terms: low (L), medium-low (ML), medium (M), medium-high (MH) and high (H).

Once the inputs have been designed they can be used to define a group of linguistic rules. For simplicity, in this first prototype, both variable and rule definitions are only based on expert knowledge.

Defined rules can be used whenever the environment does not suffer a great modification, i.e. when some access points are switched off. In this case, the system should be adjusted, but usually these things do not happen and the fuzzy system is able to deal with slight modifications like people moving in the environment or changes in the state of the doors.

IV. Implementation and Results

This section describes the test bed environments used in this work, some implementation features and the experimental results obtained on the designed tests.

IV-A. Test bed Environment

The environments to test the fuzzy localization system were established on the Polytechnic School of University of Alcalá (UAH) and on the European Centre for Soft Computing (ECSC) premises.

The layout of UAH environment is shown in Figure 5. It has a surface of 60 x 60 metres with 4 laboratories and 32 offices. There are 54 APs distributed over the whole environment. For simplicity, the samples were achieved in the fourth corridor, because the environment is symmetrical from the main diagonal.

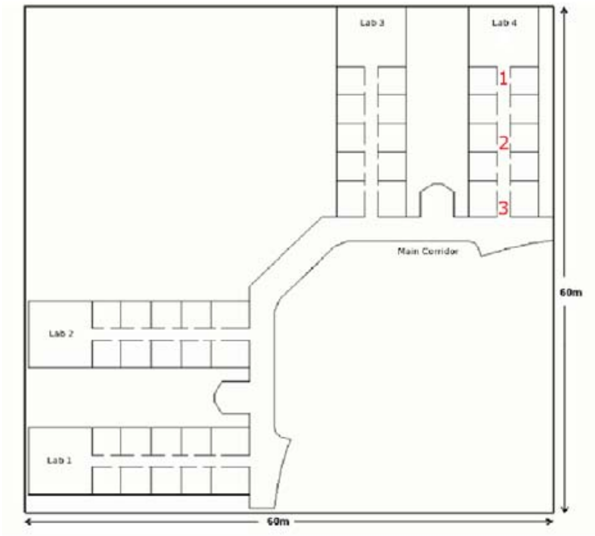

Fig. 5. UAH Environment

The layout of ECSC environment is shown in Figure 6. It has a surface of 49 x 9 metres with 4 offices. There are 6 APs distributed over the whole environment.

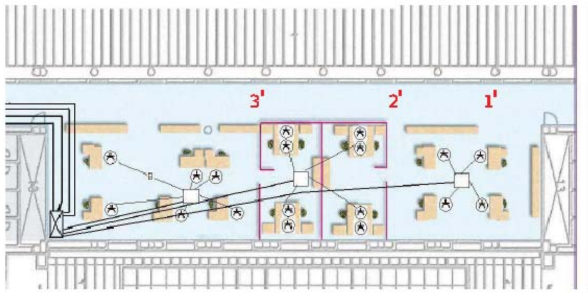

Fig. 6. ECSC Environment

IV-B. Implementation

The tests have been performed with a laptop computer using an Orinoco PCMCIA Silver Wireless, Linux Kubuntu 8.04, Wireless Tools v29 and Matlab 2008a.

SL measures are obtained by the WiFi interface installed in the laptop. This interface scans the APs close to the device. Samples are got at 4 Hz, which is the highest frequency that the interface supports.

IV-C. Small scale measures

A group of 300 samples small scale variations measures have been performed to test the fuzzy localization system. Several measures of WiFi signal level are acquired at different positions with distances around the wavelength (12.5 cms at

2.4GHz) between each one. They have been performed as detailed below:

- A grid of 12.5 cm x 12.5 cm divided in 1 cm side squares has been created. This grid is shown in Figure 7. This way, the positions where the device should be placed to make the different measures are clearly identified.
- Initially, the device is placed at position A0 (Figure 7) and 300 samples are collected. This position is taken as the reference position (λ).

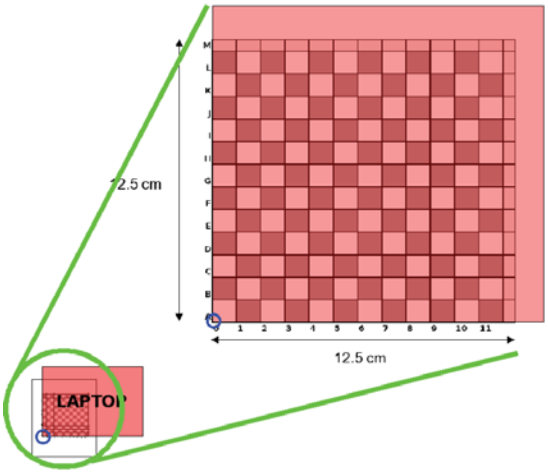

Fig. 7. Small scale grid - Position A0

- From position λ, new measures are carried out in three different directions (Figure 8) to check the small scale variation effects:
  1. Horizontal: SL are measured on λ (A0), $\lambda + 3cm$ (A3), $\lambda + 6cm$ (A6), $\lambda + 9cm$ (A9), $\lambda + 12cm$ (A12) positions. These positions are shown with circles in Figure 8.
  2. Vertical: SL are measured on λ (A0), $\lambda + 3cm$ (D0), $\lambda + 6cm$ (G0), $\lambda + 9cm$ (J0), $\lambda + 12cm$ (M0) positions. These positions are shown with diamonds in Figure 8.
  3. Diagonally: SL are measured on λ (A0), $\lambda + 3\sqrt{2}cm$ (D3), $\lambda + 6\sqrt{2}cm$ (G6), $\lambda + 9\sqrt{2}cm$ (J9), $\lambda + 12\sqrt{2}cm$ (M12) positions. These positions are shown with squares in Figure 8.

Moreover, these measures have been taken at different locations. These positions should be properly classified by the fuzzy localization system without mistakes among small scale positions.

IV-D. Results

This section shows the results achieved in this work. To test the fuzzy localization system two data sets has been created, one of them using all the points described in section IV-C and the other one using only the centered position (G6).

For each environment two rule bases are designed, the first one consider only the center of the grid and the second one regards all the measures in the grid. They are described in

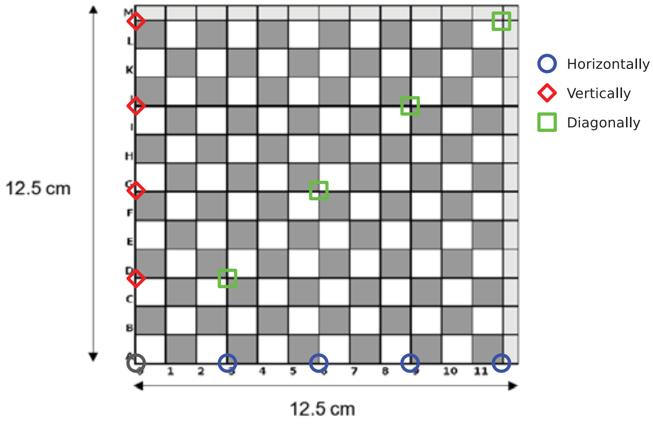

Fig. 8. Small scale positions

TABLE I
FUZZY SYSTEM RULES UAH (CENTRE)

Position	AP1	AP2	AP3
1	L	L	MH
	ML	L	MH
	ML	L	H
	L	L	H
2	ML	ML	H
	ML	ML	MH
	M	L	H
	M	ML	H
	M	ML	MH
3	M	M	M
	ML	MH	M
	ML	M	M
	M	MH	M

Tables I and II for UAH environment and III and IV for ECSC environment. Where L, ML, M, MH, H are the linguistic terms for low, medium low, medium, medium high and high SL.

- UAH Environment: the best classification rate was 99.65 % for rules obtained with all small scale positions and 10 samples means and 82.57 % with center position and 4 samples means. These results are shown in Table V. Moreover, these results are compared with the results obtained with Nearest Neighbour (NN) algorithm, which are shown in Table VI. The fuzzy system obtains better results than the NN system.
- ECSC Environment: the best classification rate was 99.66 % for rules obtained with all small scale positions and 10 and 4 samples means. These results are shown in Table VII. The NN results are shown in Table VIII, this Table shows that the fuzzy system overwhelms the NN results.

It is important to highlight that acquisition frequency of WiFi interface is 4Hz, so the results doing means of 4 samples or without doing means are a little worse, but it is only needed

TABLE II

FUZZY SYSTEM RULES UAH (ALL)

Position	AP1	AP2	AP3
1	ML	L	H
	L	L	H
2	M	ML	MH
	M	ML	H
	M	L	MH
	M	L	H
	ML	ML	MH
	ML	ML	H
	ML	L	MH
3	M	M	M
	ML	MH	M
	ML	M	M
	M	MH	M

TABLE III

FUZZY SYSTEM RULES ECSC (CENTRE)

Position	AP1’	AP2’	AP3’
1’	ML	M	ML
	ML	M	L
	ML	ML	ML
	ML	ML	L
	L	M	ML
	L	M	L
	L	ML	ML
	L	ML	L
2’	H	M	ML
3’	M	MH	L
	M	H	L

TABLE IV

FUZZY SYSTEM RULES ECSC (ALL)

Position	AP1’	AP2’	AP3’
1’	ML	M	ML
	ML	M	L
	ML	ML	ML
	ML	ML	L
	L	M	ML
	L	M	L
	L	ML	ML
	L	ML	L
2’	H	M	ML
	H	M	L
	H	MH	ML
	H	MH	L
3’	M	MH	L
	M	H	L
	MH	MH	L
	MH	H	L

TABLE V

FUZZY CLASSIFICATION RESULTS (UAH)

Data Knowledge	Number of samples mean	Classification Rate
All Positions	1	99.35 %
	4	99.58 %
	10	99.65 %
Center Position	1	81.76 %
	4	82.57 %
	10	82.34 %

TABLE VI

NN CLASSIFICATION RESULTS (UAH)

Number of samples mean	Classification Rate
1	63.08 %
4	66.49 %
10	64.19 %

to spend one second or less measuring at the same place. A comparative of all the results can be seen in Figures 9 and 10. As it can be seen, in the worse case the classification rate is around 82.5 % for rules obtained with a center position in UAH environment and around 96.5 % with rules obtained with all the small scale positions in both environments.

ECSC environment results are better than UAH environment results because in the first one there are less APs. A high number of APs introduces another effect called co-channel interference which makes the environment even noisier. Moreover, at ECSC environment there are fewer walls what reduces multipath effect. This fact makes ECSC results better than UAH’s ones.

TABLE VII

FUZZY CLASSIFICATION RESULTS (ECSC)

Data Knowledge	Number of samples mean	Classification Rate
All Positions	1	96.01 %
	4	99.66 %
	10	99.66 %
Center Position	1	95.92 %
	4	99.66 %
	10	99.66 %

TABLE VIII

NN CLASSIFICATION RESULTS (ESCS)

Number of samples mean	Classification Rate
1	82.46 %
4	85.94 %
10	86.38 %

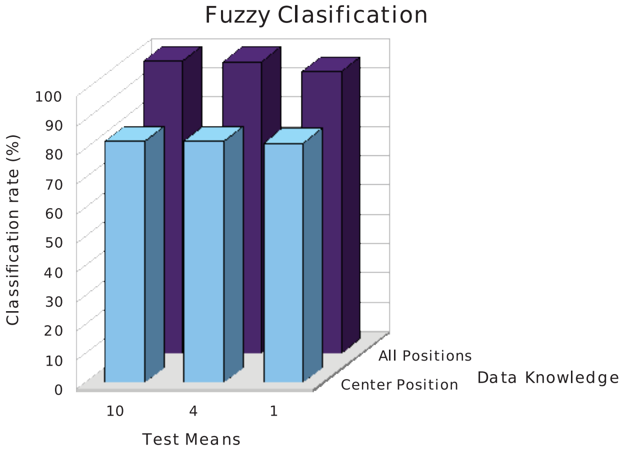

Fig. 9. Comparison of fuzzy system results (UAH)

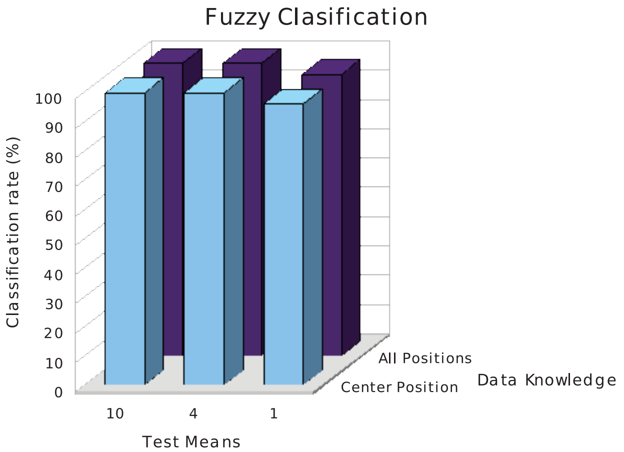

Fig. 10. Comparison of fuzzy system results (ECSC)

V. CONCLUSIONS AND FUTURE WORKS

In this work an fuzzy localization system has been presented. Our work demonstrates that using Soft Computing techniques is a useful and robust way to solve the traditional WiFi localization problems.

The uncertainty generated by small scale variations has been minimized with the designed fuzzy localization system. The position estimation error has been reduced to 0.34 % considering ten samples. Furthermore, system can estimate the device position with one sample obtaining a maximal error of 3.65 %. This allows decreasing the processing time because it is not necessary to waste time acquiring more samples and averaging them during the localization stage.

A high-level layer is being developed to select the zone where the device stays for applying the designed fuzzy system. Thus, device localization is possible in wide areas decreasing the environment complexity to a few positions.

VI. ACKNOWLEDGEMENTS

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