Bluetooth Indoor Localization with Multiple Neural Networks

Marco Altini #1, Davide Brunelli *2, Elisabetta Farella #3, Luca Benini #4

University of Bologna, DEIS – Department of Electronics, Computer Sciences and Systems

1 marco.altini3@studio.unibo.it

3 elisabetta.farella@unibo.it

4 luca.benini@unibo.it

*University of Trento, DISI – Department of Information Engineering

2 davide.brunelli@disi.unitn.it

***Abstract*— Over the last years, many different methods have been proposed for indoor localization and navigation services based on Radio frequency (RF) technology and Radio Signal Strength Indicator (RSSI). The accuracy achieved with such systems is typically low, mainly due to the variability of RSSI values, unsuitable for classic localization methods (e.g. triangulation). In this paper, we propose a novel approach based on multiple neural networks. We demonstrate with experimental results that by training and then activating different neural networks, tailored on the user orientation, high definition accuracy is achievable, allowing indoor navigation with a cost effective Bluetooth (BT) architecture.**

I. Introduction

In the last decade, localization and navigation systems have become popular, thanks to the availability of effective and accurate technologies for outdoor positioning such as the Global Positioning System (GPS). People and object tracking is in fact one of the most important enabling technologies for many ambient intelligence and context-aware service provisioning scenarios. However, the established GPS technology does not work well indoor, because of the absence of direct line of sight with the satellites, therefore alternative solutions are needed for indoor environments. Indoor localization is of great interest in many fields, e.g. enabling context-aware assistance to elderly both at home and in public structures such as hospital, enabling smart guidance to museum visitors, providing information on user preferences and habits to feed personalized service provisioning. Indoor localization based on RF signal is one of the most used techniques, as low-power wireless technologies are widely available and low-cost. However, RF technology is not robust for localization purposes, because of signal reflections and power absorption by obstacles, bodies, etc. For example, Bluetooth (BT) [1] has been used among other RF technologies for indoor localization since it is a cost effective and easy-to-deploy solution. In fact, BT transceivers are present in almost any computer, mobile phone, or PDA. Moreover, the on-coming Bluetooth Low Energy will make this technology even more attractive [2]. Many Bluetooth based localization and positioning systems are based on the use of RSSI (Received Signal Strength Indicator) to determine the user location. Unfortunately, the shortcomings that affect this parameter are manifold, mainly due to propagation effects. Thus, it is difficult to obtain accurate location services using standard techniques such as triangulation from three or more Bluetooth base stations. In this context, a solution that might well improve performance is the use of neural networks (NNs). In fact, NNs are capable of tackling noisy measurements and are widely used when the correlation between the input and output values of a system is unclear or subject to noise. To the best of our knowledge, NNs have not been largely exploited for localization so far, especially in Bluetooth based system. Another problem that arises in a real indoor navigation scenario is the RF signal power absorption caused by the body of the user carrying the localization device. This problem affects any positioning algorithm that does not take into account the user orientation. NNs can actually deal with noisy measurement but often the differences in RSSI values depending on user orientation cause a significant performance drop. The contribution of this paper is therefore twofold:

1. We designed a multiple neural networks architecture that can handle: (i) changes in RSSI values due to user orientation, (ii) failure of base stations.
2. We developed a predictive connection system that is able to speed up the localization process, avoiding time consuming BT inquiries. Adopting such system, we achieved delays below 1 s.

In fact, the NN architecture can cope with the power absorption of the carrier's body and shows high accuracy during a navigation task. The system can provide position estimate with 90% of precision and 0.5 meters of accuracy during a walk. Furthermore, a recovery system based on back-up neural networks improves system performance from 48 to 74% in case a subset of nodes fails (up to 40% node failures).

The reminder of the paper is organized as follows. An overview of the existing solutions for indoor and Bluetooth localization is given in Section II. In Section III we describe the hardware used for our system while Section IV depicts the software architecture. Experimental results are presented in Section V whereas Section VI concludes the paper.

II. Related Work

Several technologies for indoor localization are available and have been proposed over the past few years. Some of them

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are ad hoc technologies (e.g. infrared [3] and ultrasonic technologies [4]) that achieve accuracies in the range of few centimeters; others instead guarantee coarser accuracy such as few meters, however they are standard and therefore easily available everywhere (e.g. wireless technologies such as Wi-Fi, Bluetooth, GSM). WLAN, Bluetooth and ZigBee are the most common among the second category. These technologies are actually available almost everywhere and ensure a cost-effective solution. Bluetooth is the most widespread since it became a standard in consumer short-range wireless devices. Moreover it consumes less power than WLAN and it is easier and less expensive to install.

Three localization methods among others are widely explored in literature: proximity, triangulation or scene analysis (also called fingerprinting). Usually, the proximity method requires a big amount of base stations. In fact the user needs to be close to the base station (within a meter or less in case the technology adopted is RFID [5], [3]). The triangulation and fingerprinting methods are instead widely used with WLAN [6], Bluetooth [7] and ZigBee [8] networks. Triangulation needs at least three base stations to compute user location, while fingerprinting requires two phases: a) an off-line phase in which a database of localization parameters is collected in different positions; b) an online phase where the retrieved data are compared real-time with the database and a location is estimated.

Bluetooth positioning services can be also provided using the inquiry procedure, nevertheless this approach is slow because the inquiry process can take up to 11 seconds, and usually it achieves low resolution. In [9] an inquiry command was issued at two different power levels, in this way it was possible to improve the accuracy up to 2 meters, but the resolution was still unacceptable for many applications. In [10] the authors describe a region-based localization method that employs a probabilistic approach based on inquiry responses. With this method it takes about 5 seconds to update the position, although the time is reduced compared to the default inquiry procedure, many applications, such as an indoor navigation system, would require a higher update rate. In fact, for moving people, the location estimate should be promptly available to represent their actual position.

Other systems adopted RSSI [11], [12] or Link Quality [13] parameter for localization. The RSSI compares the received signal power with two threshold levels, which define the Golden Receive Power Range (GRPR). Positive values of RSSI indicate that the signal strength is above the upper threshold while negative values stands for signal strength under the lower level. A value of zero represents the optimal condition, when the signal strength is between the two thresholds. Link Quality is not well defined in Bluetooth specification but it can be related to the bit error rate. These parameters are well suited for systems based on the fingerprinting and triangulation approach. One of those systems is RADAR [14], the first indoor localization system based on WLAN that introduced the possibility to use Received Signal Strength as a localization parameter. In that case the Nearest Neighbor algorithm was used to compare RSSI values with vectors previously stored in a fingerprinting base. In [7] a direct mapping between RSSI values and distances was established, using this mapping and triangulating results from different base stations, an accuracy of about 2.5 meters was achieved. The main shortcoming of this approach is the high degree of uncertainty of RSSI and Link Quality [15], they are subject to noise and triangulation risks to provide significantly different position estimate even in case of small changes in these parameters. Thus room level precision is often obtained in Bluetooth based localization systems [13, 11, 16].

Neural networks for Bluetooth localization are mentioned in [17] even if just a few details are given. In fact as [18] states, neural networks are not widely used in positioning and localization systems although the noisy environment that characterizes such systems, especially indoor, is well suited for fingerprinting systems based on neural networks. Even when neural networks are adopted for such systems, like in [6] where the author developed a WLAN localization system, no effort has been made to solve the problem given by how RSSI values change depending on user orientation and the result is often a low resolution system.

III. HARDWARE ARCHITECTURE

The overall system is based on (i) the deployment of a certain number of Bluetooth enabled devices distributed in the surrounding, indicated here after as basestations, at least one per room and in large areas one each 20 meters; (ii) a mobile device, Bluetooth enabled, carried by the user to be tracked, (iii) a compass module. As mentioned in section 2, the RSSI value tends to stay within the GRPR. This guarantees the optimal power level needed to reduce battery consumption and typically happens when there is direct line of sight between two nodes. However, the consequence is that the RSSI value is close to zero, which is not desirable for localization purposes. Therefore, this must be considered during the deployment of the nodes in the environment, spreading them sufficiently to avoid line of sight between nodes and therefore to have RSSI values rather different one from the other, which also means to obtain good fingerprints. The mobile node is enriched by an important hardware component: a compass module (HMC6352 by Honeywell) needed to support the multi neural network architecture. In fact, the compass provides information about user orientation, which improves the selection of the most adequate neural network to use, as it will be clarified in the following section.

IV. SOFTWARE ARCHITECTURE

The system exploits Bluecove [19] JSR-82 implementation as Bluetooth stack and RSSI value is provided when the connection is established.

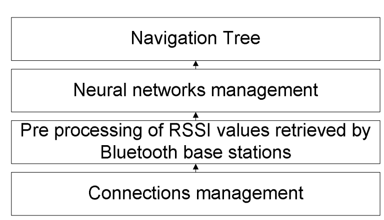

Figure 1. System software architecture

Fig. 1 shows the software architecture of the system. The first layer takes care of the connections with the BT nodes, while the second layer retrieves RSSI values that are then used by the neural networks. The third layer includes the most important contribution of our system, which is the management of multiple neural networks.

The last layer represents the structure of the building in which the localization system is installed. Experimental results show that, by providing such structure to the application, system performance is improved. The third layer includes a recovery subsystem, necessary to cope with the low flexibility of NNs.

A. Connections Management without Inquiry

To provide fast and accurate localization estimates, no inquiry command is issued during the execution, but a predictive connection is used (see Fig. 2) that depends on user orientation and location. In this way, the system tries repeatedly to connect to the nodes the user is approaching, making the connection process faster. The algorithm implemented to perform this process is based on a navigation tree, whose structure reflects the topology of the building in which the nodes are deployed. The branches of the tree connects only positions that in the real environment are contiguous to each other and for which it is possible to move from one to the other (e.g. two positions close to each other but separated by a wall are not connected).

Taking into account user direction of walk, obtained from the compass module, the algorithm can easily determine which nodes the user is approaching. As a result, system performance is significantly improved, widening the range of application in which indoor Bluetooth localization could be employed.

B. Multiple Neural Networks Layer, Architecture and Management

On top of the first two layers (see Fig. 1) we developed the multiple neural network management layer. The benchmark used to test the application concerns indoor navigation where a reliable localization system is necessary to provide the correct directional information to the user. Fig. 4 shows a map of the building used for tests; the gates and the door are critical positions the service must detect. The map shows also the base stations location; as we said before none of them has direct line of sight with each other.

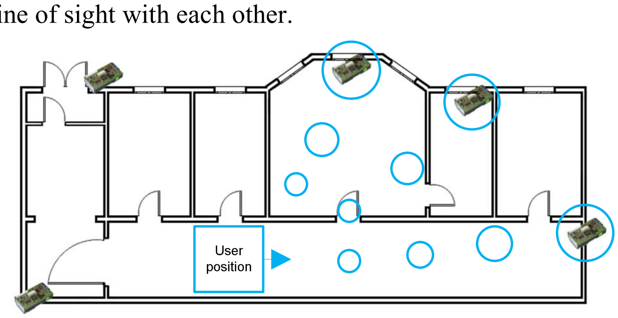

Figure 2. The predictive connections system. The user is moving from left to right potentially approaching the highlighted base stations.

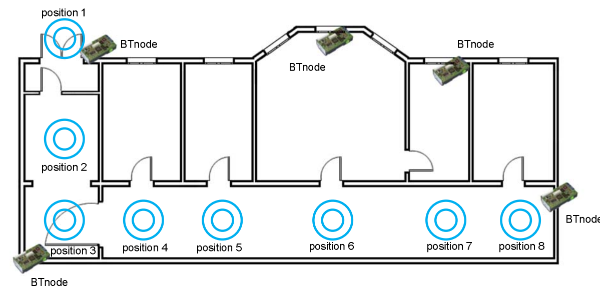

Figure 4. The map of the building in which the system was tested. Blue circles represent the locations that the system is able to detect. Basestations positions are also shown (BTnodes [20] were used as basestations).

Artificial Neural Networks [21] are information processing tools inspired by the learning ability of the human brain. Neural networks can automatically learn the features of inputs and associate them to the appropriate outputs, even if the user is not aware of the correlation between them. Thus they are well suited for RSSI based localization systems. The mathematical model follows the biological one. Synapses are modeled as weights, where the strength of the connection is represented by the value of the weight. The activity of the neuron cell is split into two components. (i) An adder that sums up all the weighted inputs, (ii) an activation function (in our case a sigmoidal function) which controls the amplitude of the output of the neuron (see Fig. 3).

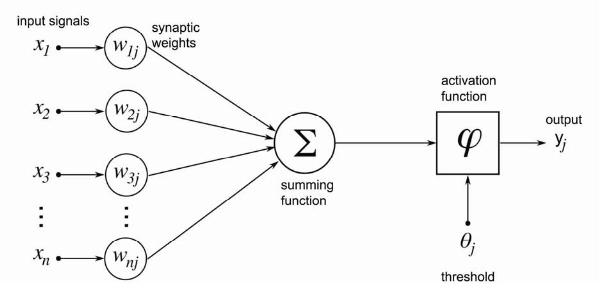

Figure 3. Mathematical model of the biological neuron

The most used type of artificial neural network consists of three layers of units: a layer of input units is connected to a layer of hidden units, which provides information to a layer of output units. In order to train a neural network to perform some tasks, the weights of each unit have to be adjusted to reduce the error between the desired output and the actual output. This process requires that the neural network calculates how the error changes as each weight is increased or decreased slightly. The backpropagation algorithm is the most widely used method for this purpose. Backpropagation is a supervised learning method, thus, it requires a learning phase in which it is necessary to know the desired output for any given input. In this way the neural network can learn how to perform. In our case the output of the function is a position among the set that we decided (see Fig. 4). Goal of the network is the classification of the input data, generalizing from the training data to unseen situations. The number of input nodes is a design choice and depends on the number of BT basestations deployed in the environment. Since the RSSI values retrieved during a connection are unstable, an update frequency of 80 Hz is used to address the unpredictable variation of RSSI by averaging buffers of eight consecutive elements. After collecting eight consecutive averages for each base station we had 40 values, which correspond to 40 input nodes for each neural network. The output nodes number depends on how many different positions the system can discriminate. In our case 8 nodes are used to detect 8 different positions. The number of hidden units in the neural network can be determined with the following equation:

$$\#HiddenNodes = \frac{\#InputNodes + \#OutputNodes}{2} \quad (1)$$

The last part of the procedure requires to determine which paths can be taken by users during a route. Finally, different network for each path can be trained.

As already remarked, a localization procedure based on the fingerprinting approach requires two phases. During the offline phase we collected RSSI data at about 80 Hz when a connection is established. Those values were collected performing different routes to train, and then use, different NN. The importance of this step is straightforward once we take a look at RSSI data retrieved in the same position but changing the orientation. In fact, Fig. 5 shows that the RSSI values are strongly dependent on user orientation. From this figure, it is also easy to understand why triangulation gives poor resolution in Bluetooth systems. These values varies in a small range (about twenty integer values), therefore it is not possible to use a single neural network trained collecting data in different directions, unless the number of positions discriminated is decreased significantly. On the other hand, the online phase corresponds to the execution of the system. In this phase we retrieve RSSI data and process it in the same manner we did during the offline phase, however this time the data is used as input for the neural networks previously trained. If a base station is too far from the user a value of 1 is assigned to the input node of the neural network. The network that will be adopted is chosen depending on the orientation given by the compass module. Experimental results obtained during this phase are shown later in this paper.

C. Navigation Tree

The navigation tree data structure, mentioned in Section IV is employed to improve system performance. In fact, the output provided by the Multiple Neural Networks (MNN) layer can be either directly used as a position or given as an input to the navigation tree.

If the latter option is employed, the system returns the user position as follows. By default, the NN that is currently activated provides a current output position, which is cross checked by the navigation tree and validated only if corresponds to a position possible in the tree structure considering the previous position (therefore if a branch between the current and the previous position exists). Moreover, the position is changed only if the NN gives the same output for at least n consecutive values.

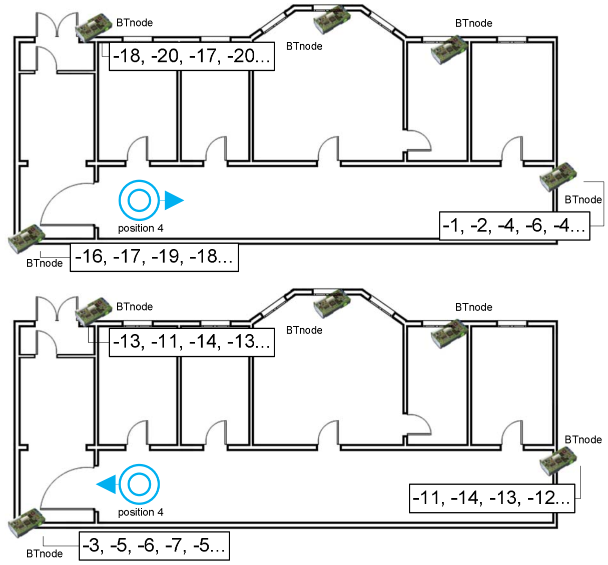

Figure 5. Differences in RSSI values depending on user orientation

This first control aims at improving the robustness and accuracy of the recognition. Using the tree instead of the direct output of the NN avoids jumping between positions that are not connected with each other, situation that can happen due to very noisy measurements or due to classification errors. However in parallel to what we described, the system performs a second control considering k consecutive values, where k is bigger than n (e.g. k=20, n=5).

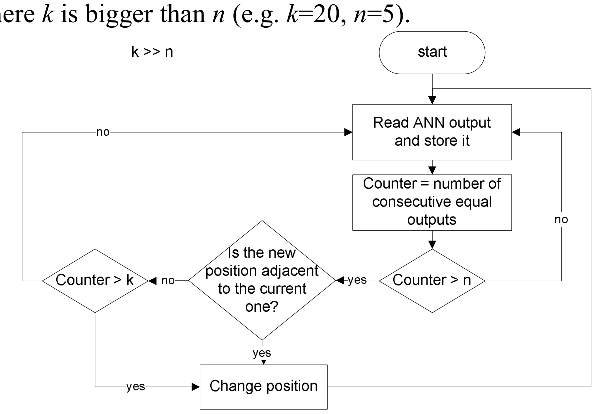

Figure 6. Different ways in which the system can change the current position

The position determined by these k values is accepted, even if violates the contiguity with the previous position in the navigation tree. The goal of this mechanism is to correct potential errors done by classifying the position on n values only. In fact, in case the system fails in recognizing a position and in the meanwhile the user is still moving, it can happen that she/he reached a position considered impossible in the navigation tree (e.g. the user is two positions away from the last correct position). Therefore, the second control is used to avoid the risk for the system to get stuck. Of course, this control is slower than the first one, requiring a higher number of equal consecutive values (see flow chart in Fig. 6).

D. The Recovery Subsystem

A well known problem of neural networks is the low flexibility. The result obtained during the execution and all the classification process that is performed by the networks is strongly dependent on the values retrieved by each node. A change in the input structure, for example due to a node failure, will probably cause an error in the detection of the user location. This problem has been addressed by the development of a solution based on back-up NNs: firstly we trained more neural networks, each of them with a different configuration (e.g. turning off a different node) and then we implemented a system able to activate the correct neural network in case a node failure is detected. In this way it was possible to keep the system operating even with 60% active nodes (i.e. 3 out of 5). The system performance is reduced but significantly improved with respect to the results provided by a system without a recovery mechanism. The detection of the failure of one or more node is handled by a software component that every *n* RSSI samples determines the status of the Bluetooth network, depending on the current position of the user and RSSI values.

V. EXPERIMENTAL TESTS IN A NAVIGATION TASK

In this section we present results of experimental tests. The building in which they were run as well as the base stations positions is shown in Fig. 4. The tests aim at detecting three proprieties of the system: precision, accuracy and time of response. Precision is the probability to obtain the right response during repeated tests in two different modalities, standing still within a location and walking. Accuracy is determined as standard deviation:

$$\sigma = \sqrt{\frac{\sum (Valr - Vale)}{n}} \qquad (2)$$

Where *Valr* represents the value, hence the position, determined by the localization system, while *Vale* is the actual position of the user over *n* measurements. Time of response is the time necessary for the system to detect the new user position and update the current status.

Fig. 7 and 8 show the differences in precision and accuracy that was obtained using: 1) a neural network trained while walking (walking speed: 3 km/h) in different directions, hence assuming different orientations, without the navigation tree layer and 2) with the navigation tree layer, 3) Our multiple neural networks (MNN) system without the navigation tree and 4) with the navigation tree. MNN permits to distinguish with high degree of accuracy between 8 positions in a corridor 20 meters long. This result would be impossible to achieve adopting a classic fingerprinting method, based on just a NN, due to the high variability of the RSSI. In fact, as it is shown in Fig. 7, the MNN system is able to localize correctly the user 89% of the times while a single NN works properly only 55% of the times. System accuracy is also improved from 1.4 to 0.5 meters on the average. Note that, low values of accuracy (in meters) means better performance since a result equal to zero corresponds to a precision of 100%. If the user is standing still in one of the positions the precision of the MNN system reaches 100%. Performance is slightly reduced if the user is walking. The time of response is computed as the time necessary for the system to detect that the user reached a new position. Therefore it is not related to the update frequency of the system, which is dependent on the high frequency of the RSSI values retrieved from the nodes.

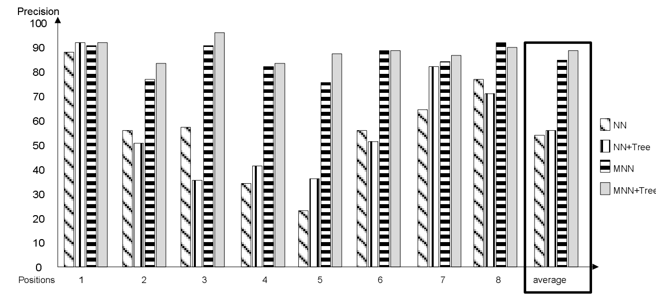

Figure 7. Improvement in precision adopting the MNN system (NN:standard method with one neural network, NN+Tree: standard method and navigation tree, MNN: multiple neural networks system, MNN+Tree: multiple neural networks system and navigation tree).

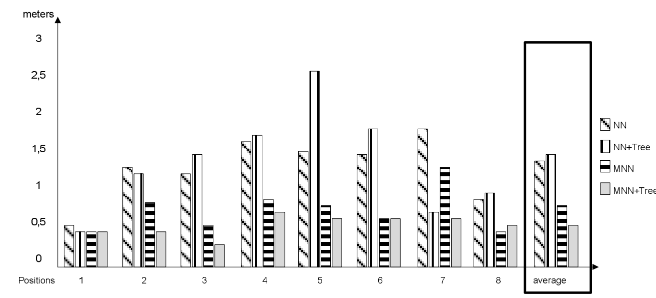

Figure 8. Improvement in accuracy adopting theMNN system (same legend as in Fig. 7).

The average time of response is 0.88 seconds, the high degree of accuracy of the system and the fast time of response made the system suitable for an indoor navigation setup (see Fig. 9).

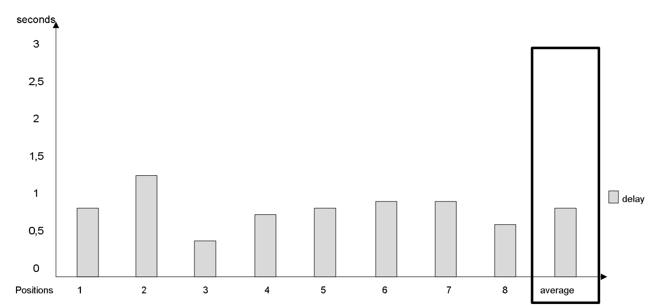

Figure 9. System delays (in seconds) during a walk

A. *Recovery System Results*

Experiments were performed to assess also the third layer of the system architecture, which includes a recovery subsystem, essential to cope with the low flexibility of neural networks. To point out the importance of this mechanism Fig. 10 and 11 show the output of the system in the worst case, which is when two nodes fail. The result is that system performance drops and positioning engine cannot distinguish properly several positions. In fact, positions 2, 3, 4 and 7 reach a precision of 0%, with accuracy above 2.5 meters in the worst case. Adopting our recovery system, based on NN trained in limited conditions, performance is improved significantly, even though, obviously, not reaching the level we had with the optimal configuration. Precision is actually increased up to 26 percentage points while accuracy is close to the optimal value.

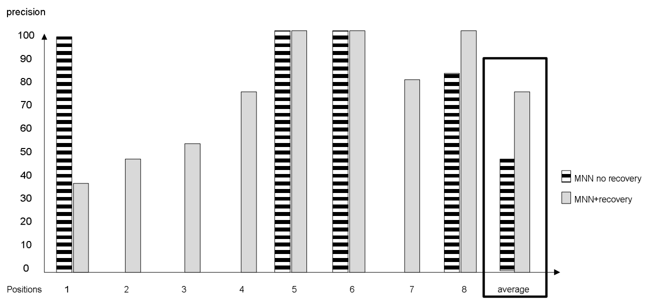

Figure 10. Improvements in precision due to the recovery subsystem

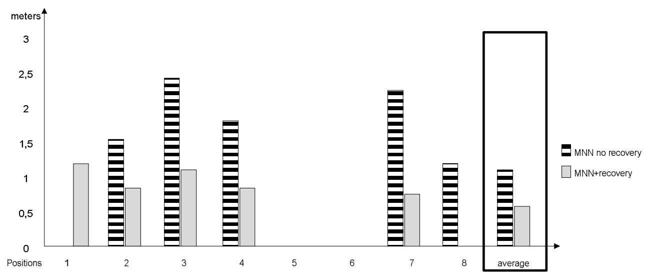

Figure 11. Improvements in accuracy due to the recovery subsystem

VI. CONCLUSIONS

In this paper, a low-cost Bluetooth based localization system has been proposed. We introduced a novel approach based on multiple neural networks. The most suitable one is automatically selected and loaded by the system depending on user orientation, estimated with a compass. In this way, the system copes with the power absorption of the human body, achieving higher accuracy. In fact, taking into account the user orientation during both training phase and use, we proved that the indoor user tracking improves significantly. Using a few basestations and common office devices such as a laptop and a PDA, we obtained results significantly better than the current state of the art, where Bluetooth systems are usually limited to room level localization [10, 11]. Our results show that the system could be employed in a navigation task, where high degree of confidence on the localization is necessary to reach the expected destination. 90% of precision and 0.5 meters of accuracy were achieved during a walk along the corridor. Moreover a recovery system able to improve system performance in case of base stations failure has been implemented. It increases the accuracy of the system from 48% to 74% even when only 60% of the original deployed nodes are active.

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