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WIPS: the WiSARD Indoor Positioning System

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Abstract. In this paper, we present a WiSARD-based system facing the problem of Indoor Positioning (IP) by taking advantage of pervasively available infrastructures (WiFi Access Points – AP). The goal is to develop a system to be used to position users in indoor environments, such as: museums, malls, factories, offshore platforms etc. Based on the fingerprint approach, we show how the proposed weightless neural system provides very good results in terms of performance and positioning resolution. Both the approach to the problem and the system will be presented through two correlated experiments.

1 Introduction

Positioning estimation can be defined as the process of estimating the position of a target node in a wireless network (cellular phone, base station, wireless sensor), by exchanging signals between the target node and a number of reference nodes [1]. The position of a target node can be estimated by the target node itself (*self-positioning*), or it can be estimated by a central unit that obtains information via reference nodes (*remote-positioning*)[2].

There exist three main approaches to the IP problem with *off-the-shelf* hardware: *distance measurement* systems, where locations of multiple transmitters have to be known; as well as for *angle of arrival* systems [3]; and *fingerprinting* [4] [5]. The latter is based on the idea of selecting a number of reference points (fingerprints) and measuring the signal strengths of visible transmitters at those points. This information is then used to compare the signal strength during the actual positioning to find the best match or matches by some method of interpolation [6].

The fingerprint positioning method is divided into two main phases: a *training phase* (calibration phase) and a *positioning phase*. In the first phase, the area is split in several reference points (fingerprints) where the system collects and stores Received Signal Strength (RSS) values measured at each point. Then, in

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the second phase, the system uses those values to compare the values measured by the target node in order to determine its position.

This can be carried out both in a probabilistic way (such as: kernel [7], histogram [8]) and in a deterministic way (such as: k-nearest neighbour, compressive sensing [9], artificial neural networks [10]). Also, in order to help the positioning system, the idea of modelling user mobility can improve the system performance. Most of the related approaches are based on Kalman filters [11] and on particle filters [12].

The following is how the remainder of the text is organised. The next section presents WIPS, implemented by means of a weightless neural system and based on the fingerprint positioning approach. Section 3 describes the experimental set up and results. Conclusion and future works are discussed in the last section.

2 Setting up the WIPS

WiSARD has been the first commercial neural machine and was introduced by Aleksander *et al* in the early 80's [13]. The WiSARD is composed by a given number of discriminators, each one representing a different class. Each discriminator is built from X n-tuple RAM nodes (one-bit words), all initially set to "0". These RAM nodes are commonly called neurons. During the training phase, a $X \times n$ bits binary input pattern is presented to the corresponding discriminator so that all addressed RAM memory locations are set to "1". In the classification phase, the sum of all the memory contents addressed by a given input pattern represents each discriminator response. Such input pattern is associated to the discriminator class whose response is the highest (see [14]).

2.1 Training phase

The space where the positioning is being deployed has been discretely partitioned. Each area represents a fingerprint thus, in our case, the fingerprint is not represented as a point on the map but rather as an area. The WiSARD is formed by as many discriminators as the number of different fingerprints.

In the first experiment reported in the next section, the area has been split in 62 different fingerprints. There exist a total of 32 different APs that cover all the considered area. For each RSS, WIPS takes into account the MAC address, the signal Strength and the signal Noise (from now on referred as MSN). The

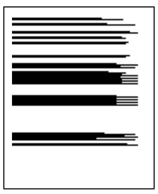

Fig. 1: Institute upper right fingerprint.

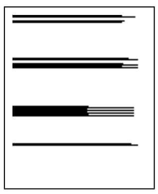

Fig. 2: Institute lower left fingerprint.

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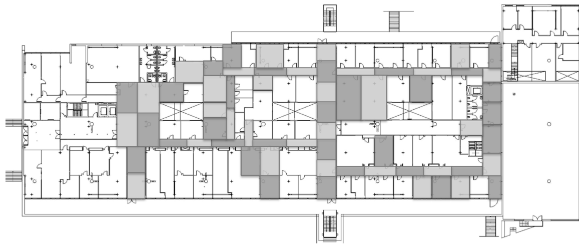

Fig. 3: Institute floor plan

system input is represented by a black and white image in which the MAC address is the row index and for every two consecutive rows, the signal strength and its noise is represented by a black bar. The graphical representation of two different MSN patterns (100×124 pixels) are illustrated by Fig. 1 and Fig. 2. Each discriminator has been trained with randomly selected MSN observations collected inside each area.

2.2 Positioning phase

User positioning is achieved by the system with just one MSN observation (the more you have the better is). No signal pre-processing is carried out by the system and all 62 discriminators analyse the input at once. The discriminator with the highest response represents the fingerprint where the input pattern (MSN observation) has been detected. We would like to point out that in those few cases in which the system does not correctly position the users, the highest response is always given by those discriminators representing immediate neighbours. Furthermore, the resolution of the system is enough to fullfill its task; in fact, even when we push the resolution to smaller fingerprints (see next section), the system performs well and it should correctly position users for the sake of emergency evacuation.

3 Experiments and results

To test our approach we carried out two different experiments. In the first one, we considered accessible areas (offices, laboratories, corridors and open spaces, see Fig. 3) of a floor of "Istituto di Cibernetica". The total area was split in 62 subareas (fingerprints) whose size varies between 8 and 12 m^2. In this case, we had in mind to adopt WIPS in case of emergency evacuation. This resolution is enough to ensure that everyone in the area will be rightly positioned by WIPS. In the second experiment, we increased the resolution of WIPS, considering the Institute hall as area to be controlled (see Fig. 4), having 24 fingerprints of 4 m^2 each.

For both experiments, we collected the RSS information walking inside each fingerprint area. Other information, such as angles and distances from APs, were not taken into account. That is, each observation consisted only of MSN data.

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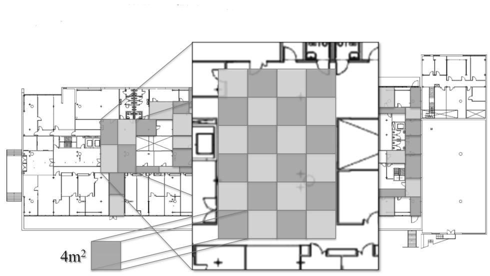

Fig. 4: Hall fingerprints

The two tests were leave-one-out cross-validation (LOOCV) procedures, where each fingerprint was considered a class to be distinguished from the others. The complete datasets consisted of 13 to 21 observations of each class, which were later divided into folds for the procedures.

Through the use of LOOCV, each dataset observation was given as a query to WIPS, producing as output a rank of all classes. A correct answer to the query is assumed according to an evaluation parameter called Confidence Threshold (CT), which represents how hard is the evaluation criterium used: a high CT means a harder criterium. Fig. 5 illustrates how the same output has different interpretations according to different CT values.

The score a WIPS instance can attribute to a class varies from 0 to its number of neurons. We compared different WIPS setups using values of CT from 90% to 100% to show how a greater range of score values lets the rank entries be relatively closer to each other, which permits better hit rates of WIPS instances with more neurons. The hit rate is the fraction of queries correctly answered considering a certain value of CT divided by the total number of queries.

The results for the first experiment are presented in Fig. 6. They show that even when considering the hardest acceptance criteria, using CT = 100%, WIPS maintains its high quality performance.

The same kind of graph for the second experiment (Fig. 7a) shows lower hit rates, which was expected since the system needed to deal with smaller finger-

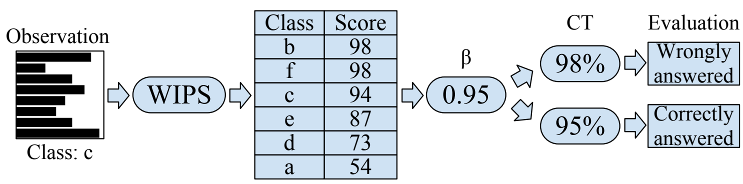

Fig. 5: To evaluate WIPS, an observation whose real class, c, is known is input as a query. A rank of all classes and their respective scores is output. Class c score divided by the highest score is $\beta = 94/98 \simeq 0.95$. Iff $\beta \geq CT$, the output is accepted as correct.

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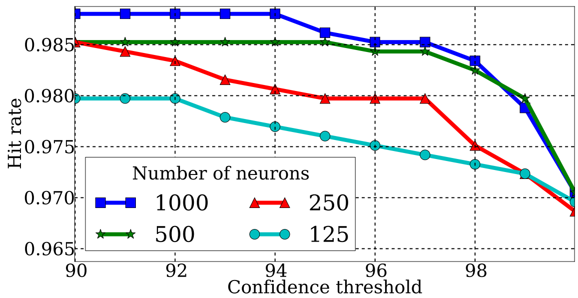
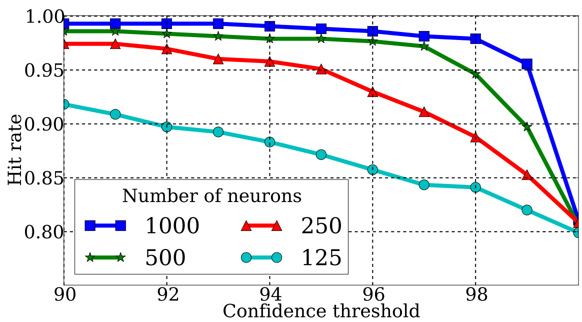
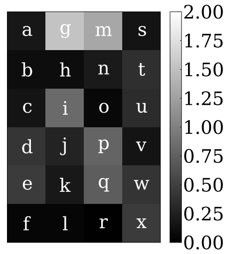


Fig. 6: Experiment 1 results. Observations size: 100×124 pixels $\Rightarrow$ Input size: 12400 bits. 1000 neurons $\Rightarrow$ 13-tuple nodes; ... 125 neurons $\Rightarrow$ 100-tuple nodes.

prints representing a finer-grain resolution. A grid graph, where the fingerprints disposition is the same used during data gathering, is reported in Fig. 7b. A generic fingerprint α is colored according to the average (Manhattan) distance from itself to the classes WIPS attributed the highest score when queried about an observation of α. This graph shows that even when missing, the system answer was good, being very close to the right one.



(a) Hit rate



(b) Mean distance

Fig. 7: Experiment 2 results. Observations size: 100×50 pixels $\Rightarrow$ Input size: 5000 bits. 1000 neurons $\Rightarrow$ 5-tuple nodes; ... 125 neurons $\Rightarrow$ 100-tuple nodes.

4 Conclusion and future work

In order to improve the WIPS performance we are going to adopt the DRASiW version of WiSARD [15] in which the bleaching is used to better identify the best response from the discriminators. Many times, there are few discriminators whose responses are very close to each other and grouped around the highest response. The bleaching procedure can refine these responses and choose the

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discriminator having the most accurate response.

A further improvement is that of adopting a hybrid strategy (Agent WiSARD [16]) for pedestrian dead reckoning. A symbolic module can follow the user movements and can help WIPS choosing the right discriminator response on the basis of a plausible user path. Such path would belong to a graph where each node represents a fingerprint and each arc the possible user movement.

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