Impact of Signal Representations on the Performance of Hierarchical WiFi Localization Systems

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Abstract. In this paper, different representations of WiFi access point signal information are tested on a hierarchical indoors localization system to identify the one that yields the least amount of localization error. Four representations were considered: Received Signal Strength (RSS) in dBm, RSS in mW, Visibility and both RSS in dBm and Visibility. The localization system was tested in two different real world environments and encouraging results were obtained for the combination of RSS in dBm and Visibility. The results point to increased accuracy in localization, especially in environments where signal is greatly distorted by the multipath effect.

Keywords: WiFi, Topology-based Hierarchical Localization, Parameter Analysis.

1 Introduction

There is a growing interest on Internet of Things enabled services that are based on context and location information. This has boosted the need for a reliable and real time localization of Internet oriented devices. The most used technology for outdoor localization is the GPS [5] but, unfortunately, this technology does not provide accurate positioning indoors. There are many ways to infer a device's indoors location using different technologies: infrared [12], computer vision [9], ultrasound [11], laser [2], radio frequency (RF) [1], or even cellular communication [10], but thanks to the huge deployment of WiFi access points and the fact that using WiFi for localization purposes has no additional costs, WiFi has become a common choice.

One of the well-known problems of this kind of systems is that the accuracy decreases as the environments grow. A first proposal to solve the so-called scalability problem has been recently sketched in [6], using a topology-based hierarchical WiFi indoor localization approach that divides the environment into sub-regions in order to improve the accuracy.

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An important characteristic of this system is that it performs a topology-based indoor localization. For human-oriented applications, such as guidance, it is more important to provide interest points positioning than the exact coordinate in the environment.

In this paper, the use of different parameters for the hierarchical localization system is explored to reach an improvement on the final distance error. The rest of the paper is organized as follows: Section 2 presents our proposal to improve performance and a brief description of the algorithms used to test the system. Section 3 describes the experimental environment and the obtained results. Finally, conclusions and future work are presented in section 4.

2 Proposal

The localization has been hierarchically approached in two classification levels as explained in [6]. First, the samples are classified into different zones using a so-called zones classifier. Then, the position inside each zone is computed using a so-called position classifier for each one of the zones.

For the classification, three algorithms have been initially considered, K-NN (K-Nearest Neighbor) [8], FURIA (Fuzzy Unordered Rule Induction Algorithm) [7] and SVM (Support Vector Machine) [4].

K-NN is a variation of the traditional nearest neighbour algorithm for dealing with noise, where the most popular class of the k nearest examples is used for prediction. This prevents a single noisy sample from incorrectly classifying the new one. The more noise in the input set, the larger k should be. As the system does not have this information a priori, a popular method is to train and test the system using a variety of k values, and adopting the one that produces the best results.

FURIA extends the well-known RIPPER algorithm [3], a state-of-the-art rule learner, while preserving its advantages, such as simple rule sets. In addition, it includes a number of modifications and extensions. In particular, FURIA learns fuzzy rules instead of conventional rules and unordered rule sets instead of rule lists. Moreover, to deal with uncovered examples, it makes use of an efficient rule stretching method.

SVM constructs a hyperplane or set of hyperplanes in a high-dimensional space which separates input classes. Intuitively, a good separation is achieved by the hyperplane that has the largest distance to the nearest training data points of any class (so-called functional margin), since in general the larger the margin the lower the generalization error of the classifier.

Four different combinations of parameters have been considered for each classifier: Received Signal Strength (RSS) in dBm, RSS in mW, Visibility (Eq. 1) and, finally, RSS in dBm and Visibility.

$$Visibility\, AP_i = \frac{SamplesReceived\, AP_i}{Total\, Samples} \tag{1}$$

Since visibility parameter has been proved to help at the environment division stage, using it at the classification stage is likely to lead to accuracy improvement.

3 Results

Experiments were carried out in two different environments, with different characteristics, under real conditions. First environment is set on the third floor of the Polytechnic School at the University of Alcalá (UAH). In this building, mainly made of concrete, the signal measurement is highly affected by the multipath effect. The test-bed environment is shown in Fig. 1 and contains 30 topological positions set at a distance from 2.3 to 8.1 metres from each other.

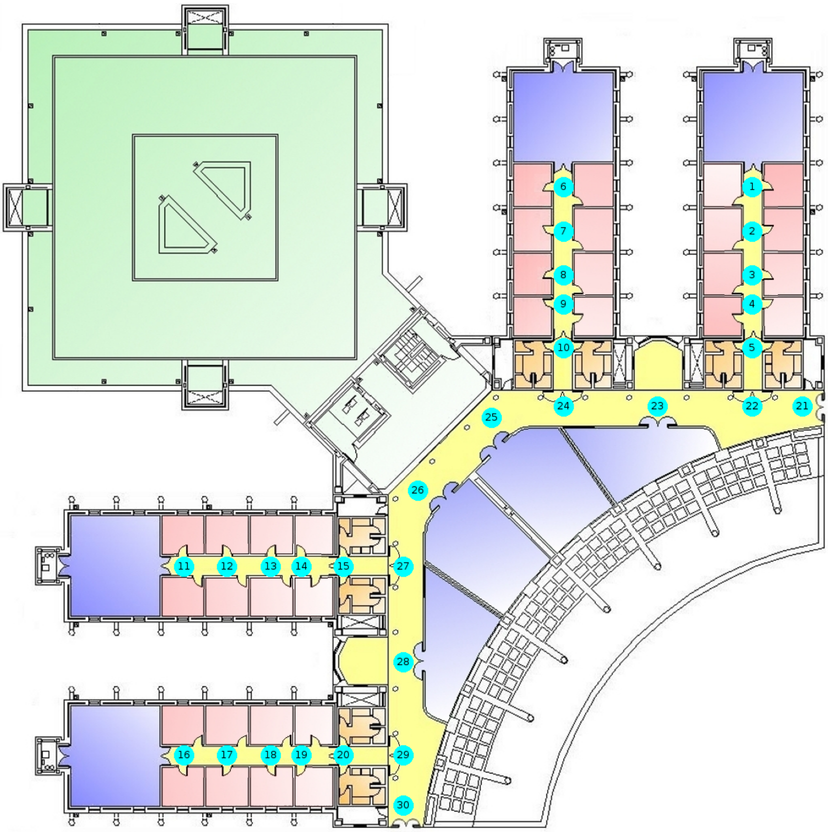

Fig. 1. UAH Environment

Second environment is set on the first floor of the Informatics FORUM at the University of Edinburgh. Lot of interferences affects the signal measure since the building is located on the city centre. In this building, mainly made of glass, the attenuation of the signal is lower than usual and makes hard to differentiate between positions. The test-bed environment is shown in Fig. 2 and contains 47 topological positions separated 4 metres from each other.

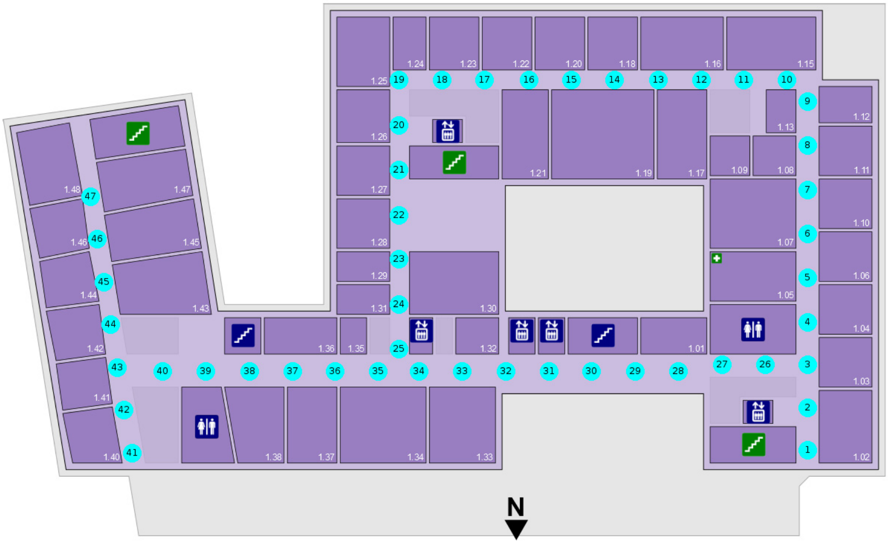

Fig. 2. FORUM Environment

Tables 1 and 2 summarize the results for both UAH and FORUM environments. As shown, the most promising results are achieved using just RSS in dBm, while using the RSS in dBm along with the Visibility parameter makes accuracy slightly decrease in most of the cases. As will be shown, although the best accuracy results are achieved using only RSS in dBm, the lowest distance error is achieved adding the Visibility parameter to the system.

Figs. 3 and 4 show an analysis of the error distance using the different classifiers and the parameters which provide the highest accuracy.

Table 1. Summary of the Localization Results. UAH environment.

	RSS (dBm)	RSS (uW)	Visibility	RSS (dBm) and Visibility
FURIA	**67,77%**	66,22%	52,66%	67,11%
K-NN	**72,88%**	67,33%	55,77%	68,88%
SVM	70,44%	63,77%	63,33%	**70,66%**

Table 2. Summary of the Localization Results. FORUM environment.

	RSS (dBm)	RSS (uW)	Visibility	RSS (dBm) and Visibility
FURIA	51,60%	40,69%	47,61%	**52,13%**
K-NN	**61,44%**	46,28%	51,33%	57,45%
SVM	**57,18%**	40,96%	53,19%	55,59%

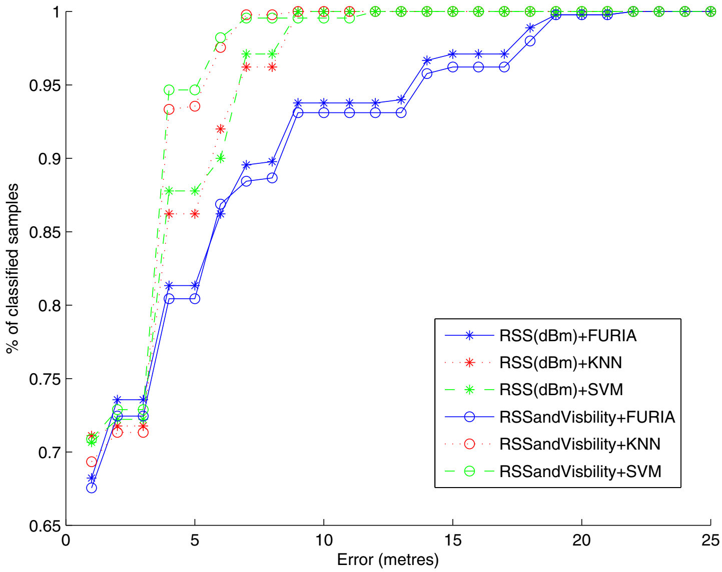

Fig. 3. Percentage of classified samples with *error* <= *x* (metres). UAH environment.

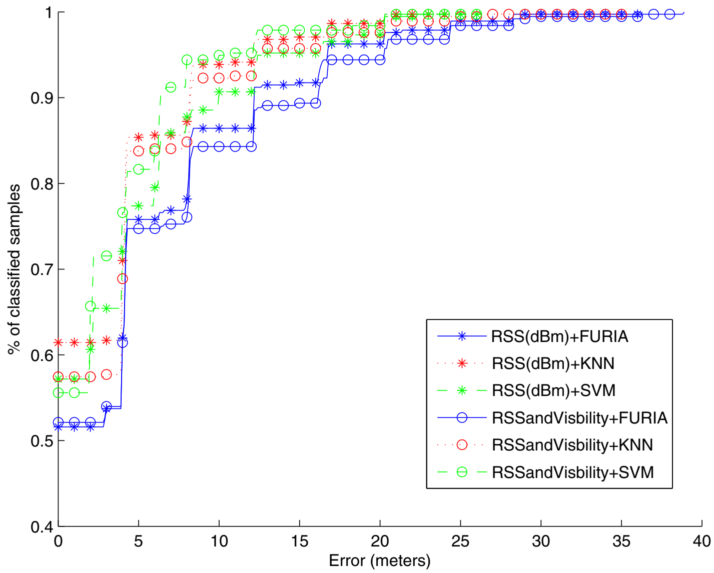

Fig. 4. Percentage of classified samples with *error* <= *x* (metres). FORUM environment.

In the UAH environment, the best results are achieved by the classifiers using RSS along with Visibility, obtaining an error inferior to 4 metres 95% of the time and 7 metres 100% of the time, while the error using RSS(dBm) is less than 8 metres 95% of the time.

In the FORUM environment, the best results are obtained by the SVM classifier using RSS along with Visibility obtaining an error inferior to 10.5 metres 95% of the time, while using only the RSS(dBm) is less than 13 metres 95% of the time. Using the KNN classifier the best results are achieved using the RSS in dBm obtaining an error inferior to 12.2 metres 95% of the time while using the RSS along with Visibility is less than 12.4 metres 95% of the time. Even though KNN provides better accuracy than SVM (61.44% vs. 57.18%), the error in metres using SVM with the RSS along with Visibility is lower 62% of the time than the error in metres using KNN with the RSS.

Figs. 5 and 6 show the confusion matrix in both environments for the configuration providing the lowest distance error, achieved by SVM classifier using both RSS and Visibility. As can be seen, although the distance error seems to be high, specially at the FORUM environment, most of the classification errors occur within the nearest positions. It is important to highlight that, since we perform a topology-based indoor localization, the distance error depends on the minimum distance between the topological positions.

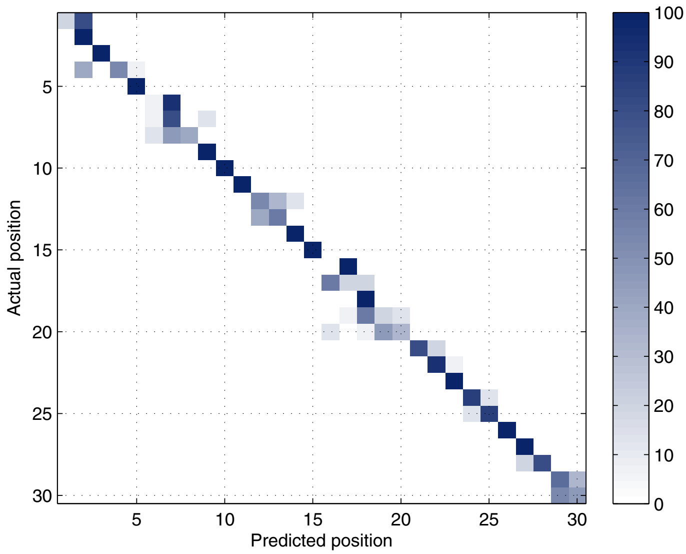

Fig. 5. Confusion Matrix. RSS and Visibility using SVM. UAH environment.

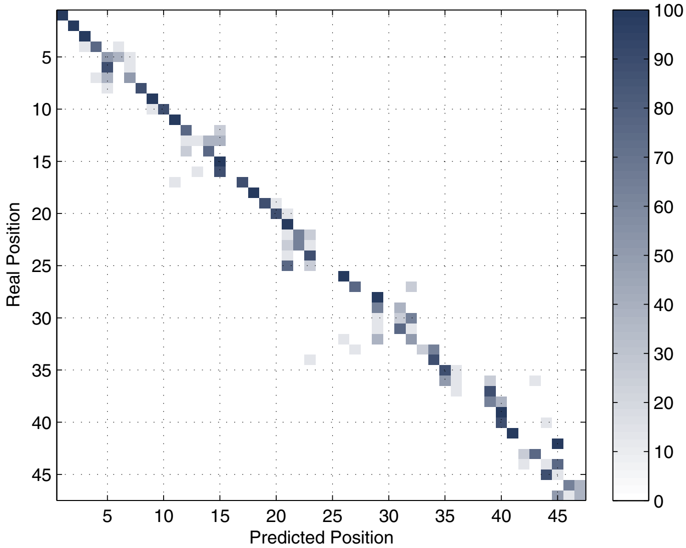

Fig. 6. Confusion Matrix. RSS and Visibility using SVM. FORUM environment.

4 Conclusions

In this work different representations of WiFi access point signal information are tested on a hierarchical localization system to increase the accuracy in indoors environments. We have achieved the best results adding Visibility information to the classifiers, specially at environments where the multipath effect affects more than usual, reducing the distance error to less than 4 metres 95% of the time. On the other hand, the Visibility parameter seems to help to a lesser extent in environments where the signal attenuation is less than usual, but it helps to reduce the distance error to less than 10.2 metres 95% of the time. Thus, in the near future we plan on applying the RSS (dBm) plus Visibility combination in larger environments, using data from different floors and closer positions, to check its effect in more complex scenarios.

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