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Multi-Layer Perceptron Neural Network and Nearest Neighbor Approaches for Indoor Localization

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***Abstract*—Most range-free techniques for indoor localization depend on the received signal strength (RSS) fingerprints. Their performances are relied to the structure of the considered indoor environments. We consider in this paper RSS-based methods: Multi-Layer Perceptron Neural Network (MLPNN), and K-nearest neighbor (KNN), and compare their performance under the same indoor environment. One of the advantages focused by the choice of these techniques is their robustness against external disturbances that may affect the received RSS signal. Moreover, we propose a new metric to enhance the performance of the KNN method, called δ-nearest neighbor. In order to test the different techniques, we build a heterogeneous fingerprint database with different resolutions. The obtained results show the efficiency of the proposed enhancement in the case of a heterogeneous high resolution database.**

I. Introduction

In the last decade, many researches contributed to develop and to adapt the artificial neural network concepts to practical applications. MLPNNs have proved their efficiency and robustness in many research fields and they can be applied to a wide variety of problems. The choice of MLPNN is motivated by its characteristics of universal approximation of nonlinear continuous functions [1][2]. MLPNNs can be used to model a sensor node, or the node's dynamics, and interconnections with other sensor network nodes, in the case of fault detection in wireless sensor networks [3]. Numerous applications are in breast cancer detection [4], classification of satellite imagery [5], image compression [6], stock market prediction [7], etc. It is known that generating data for learning is not a secondary task and it is very important for the localization. Indeed, having a diversified and enough data allows to make learning efficient to meet the target location with a good precision. The rest of the data cannot be used to achieve the learning due to their low representativeness of the dynamics of the wireless sensor network and its environment. Knowing the position of a wireless sensor allows to have an idea about the credibility of the measure that it provides. Then, it would be easier to communicate with a localized sensor and request it for measures.

Location-based applications and services (LBA, LBS) have become very important thanks to the substantial increase in the number of mobile terminals such as smart phones and network devices. Positioning systems and range-free software approaches are not linked to the infrastructure where they will be installed in the indoor environments. On the contrary, the available positioning systems on the market, like Cricket [8], AwareMedia and AwarePhone [9], need specialized hardware requirements or installation of added infrastructure to perform the localization process.

A direct consequence of the range-based coordinate clustering method for indoor location presented in our previous work [10] is the need for a positioning system that overcomes the limitation caused by the blind or dead zone where the mobile terminal cannot be localized.

A comparative study using several techniques has been done in [11]. Nevertheless, these techniques have been applied in different environments equipped with different numbers of access points. In the literature there is no objective study applying these several techniques on the same test-bed. Hence, the need for an objective comparison between different methods of indoor localization.

We can summarize the objectives of this work in these points:

- Experiment and compare two range-free positioning techniques: artificial neural network (MLPNN) technique and K-nearest neighbor (KNN) technique, on the same test-bed;
- Propose a new metric for the nearest neighbor technique called δ-nearest neighbor;
- Study heterogeneous fingerprint database influence on the performance of the localization method.

This paper is organized as follows. The problem formulation is presented in section II. Then, section III is dedicated to the proposed MLPNN-based algorithm for indoor localization and the experimental results. K-nearest neighbor algorithm and its experimental results are presented in section IV. The comparison of these two range-free techniques is figured in section V. We conclude this paper in section VI.

II. Problem formulation

Range-free techniques provide an alternative solution to localize the mobile terminal in critical blind areas because most range-free techniques use fingerprint-based methods: for example RSS-based localization technique exploits the signal propagation of WLAN [12]. This class of systems is based

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on two main phases, offline phase and online phase. During the offline phase, a fingerprint database is built by collecting data throughout the considered indoor environment. Then, to retrieve a position we look for the nearest fingerprint according to a chosen metric. Fig (1) illustrates the two phases, offline and online, of a fingerprint-based localization system.

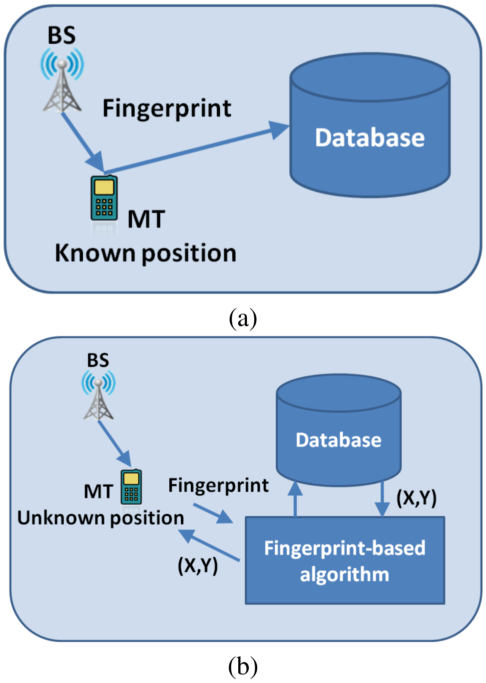


Fig. 1. Fingerprint-based system phases: (a) Offline phase and (b) Online phase.

In the following, we present the case study and the used algorithm to collect fingerprints and to build the database.

A. Case study

Hospitals, museums, libraries, or any closed environment where GPS signal is not available anymore, are considered as case studies for indoor localization process. Several base stations or WLAN access points are distributed to cover the area of the case study at hand. Unfortunately, WLAN signals are scattered, diffracted, or reflected by existing obstacles: walls, furniture, and even by moving people. Therefore, fingerprint values vary significantly from day to day and also from hour to hour. Afterwards, regular updates can be performed on this fingerprint cartography, particularly in the case of adding (activating) or removing (deactivating) WLAN access points, idem in the case of change in the inner structure of the case study.

Several works in the literature proposed different test-beds to realize their experiments (see Table I). Each test-bed has different total area, number of base stations (or WLAN access points), and number of fingerprint locations and orientations. Therefore, the fingerprint density is calculated as the total area divided by the number of locations and represents the area covered by a single fingerprint. Obtained results strongly depend on the fingerprint density, thus, high fingerprint density implies high accuracy and good performance. For example, a fingerprint density of $39\ m$ provides an average distance between fingerprints of $6.2\ m$, while a fingerprint density of $9\ m$ yields a distance of $3\ m$. An error of $6.2\ m$ represents at worst the location of the nearest base station to the actual location. Table (I) lists some test-beds presented in previous researches and compares their total area, number of fingerprints, and fingerprint density.

B. Fingerprint collection

The step of fingerprint collection involves scanning all channels in the WLAN spectrum to identify all available base stations (access points APs). Fingerprint collection also requires the time correlated sampling of the WLAN band to build a robust image of the signal strength characteristics of APs. Some programs were developed, called RSSI Loggers, to handle the fingerprints collection process. Two main methods allow to obtain a fingerprint in a specific place. The first method is simple and manual; we leave to the specific location and capture WLAN signals during a period of time until the acquiring fingerprint becomes stable. Different orientations (north, south, east, and west) lead to register different fingerprints for the same location. The second method consists in applying a path loss model used for indoor propagation, taking into account the existing obstacles, as shown in (1) [17]:

$$P(d) = P(d_0) - 10\alpha \log(\frac{d}{d_0}) + \sum_{i=0}^{M} n_i R_i + \sum_{i=0}^{N} n_i T_i \quad (1)$$

where R_i and T_i are the attenuations introduced during the reflections and transmissions through the material i existing in the environment. In this model, we consider M different materials on which there is at least one reflection, and N different materials through which we have at least one transmission. The optimal parameters (α, R_i and T_i) that characterize the environment can be found by solving the following minimization problem (2):

$$[\alpha, R_i, T_i]^{opt} = \arg\min_{\alpha, R_i, T_i} (A - B)^2 \quad (2)$$

where:

$$A = P(d) - P(d_0) + 10\alpha \log(\tfrac{d}{d_0})$$

and

$$B = \sum_{i=0}^{M} n_i R_i - \sum_{i=0}^{N} n_i T_i$$

The advantage of the first method is to collect real fingerprints but in limited physical locations, while the second method can generate more theoretical fingerprints and calibration to quickly build the database [18].

Our strategy to build the fingerprint database is divided into four steps:

TABLE I
LOCALIZATION TEST-BED AND FINGERPRINT DENSITY.

Study	Area (m^2)	Number of locations	Fingerprint density	fingerprint spacing (m)
[13]	2160	56	1:39	6.2
[14]	540	62	1:9	3
[15]	1768	110	1:16	4
[16]	940	49	1:19	4.4

- for each base station, collecting the available measurements, such as RSS and RTT;
- correction process for the blind and dead zones in the test-bed;
- normalization procedure to have fingerprint values in the interval $[0, 1]$;
- the fusion step to build heterogeneous fingerprints composed of received signal strength (RSS) and round-trip time (RTT).

Fig (2) illustrates our approach to collect signals and to build the whole fingerprint database.

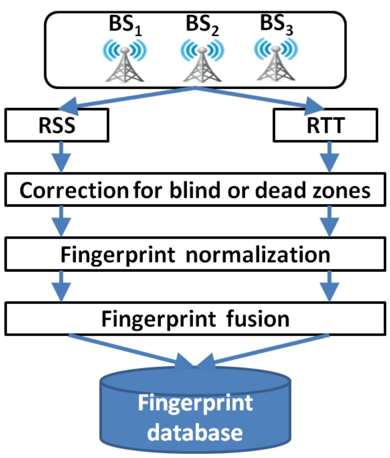


Fig. 2. Procedure of building fingerprint database.

III. PROPOSED MLPNN-BASED ALGORITHM FOR INDOOR LOCALIZATION

Artificial neural networks have been introduced in indoor localization field. The results indicate that MLPNN-based positioning systems can provide accuracy and precision, which is quite adequate for the development of indoor location systems (ILS), while using the already available WLAN infrastructure. The reason for selecting MLPNN is its robustness against noise and interference which are major factors affecting the accuracy of ILS [19].

Once the fingerprint database has been built (offline phase), a new fingerprint database with Gaussian additive noise is constructed to evaluate the performance of our MLPNN-based algorithm. Then, the MLP network is ready to be figured with optimal parameters, such as the number of hidden layers, the number of hidden units in each hidden layer, the activation function, the training iterations, etc. To do so, we take the fingerprint database as input of the MLP network and desired outputs are provided when using a supervised training method. The learning procedure with given MLP parameters, is launched. At the end of the learning procedure, we test the obtained MLP on a noisy fingerprint database. Depending on the achieved performance, modifications to the MLP network parameters are done. The fitting procedure is stopped when there is no improvement on the performance. Fig (3) illustrates the proposed MLPNN-based algorithm to solve the indoor localization problem.

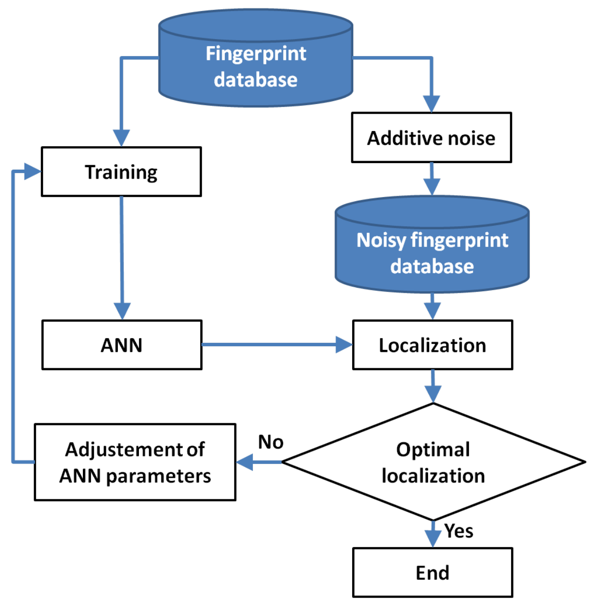


Fig. 3. MLPNN indoor localization algorithm.

A. MLPNN experimental results

To perform experiments for MLPNN technique (and later for KNN technique), and to compare the achieved results and performances, we selected a test-bed that corresponds to a real indoor environment. To compare the results with those obtained in our previous study (coordinates clustering), we have to choose the same indoor environment designed in [10]. As mentioned before, the case study is a simulated environment with an area of (17×10) m^2 created by Radiowave Propagation Simulator (RPSim) software [20]. Multiple rooms with different sizes, and a big hall connected by a long corridor have been designed. Walls and furniture scatter the ray tracings, as well as the floor and the ceiling. It is a typical example of an indoor environment. Complex indoor environments could be designed by joining multiple simple indoor environments. In addition, RPSim software allows to produce fingerprint cartography with different densities easily, and provides different useful measurements for indoor localization process as RSS (in dBm) and RTT (in nsec).

Our fingerprint database was constructed based on the fingerprint pattern presented in Fig. (4)

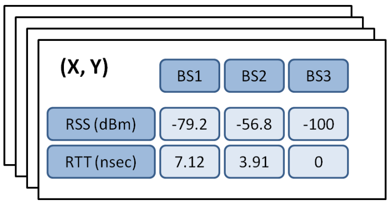


Fig. 4. Fingerprint pattern database.

The couple $(RSS = -100\, dBm, RTT = 0\, nsec)$ describes the dead or blind zones, while the couple $(RSS = -100\, dBm, RTT = 0\, nsec)$ describes the very close zone to the active BS, for this reason the delay spread is considered as null. Fig. (5) (a) illustrates the RSS covered area in our test-bed for BS_1.

Two fingerprint databases with different resolutions were built using RPSim. The first database contains 153 physical location fingerprints with a resolution of $1\ m^2$, while the second database is built by using 2448 physical location fingerprints with a resolution of $25\, cm^2$.

Experiments have been performed by applying a superposition of the three BS_s (BS_1, BS_2, BS_3), and using a feed forward neural network model (MLP).

Table (II) summarizes the different parameters of the used MLP model.

TABLE II
MAIN ELEMENTS OF THE FEED FORWARD NEURAL NETWORK MODEL.

Description	Default value
The fingerprint database	(RSS_1, RSS_2, RSS_3)
The real physical positions	(x, y, z)
For one hidden layer	40 neurons
For two hidden layers	20 neurons for each layer
The transfer function	Hyperbolic tangent

1) Impact of hidden layers number: At the first time, experiments were done using a feed forward neural network model with one hidden layer. Obtained results are in Table (III). It is clear that the best performance is achieved when all the base stations are active. On the other hand, the worst performance is registered for RSS_3 fingerprints that come from BS_3. One can see that the combination of more than one RSS value allows to have distinguishable fingerprints, and better performance. The best performance is around $70\ \%$ within $1\ m$ distance error using RSS_{123} fingerprints of the three active BS_s. It means that 70% of the tested fingerprints are localized within a circle centered on the real position of the fingerprint, and the radius of this circle is $1\ m$.

To study the impact of the number of hidden layers, we choose MLP network with two and four hidden layers with the respect of the total number of hidden neurons, that means that 40 neurons in all MLP models are used in these experiments. In Table (IV), one can see that the significant improvement in performance takes place only in combination of two RSS values RSS_{12}, RSS_{13}, and RSS_{23} fingerprints. Comparing to the obtained results using MLP with only one hidden layer, the performance for RSS_{12} fingerprints attains 35.48% within $1m$ distance error, while the performance using MLP with two hidden layers attains $43.05\ \%$ within the same distance error. Idem for RSS_{13} and RSS_{23}, where the achieved performance is $42.98\,\%$, and $39.53\,\%$ using one hidden layer. The achieved performance is $58.08\,\%$ and $48.61\,\%$ using two hidden layers respectively with the same distance error $1\, m$.

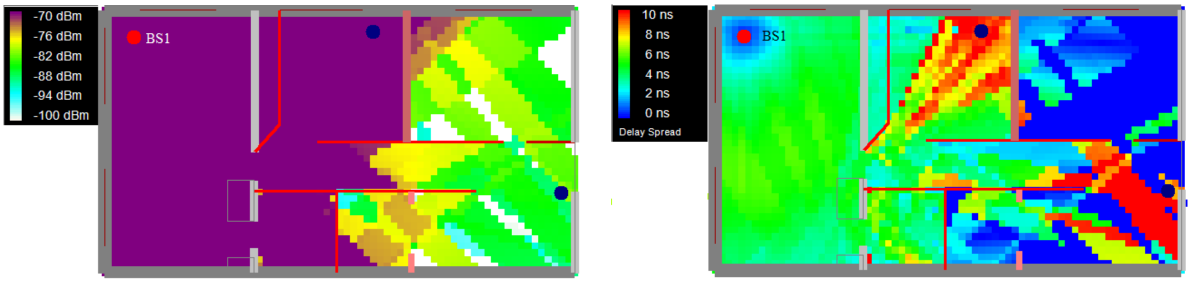
2) Impact of heterogeneous fingerprints: Received signal strength is not the only available information on the base station side. Other information as RTT could be useful for localization process. Although RTT values are very different from those of RSS, the couple (RSS, RTT) is a more distinguishable fingerprint. For each active base station a couple of information $(RSS_i,\ RTT_i)$ $i \in \{1,\ 2,\ 3\}$ represents a fingerprint. The input layer contains two, four, or six neurons according to the active base stations, while the hidden and the output layers remain as described in Table (II). Table (V) summarizes the obtained results of MLP with one hidden layer. As expected, the best result $85.41\,\%$ within $1\, m$ distance error is obtained for three active base stations.

3) Impact of fingerprint database resolution: Then, the impact of MLPNN variants has been studied using the same fingerprint database with 2448 samples (resolution of $25 cm^2$). The database resolution effect was also studied.

To show the impact of the database resolution, another fingerprint database with 153 samples (resolution of $1\ m^2$) was built. The experiments have been made by applying MLPNN technique with one hidden layer using homogeneous fingerprints (RSS_1, RSS_2, RSS_3). Fig (6) illustrates the obtained results and proves the superiority of large size fingerprint database. A straightforward remark can be made: the significant improvement of the performance of MLPNN technique.

IV. PROPOSED KNN-BASED ALGORITHM

KNN technique approximates the mobile terminal location in an indoor environment, depending on the fingerprint database that is constructed in the offline phase. Using the current fingerprint, transmitted by the mobile terminal, the KNN technique searches for the K-nearest matches in the initial fingerprint database. Neighbors are defined according to a chosen metric or a distance function in the fingerprint space. In [21], authors introduced a novel approach to learn the distance function that maximizes the clustering of objects (fingerprints) belonging to the same class, using a traditional 1-NN classifier and a compressed one called NCC, that uses the learnt distance function and cluster centroids instead of all the points of a training set. Table (VI) summarizes the distance functions between two fingerprints (RSS_1, RSS_2, ..., RSS_n)



(a) (b)

Fig. 5. Covered area in our test-bed for BS_1: (a) RSS coverage and (b) RTT spread.

TABLE III
THE PERFORMANCE OF MLPNN TECHNIQUE USING ONE HIDDEN LAYER.

Accuracy	RSS_1	RSS_2	RSS_3	RSS_{12}	RSS_{13}	RSS_{23}	RSS_{123}
$Acc <= 25\ cm$	1.44 %	0.39 %	0.11 %	3.91 %	4.36 %	3.66 %	9.79 %
$Acc <= 50\ cm$	4.96 %	2.04 %	1.02 %	13.69 %	14.11 %	13.34 %	29.81 %
$Acc <= 75\ cm$	11.37 %	5.28 %	2.89 %	24.39 %	27.81 %	26.33 %	52.13 %
$Acc <= 1\ m$	18.3 %	9.47 %	5.88 %	35.48 %	42.98 %	39.53 %	70.29 %

TABLE IV
THE PERFORMANCE OF MLPNN TECHNIQUE USING TWO HIDDEN LAYERS.

Accuracy	RSS_1	RSS_2	RSS_3	RSS_{12}	RSS_{13}	RSS_{23}	RSS_{123}
$Acc <= 25\ cm$	1.51 %	0.74 %	0.28 %	5.14 %	7.43 %	6.48 %	11.33 %
$Acc <= 50\ cm$	4.72 %	2.53 %	1.09 %	16.83 %	24.78 %	20.27 %	35.2 %
$Acc <= 75\ cm$	10.84 %	6.2 %	3.56 %	31.5 %	42.59 %	35.73 %	56.88 %
$Acc <= 1\ m$	18.34 %	10.52 %	6.62 %	43.05 %	58.08 %	48.61 %	71.28 %

TABLE V
THE PERFORMANCE OF MLPNN TECHNIQUE USING (RSS, RTT) HETEROGENEOUS FINGERPRINTS AND ONE HIDDEN LAYER.

Accuracy	$RSS_1 RTT_1$	$RSS_2 RTT_2$	$RSS_3 RTT_3$	$RSS_{12} RTT_{12}$	$RSS_{13} RTT_{13}$	$RSS_{23} RTT_{23}$	$RSS_{123} RTT_{123}$
$Acc <= 25\ cm$	1.51 %	1.09 %	0.99 %	3.31 %	5.46 %	5.17 %	11.66 %
$Acc <= 50\ cm$	5.21 %	4.26 %	3.7 %	12.88 %	19.18 %	16.3 %	34.26 %
$Acc <= 75\ cm$	11.47 %	8.87 %	8.1 %	25.94 %	34.78 %	30.1 %	59.34 %
$Acc <= 1\ m$	19.39 %	15.38 %	13.62 %	36.61 %	49.63 %	44.03 %	85.41 %

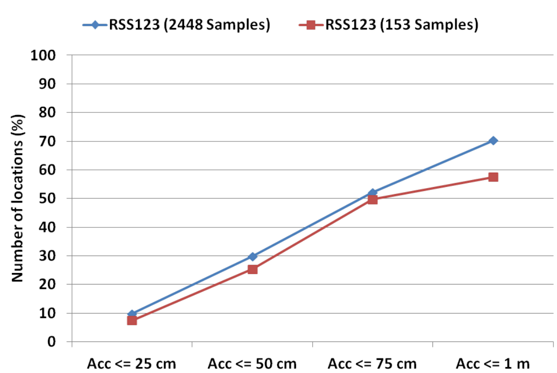


Fig. 6. Illustration of the MLPNN performance with one hidden layer, using different database resolutions (2448 samples with resolution of 25 cm^2, and 153 samples with resolution of 1 m^2).

and $(RSS'_1, RSS'_2, ..., RSS'_n)$ where n is the number of base stations.

To optimize the location process, least mean square (LMS) method is used. Then, the estimated location of the MT is obtained by averaging the location candidates. Choosing an appropriate value of the parameter K affects the performance of this technique. If $K = 1$, then the MT location is simply assigned to the location candidate of its nearest neighbor, referred also by closest neighbor (CN). In [22], the authors use the analysis of the fingerprint structure to identify and eliminate bad location fingerprints stored in the fingerprint database.

The same constructed fingerprint database for MLPNN technique (see section II-B) is used to perform the indoor localization process based on KNN algorithm. To evaluate the algorithm performance, a noisy fingerprint database is derived from the original one by adding Gaussian noise. Multi-output procedure has been developed to obtain experimental results for all variants of KNN algorithm, by varying parameters such as the number of neighbors K, the chosen metric δ, the heterogeneous fingerprints, and the database resolution. Fig (7) illustrates our KNN algorithm to perform the indoor

TABLE VI
DISTANCE FUNCTIONS BETWEEN TWO FINGERPRINTS: (RSS_i) AND (RSS'_i), $1 \leq i \leq n$.

Distance	Parameter	Function
Manhattan	1-norm distance	$\sum_{i=1}^{n} \lvert RSS_i - RSS'_i \rvert$
Euclidean	2-norm distance	$\left(\sum_{i=1}^{n} (RSS_i - RSS'_i)^2 \right)^{1/2}$
Minkowski	p-norm distance	$\left(\sum_{i=1}^{n} (RSS_i - RSS'_i)^p \right)^{1/p}$
Tchebychev	∞-norm distance	$\lim_{p \to \infty} \left(\sum_{i=1}^{n} (RSS_i - RSS'_i)^p \right)^{1/p} = \sup_{1 \leq i \leq n} \lvert RSS_i - RSS'_i \rvert$
Mahalanobis	σ-norm distance	$\left(\sum_{i=1}^{n} \frac{(RSS_i - RSS'_i)^2}{\sigma^2} \right)^{1/2}$

localization process.

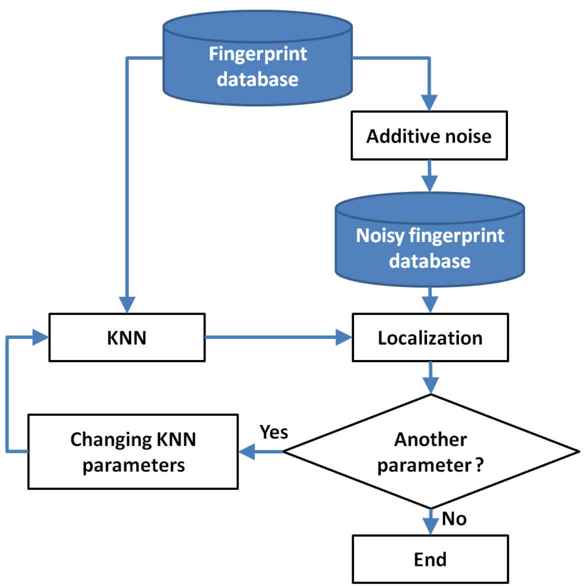


Fig. 7. KNN-based indoor localization algorithm.

A. KNN-based experimental results

To illustrate the performance of the KNN-based indoor localization technique, we show the results on different fingerprints. Experiments have been performed by applying superposition of three BS_s (BS_1, BS_2, BS_3). In the following, we discuss the impact of the nearest neighbor number K, the chosen metric δ-nearest neighbor, the heterogeneous fingerprints, and the database resolution. In all tests, we consider the Euclidean distance defined in Table (VI) to denote neighbors of the fingerprint at hand.

1) Impact of nearest neighbor number K: It is obvious that $K = 1$ is an easy choice of the critical parameter K of the nearest neighbor technique, called also the closest neighbor (CN). Obtained results are shown in Table (VII). For different lengths of the fingerprints in our database, the 1-NN proves its good performance, particularly, for the triplet fingerprints (RSS_1, RSS_2, RSS_3) 1-KK attains $57.16\ \%$ within $25\,cm$ distance error, and $87.68\,\%$ within $1\,m$ distance error. However, the worst performance, $16.33\ \%$ within $1\ m$ distance error, is obtained from the fingerprints of BS_3. In fast revision of these RSS_3 fingerprints, we noticed slight differences between them, due to the uniform coverage of RSS throughout the test-bed when BS_3 is active.

For $K = 3$ the experimental results are presented in Table (VIII). Thanks to the high fingerprint density in our database, the results obtained for $K = 1$ and $K = 3$ are close. For a lower fingerprint density, the best performance has been achieved for $K > 1$.

2) Impact of the chosen metric: δ-nearest neighbor (δ-NN): In this experiment, we denote by δ_{RSS} the radius of the circle whose center is the fingerprint at hand RSS. δ_{RSS} is a percentage of a fingerprint value, for example $\delta_{RSS} = 3$ means $3\,\%$ of the actual fingerprint value RSS. δ-nearest neighbor is every fingerprint situated within this circle. However, δ_{RSS} strongly depends on the fingerprint density. In the worst case, whereas no neighbors are found in the δ_{RSS}-circle, the mobile terminal is not "localizable". The obtained results for $\delta_{RSS} = 3$ and $\delta_{RSS} = 10$ are presented in Tables (IX) and (X) respectively. For these results, one can notice that smaller δ_{RSS} implies better performance, because only close fingerprints participate in the localization process.

3) Impact of heterogeneous fingerprints: As seen in (III-A2), we use the available information RSS and RTT to form one heterogeneous fingerprint. Experimental results in Table (XI) show the best performance for the heterogeneous fingerprint database.

4) Impact of fingerprint database resolution: The impact of KNN variants has been studied using the same fingerprint database with 2448 samples (resolution of $25\,cm^2$). We have also tested the database resolution effect.

To show the impact of the database resolution, another fingerprint database with 153 samples (resolution of $1\ m^2$) was built. The experiments have been made by applying KNN technique with $K = 3$, using homogeneous fingerprints

TABLE VII
THE PERFORMANCE OF KNN TECHNIQUE USING EUCLIDEAN DISTANCE METRIC AND ($K = 1$).

Accuracy	RSS_1	RSS_2	RSS_3	RSS_{12}	RSS_{13}	RSS_{23}	RSS_{123}
$Acc <= 25\,cm$	6.12 %	4.82 %	4.58 %	30.41 %	28.16 %	29.88 %	57.16 %
$Acc <= 50\,cm$	10.14 %	8.34 %	7.81 %	41.85 %	42.59 %	41.64 %	71.56 %
$Acc <= 75\,cm$	15.8 %	14.36 %	12.57 %	52.41 %	55.16 %	53.22 %	81.91 %
$Acc <= 1\ m$	21.72 %	19.18 %	16.33 %	59.52 %	65.26 %	61.77 %	87.68 %

TABLE VIII
THE PERFORMANCE OF KNN TECHNIQUE USING EUCLIDEAN DISTANCE METRIC AND ($K = 3$).

Accuracy	RSS_1	RSS_2	RSS_3	RSS_{12}	RSS_{13}	RSS_{23}	RSS_{123}
$Acc <= 25\,cm$	1.94 %	1.16 %	0.67 %	20.49 %	17.74 %	19.25 %	44.63 %
$Acc <= 50\,cm$	6.62 %	4.61 %	3.03 %	38.01 %	37.56 %	37.91 %	71.35 %
$Acc <= 75\,cm$	11.83 %	8.59 %	6.09 %	49.95 %	53.71 %	50.65 %	82.75 %
$Acc <= 1\ m$	18.09 %	13.23 %	9.86 %	58.68 %	65.75 %	61 %	89.41 %

TABLE IX
THE PERFORMANCE OF δ-NN TECHNIQUE USING $\delta_{RSS} = 3\%$ EUCLIDEAN METRIC.

Accuracy	RSS_1	RSS_2	RSS_3	RSS_{12}	RSS_{13}	RSS_{23}	RSS_{123}
$Acc <= 25\,cm$	0.92 %	0.74 %	0.42 %	7.99 %	7.95 %	8.98 %	20.73 %
$Acc <= 50\,cm$	4.29 %	2.18 %	1.34 %	22 %	23.83 %	24.01 %	51 %
$Acc <= 75\,cm$	10.38 %	5.56 %	2.96 %	36.25 %	42.1 %	39.85 %	73.64 %
$Acc <= 1\ m$	16.83 %	9.68 %	6.16 %	47.03 %	57.51 %	52.69 %	85.04 %

TABLE X
THE PERFORMANCE OF δ-NN TECHNIQUE USING $\delta_{RSS} = 10\%$ EUCLIDEAN METRIC.

Accuracy	RSS_1	RSS_2	RSS_3	RSS_{12}	RSS_{13}	RSS_{23}	RSS_{123}
$Acc <= 25\,cm$	1.44 %	0.53 %	0.42 %	3.24 %	3.48 %	4.82 %	8.38 %
$Acc <= 50\,cm$	4.12 %	1.9 %	1.3 %	11.44 %	12.53 %	14.33 %	26.43 %
$Acc <= 75\,cm$	9.19 %	4.68 %	2.96 %	21.93 %	25.94 %	25.98	45.23 %
$Acc <= 1\ m$	15.95 %	8.76 %	5.95 %	33.37 %	41.43 %	37.63	62.48 %

TABLE XI
THE PERFORMANCE OF KNN TECHNIQUE USING RSS AND RTT MEASUREMENTS, EUCLIDEAN DISTANCE METRIC, AND ($K = 1$).

Accuracy	$RSS_1 RTT_1$	$RSS_2 RTT_2$	$RSS_3 RTT_3$	$RSS_{12} RTT_{12}$	$RSS_{13} RTT_{13}$	$RSS_{23} RTT_{23}$	$RSS_{123} RTT_{123}$
$Acc <= 25\,cm$	16.26 %	20.49 %	17.18 %	58.04 %	56.42 %	55.76 %	76.24 %
$Acc <= 50\,cm$	22.81 %	28.05 %	23.86 %	70.22 %	68.85 %	66.81 %	87.05 %
$Acc <= 75\,cm$	31.33 %	35.52 %	31.01 %	80.22 %	79.27 %	76.7 %	92.57 %
$Acc <= 1\ m$	37.52 %	41.68 %	36.54 %	84.79 %	84.62 %	82.61 %	94.9 %

(RSS_1, RSS_2, RSS_3). A straightforward remark can be made again: the significant improvement of the performance of KNN technique.

V. MLPNN VS KNN: COMPARISON AND DISCUSSION

As we have seen previously, the performance of any fingerprint-based indoor positioning technique depends on the chosen test-bed, the database characteristics, and the different variants of each technique. For MLPNN and KNN which were presented in this comparative study, the obtained results proved their capability and efficiency to locate a MT in an indoor environment with satisfactory accuracy (according to the application). To evaluate, objectively, which technique is better, we have to compare the best performance of MLPNN technique with the corresponding KNN performance using the same fingerprint database in terms of homogeneous or heterogeneous fingerprints and database resolution. Fig. (8) illustrates this comparison.

From the obtained results, KNN positioning technique shows its superiority and robustness for higher fingerprint database resolution. As shown in Fig. (8)(a), there is no significant difference between MLPNN and KNN technique for low resolution fingerprint database. However, KNN technique outperforms MLPNN technique for high resolution fingerprint database (see (8(b)). Then, the construction of the fingerprint database has a major impact in the behavior of fingerprint-based indoor positioning systems, and remains a key issue.

Finally, the complexity of the KNN-based algorithm restricts us to compute the distance from the target fingerprint to every other fingerprint in the database. This algorithm has a running time of $O(N \times D)$ where N is the cardinality of fingerprint samples, and D is the search space dimension. Since the search space dimension is equal to the fingerprint dimension (6 in the case of three BSs: 3 RSS values and 3 RTT values in extreme cases), the KNN algorithm has no

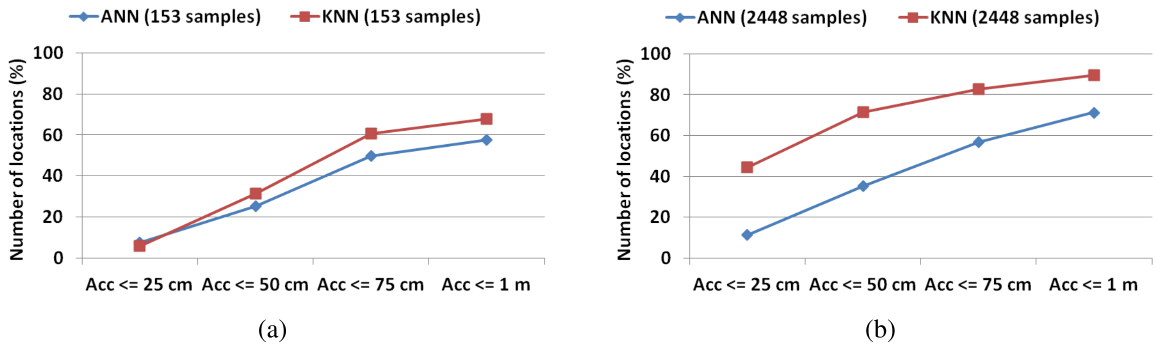


Fig. 8. MLPNN and KNN best performance comparison: (a) Homogeneous fingerprint database with 1 m^2 resolution and (b) Homogeneous fingerprint database with 25 cm^2 resolution.

complexity beyond the storage of the database. However, for MLP networks, the computational complexity will be drastically increased by increasing the number of hidden neurons. The MLP has complexity $O(M^2)$, where M is the greatest number of nodes in the hidden layers.

VI. Conclusion

In this paper, two range-free techniques for indoor location (MLPNN and KNN) were presented. Experimental results for homogeneous and heterogeneous fingerprints showed the good performance of those techniques. Nevertheless, the KNN method overcomes the MLPNN learning technique in most cases. MLPNN-based and KNN-based algorithms, which calculate location estimation based on fingerprint observations, offer good efficiency in terms of accuracy versus computational cost. Simplicity, effectiveness in highly variable environments, and use of the infrastructure that is already installed in the indoor environment without any extra requirements make these methods favorable. Although their performance is not as good as our coordinate clustering method presented in our previous work [10], these techniques showed their superiority in case of lacking information in blind or dead zone.

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