Indoor Location Fingerprinting Based on Data Reduction

Dragan Kukolj
Faculty of Technical Science, Univ. of Novi Sad, Serbia
dragan.kukolj@rt-rk.com

Marina Vuckovic
RT-RK Computer Based Systems, Novi Sad, Serbia
marina.vuckovic@rt-rk.com

Szilveszter Pletl
Univ. of Szeged, Department of Informatics, Hungary
pletl@inf.u-szeged.hu

Abstract—Agent localization in indoor wireless environments is a challenging issue. Numerous techniques have been developed. Location fingerprinting, which is based on received signal strength measurements, is a frequently used approach for indoor applications. In this paper, we examine the possibility to obtain the location fingerprinting method characterized with more accurate mapping between the signal-space and the physical-space. An implemented well-known weighted $k$-nearest neighbor (WkNN) method is enhanced by two steps: a) pre-processing by the unsupervised learning technique during radio map building and b) post-processing of initial estimates obtained by the WkNN localization method. In this post-processing step signal-space and physical-space are transformed and mapped using two techniques of the dimension reduction: principal component analysis and multidimensional scaling. The aim of this transformation step is to de-correlate and refine initially obtained location estimates. Parameters such as number of access points and number of nearest reference nodes are examined for their impact on accuracy of the presented localization techniques. Performances are examined and verified through the experiments with real environment data.

Keywords—Location Fingerprinting; Received Signal Strength; Topology-Preserving Mapping; Data Reduction.

I. INTRODUCTION

Indoor localization techniques have different and numerous applications in the wireless network technology for the positioning and tracking of people or objects. The most popular indoor localization technique is fingerprint-based localization, having the major advantage to exploit already existing wireless network infrastructures, like IEEE 802.15 or IEEE 802.11, which avoids additional deployment costs. The location fingerprinting (LF) is a method of predicting location on basis of pre-recorded measurements of received signal strength (RSS) in a deployment area and inspection of currently measured RSS at the tracked agent. Depending on how the database of pre-recorded RSSs is formed and processed, fingerprinting localization approaches are grouped into deterministic [1] and probabilistic methods [2].

Several techniques that are able to adapt to variations of signal strength over different time periods have been proposed [3], [4]. Fang and Yin [5] shows that, the projection of measured RSS into a de-correlated signal space could improve localization accuracy. In the paper [6] Fang and Yin presented a localization algorithm named discriminated-adaptive neural network able to create nonlinear relationship between RSS and the position.

The work of Ni et al. [7] describes enhancement of the WkNN in the indoor environment applying multidimensional scaling (MDS) at pairwise squared distances between RFID tags and the reference points. An approximated RFID tags’ distribution is refined by the subsequent use of Procrustes analysis in order to obtain LF estimation of higher accuracy.

The LF approach consists of two phases: an off-line training phase and on-line localization phase. In the off-line phase, RSSs are collected at predetermined positions of the reference points to build the database called a radio map. During the on-line localization phase the localization algorithm estimates the unknown position of tracked wireless sensor using real-time measured RSS samples, the stored radio map database and learned estimation model.

The basic idea of this work is to show how accuracy of the classical Euclidean based weighted $k$ - nearest neighbors algorithm applied in LF for an indoor environment can be improved by inserting two independent algorithmic steps: 1) data pre-processing during training phase of LF process using an unsupervised learning algorithms; and 2) the linear transform of the distances / similarities between the appropriate RSS vectors and spatial distances.

In the pre-processing step two alternative unsupervised techniques characterized by the common topology-preserving feature are used. These techniques are: the Neural Gas (NG) algorithm [8], [9], and Re-Organizing Neural Network (RONN) [10], [11]. The aim of this step is
to compress and select most representative RSS vectors during a radio map building. Moreover, in the on-line localization phase the process of localization estimation is enhanced by further processing of the initial WkNN results using a linear transform of pairwise distances between tracked wireless sensor and the selected reference points. For this purpose, two alternative well-known dimensionality reduction methods are used: multidimensionality scaling (MDS) [12] and principal component analysis (PCA) [13], both applying the Procrustes analysis [7]. Thanks to these methods better mapping between the RSS-vector space and the spatial location space is achieved by transforming data into their de-correlated spaces.

The rest of the paper is organized as follows. The second section formulates the problem of fingerprint-based localization. The third section presents the description of the proposed pre-processing algorithms during the training phase of the LF approach. In section four the on-line fingerprint-based localization algorithm is described. Section five presents description of experimental setup and achieved results. Section six contains conclusion and directions of the future work.

II. PROBLEM FORMULATION

Let us assume that one has a physical space defined by $N$ nodes at a two-dimensional grid, where each node of the grid represents the reference point described by the coordinate $x_i = (x_{i1}, x_{i2})$, $i = 1, ..., N$. We assume $n$ transmitters called an access points (APs) with known location, each capable to cover the whole deployment area with its signal. The signal strength vector received at a reference point $j$ can be defined as $s_j = (s_{j1}, s_{j2}, s_{j3}, ..., s_{jn})$, where $s_{ji}$ denotes the received signal strength (RSS) perceived by the $i^{th}$ AP, where $i \in (1, n)$ at the $j^{th}$ reference point. Similarly, the signal strength vector received in the on-line phase by the tracked wireless sensor at an unknown location $t$ is defined as $s_t = (s_{t1}, s_{t2}, s_{t3}, ..., s_{tn})$, where $s_{ti}$ is the RSS received at the tracked wireless sensor (WS) from the $i^{th}$ AP, where $i \in (1, n)$. The measured RSS values are treated as random variables, which are statistically dependent on the location. The task is to predict the unknown location of the tracked WS. The WS is going to be tracked using RSS information measured at the wireless sensor, and the RSS vectors ($s_i$, $j \in (1, k)$) and coordinates of the $k$ selected reference points recorded earlier.

III. DESCRIPTION OF PRE-PROCESSING IN LOCATION FINGERPRINTING TRAIN PHASE

The goals of the pre-processing of the measured received signal strength during the training phase of fingerprint-based localization could be the compression of radio map data, a reduction of unnecessary elements in RSS vectors and finding most the representative RSS vectors for each location in the deployment area. Usually, the component values of RSS vectors are collected over a specified time period. These time-dependent signal measurements are averaged for each access point at that position and the vector of location fingerprint is created and recorded. If the process of RSS measurement is taken in several separate time periods, then each spatial position can be represented by multiple fingerprint vectors. The pre-processing step may enable faster search of the radio map and may improve the accuracy of the location estimation.

In our approach, we used two unsupervised learning algorithms, the neural gas [8], [9] and re-organising neural network [10], [11] for clustering of RSS vectors measured at each particular location of a defined area. As consequence of this approach, the time instance when the measurements of RSS are taken is not directly considered. The presented algorithms are unsupervised techniques similar to Self-Organizing Map (SOM) neural networks [14], and most appropriate for preserving data topology.

A. Re-Organising Neural Network

The first algorithm proposed for learning representative fingerprint prototypes is called further on Re-Organising Neural Network (RONN) [10], [11]. The algorithm utilises training data that contain $N$ patterns of received signal strength received from $n$ access points at the $k^{th}$ given location $\{s_1, ..., s_k, ..., s_N\}$, where $s_i \in R^*$ and $k = 1, ..., N$. Basic algorithm steps are presented in the following.

$I$: The synapse weights of all neural network nodes are initialised with small uniformly distributed random numbers.

$II$: The new coordinates of the $K$ cluster prototypes are calculated as an arithmetic mean of each coordinate of the samples grouped in each cluster. A group of the $N_t$ closest fingerprint samples, associated with the $l^{th}$ cluster prototype, is found using the Euclidean distance. More precisely, the mean square error of the cluster (MSE), formed around each prototype represents the measure of deviation of the assigned samples from their cluster centre.

$III$: The verification of the condition:

$$\sum_{i=1}^{N} |w_i - w_{i}^*| < T_{MSE}$$

where the $T_{MSE}$ is a threshold, and $w_i$ and $w_i^*$ are the synapse vectors of the $i^{th}$ prototype in the current and previous iteration. If this condition is not satisfied, the algorithm returns to step II; otherwise it proceeds to the next step.

$IV$: If there are no dead-nodes (a dead-node represents the cluster center which have ended up without having the closest samples), $T_{MSE}$ is set to a small positive value. If dead-nodes do exist, the $q$ clusters ($q < K$) that have the maximum MSE values are found next. The corresponding dead-node is then moved into the vicinity of a randomly selected prototype node among the $q$ nodes-clusters with the maximum value of MSE. The new coordinates for each dead-node are now given by $w_i^{new} = w_{i}^{new} + \delta_i$, $i = l, ..., q$, where $w_{i}^{new}$ is the location of the selected prototype among the $q$
nodes with the highest MSE, \( w_i^{\text{new}} \) is the prototype position of a possible new cluster, and \( d \) is vector of small random numbers.

**V:** The procedure terminates if the number of dead-nodes in the current and in the previous iteration is equal to zero, or the maximum number of iterations has been reached. If not, the procedure returns to step II.

A detailed description of the algorithm is given in [10], [11].

**B. Neural Gas**

The Neural Gas is an unsupervised learning technique that allows the uniform placement of representative prototypes in the vector space. This algorithm determines prototypes in such a way that the Euclidean distance between data vectors and the prototype vectors is minimal. To each \( i^{th} \) prototype is assigned rank \( \tau_i(d_i^+) \in \{0, ..., K-1\} \), i.e. a rank of 0 indicates the closest and a rank of K-1 the farthest prototype to the current data sample. The adaptation rule for the \( i^{th} \) prototype in the \( k^{th} \) iteration can be described as:

\[
\Delta w_i^k = \eta_k h^k(\tau_i)[w_i^{k-1} - x^k], \quad i = 1, ..., K
\]

where \( \eta_k \) is decreasing the global learning rate and the function \( h^k(\tau_i) = \exp \left( -\frac{\tau_i}{\lambda_k} \right) \); \( i = 1, ..., K \) is exponentially decreasing with its rank \( \tau_i \) and neighborhood range \( \lambda_k \). A more detailed description of the algorithm is given in [8], [9].

**IV. DESCRIPTION OF ON-LINE LOCATION FINGERPRINTING PHASE**

During the on-line localization phase the measured RSS vector \( s_t \) is processed by the proposed fingerprint-based localization approach. This approach combines the weighted \( k \)-Nearest Neighbors algorithm (WkNN) and data transform / reduction method. In the current work, both have been adopted, the principal component analysis and classical multidimensional scaling methods. The WkNN is the initial step of the on-line localization process. Then, the composite matrix of the Euclidean distances between the observed wireless sensor and the chosen reference points is created. The composite matrix is transformed into a de-correlated and de-noised distance matrix by any of these data reduction methods. In the following sections a short overview of these methods is presented.

**A. Weighted \( k \)-Nearest Neighbour Algorithm**

The weighted \( k \)-nearest neighbor algorithm is a well-known fingerprint-based method [3]. Assuming that the radio map database of reference points of RSS vectors \( s \) exist, and \( s_t \) measurements linked to the tracked WS are performed, one may indicate the similarity in signal strength vectors of the \( j^{th} \) reference point and the wireless sensor with unknown location. The similarity is calculated as the Euclidian distance \( p_j \) shown in the following equation:

\[
p_j = \sqrt{\sum_{i=1}^{n}(s_{ti} - s_{pj})^2}
\]

The nearer the \( j^{th} \) reference point to the WS, the smaller \( p_j \) is. In other words, it may be assumed that the closest reference point would have the most similar signal strength vector to the signal strength vector of the tracked WS. It is also necessary to determine \( k \), the number of reference points that is used for an accurate coordinate localization. Finally, coordinate estimation of the WS consists of search for the \( k \) nearest reference points with the smallest Euclidean distances \( p_j, j=1, k \).

A weighting factor \( w_j, j=1,k \) is associated with the \( k \) reference points with the most similar RSS vectors to the RSS \( s_t \) measured at the tracked wireless sensor WS, based on their \( k \) smallest calculated Euclidean distances from that WS, and calculated according to eq. (3). The weighting factors are inversely proportional to the square of the Euclidean distance as shown in the equation (4).

\[
w_j = \frac{1}{D^2}
\]

The unknown coordinates of the tracked wireless sensor are estimated by the expression \( x = \sum_{k=1}^{K} w_i x_i \). Consequently, this method is called the weighted \( k \)-nearest neighbor algorithm (WkNN) [3].

**B. Principal Component Analysis**

The principal component analysis (PCA) is transformation that converts a set of potentially correlated variables into a set of uncorrelated variables representing linear combinations of the original ones. The PCA transformation calculates the dominant eigenvalues and eigenvectors of the matrix \( D \) defined by the elements \( d_{ij} = (x_i - \bar{x})(x_j - \bar{x}) \), where \( \bar{x} \) is mean of \( x \). The unknown \( i^{th} \) eigenvector and \( i^{th} \) eigenvalue can be found by solving the equation \( D v_i = \lambda_i v_i \). Rearranged expression in the form: \( D = V \Lambda V^T \), where \( \Lambda \) is a diagonal matrix of eigenvalues, can be solved by the robust singular value decomposition (SVD) method [15]. Given the eigenvector with the largest eigenvalue creates the first projection in the new transform space with the largest variance. An eigenvector with the second largest eigenvalue creates the second new projection and so on.

**C. Multidimensional Scaling**

The multidimensional scaling (MDS) is a statistical technique which explores the similarities or dissimilarities in data. Classical MDS, used in this work, requires that a pairwise Euclidean distance between selected reference points is formed. A squared distance matrix is configured from it, after which the inner product matrix is estimated that can be rewritten in manner to perform operation centering. Classical MDS estimates the new coordinate matrix that is lower-rank approximation of the original one. A detailed explanation of the method is presented in [12].
D. Overview of the On-line Localization Phase

It is assumed that an actual signal strength vector $s_k$ is recorded at the tracked wireless sensor device and the radio map database of prepared RSS vectors $S$ at the known locations is available. The proposed on-line LF algorithm contains the following steps:

1. WkNN estimation: An estimation of the coordinates of the tracked wireless sensor using the weighted $k$-nearest neighbors algorithm.

2. Data preparation for the transform of the distance matrix: In this step matrices of spatial distances and the matrices of distances between RSS vectors are created, as well as the matrix of relationships between spatial and RSS quantities are determined. Specifically, the following matrices are created:
   - the proximity matrix $P$ of Euclidian distances of signal strengths between the target WS and $k$ reference points is obtained;
   - the pairwise matrix $P_{ref}$ of Euclidian distances of signal strength between the $k$ reference points is created;
   - the spatial distances $d$ between the tracked WS and $k$ reference points is obtained;
   - the pairwise spatial distances matrix $D_{ref}$ between the $k$ reference points is determined.

Under assumption that a linear relationship between the spatial distances $D_{ref}$ and the Euclidean distances of signal strength $P_{ref}$ exists, the following equation holds

$$D_{ref} = aP_{ref} + b$$

From eq. (5) one can calculate the unknown linear scaling coefficients $a$ and $b$. Having coefficients $a$ and $b$ determined one may create a relationship between spatial distances $d$ and the Euclidean distances $P$ of the tracked WS and $k$ reference points by expression

$$d = ap + b$$

Then, the composite distance matrix $D$ is constructed by combining both matrices of spatial distances: $d$ calculated in eq. (6) and $D_{ref}$ calculated in eq. (5).

3. Distance data transform: The composite distance matrix $D$ is approximated and de-correlated into another matrix $Y$ using the data transformation and data reduction techniques like principal component analysis and classical multidimensional scaling. Either method results in a new coordinate matrix $Y$ that is characterized with de-correlated and de-noised distance information.

4. Procrustes analysis: It determines a linear transformation of $Y$ that estimates the original coordinates $X$ in the sense of least-square error. Obtained $\hat{X}$ contains an estimate of the unknown wireless sensor’s location [7]. A detail description of the Procrustes analysis is given in [12].

V. EXPERIMENTAL EVALUATION

A. Description of Experimental Setup

The experiment was conducted in a room with the size 7 m by 15 m. There were several pieces of furniture that are typical for laboratories and class-rooms. The layout of the experimental setup is shown in Fig. 1. The grid of reference points at unified distances of 60 cm is formed. The placement of the reference points is marked with black dots in the figure. The five anchor nodes, i.e., access points (APs) numbered with IDs 1 to 5, were placed in positions that form 2 equilateral triangles. The exact positions of the APs marked with red dots and titles Anchor# are also given in Fig. 1.

The Crossbow IRIS (XM2110CA) wireless sensors nodes compliant with the IEEE 802.15.4 standard were used for the measurement of the RSSI values. The measurements of RSS were taken from these reference points at the height of about 88 cm above the floor. At each reference point 100 RSSI samples of signal strength received from 5 APs are collected. These RSS measurements vectors are used for the radio map building. In addition, for the verification purposes, the mobile node with role of the tracked wireless sensor was placed on six different positions out of existing grid of reference points. These points marked with green dots and titles Unknown# are also given in Fig. 1. The measurements of 100 samples of RSSI vectors are collected and used for testing and the performances measurements. The collected samples of received signal strength at all points are separated in smaller groups of 10 samples in time order as they are recorded, and its mean is calculated. As a result, 10 measurements for each of the 6 test point form final test vector with a total length of 60 RSS samples. The radio map is formed in two ways: 1) without pre-processing and 2) with pre-processing using the above described algorithms of unsupervised learning. In the case when the pre-processing is omitted, the RSS samples collected at each reference point are compressed in 10 timely ordered groups where each group is represented with its mean vector value. In the contrary, when the pre-processing algorithms are
carried out, 10 RSS representative prototypes are algorithmically created for each reference point. The same number of 10 vectors per reference point is selected for the sake of fair comparison.

B. Experimental Results

In order to validate the effects of introduction of both described steps: the pre-processing step during radio map building and a distance transform step in the on-line phase; the achieved results of the experiments are compared with the results given by the basic LF technique - weighted \( k \) nearest neighbor (WKNN). Namely, WKNN represents in the same time the first step of the on-line phase of this approach. Moreover, the impact of the number of access points and the number of selected reference points on the accuracy of the LF before and after the introduction of the proposed algorithmic steps is explored. The distance error (DE) was adopted as the basic performance metric, which represents the Euclidean distance between the estimated position of the tracked wireless sensor and its true coordinate. Moreover, one considers the cumulative distribution function (CDF) of the DE of all location estimates for all measurements which fully describes its characteristics.

The performances of several versions of the LF algorithm are compared. The first three algorithms’ versions are:

1. basic weighted \( k \) - nearest neighbor algorithm (WkNN);
2. WkNN improved by the insertion of MDS step (WkNN-MDS) \(^{[7]} \)
3. WkNN improved by insertion of PCA step (WkNN-PCA).

Then, additional six versions is introduced by inserting in previous algorithmic versions two proposed alternative pre-processing steps based on the re-organizing neural network (RONN) or neural gas (NG) algorithm. It resulted in the following LF algorithms:

4. WkNN pre-processed by NG (NG-WkNN);
5. WkNN pre-processed by RONN (RONN-WkNN);
6. WkNN improved by insertion of MDS and pre-processed by NG (NG-WkNN-MDS);
7. WkNN improved by insertion of MDS step and pre-processed by RONN (RONN-WkNN-MDS);
8. WkNN improved by insertion of PCA and pre-processed by NG (NG-WkNN-PCA);
9. WkNN improved by insertion of PCA and pre-processed by RONN (RONN-WkNN-PCA).

From the obtained results of the WkNN based algorithm’s versions it can be concluded that the pre-processing step has the most significant and interesting impact at WkNN when the number of access points is reduced to three. Fig.2 displays the cumulative probability of error of 1.2 m with the RSS measurement from 3 APs and a variable number of considered reference points. As shown in Fig. 2, the accuracy of both pre-processed versions of the WkNN algorithm, i.e. RoNN-WkNN and NG-WkNN are significantly better than the accuracy of the original WkNN. Obviously, proposed pre-processing step improves the quality of WkNN inputting data. Additionally, signal pre-processing using the RONN algorithm display a slightly better accuracy than the alternative, NG technique. Moreover, insignificant changes are observed on localization accuracy when the number of selected reference points is increased \((k=2,\ldots,5)\).

Fig. 3 presents the localization error of the WkNN technique and the two versions improved by the PCA and MDS transformations, i.e. WkNN-PCA and WkNN-MDS. These figures report the case when the measurements of RSS values from 3 APs are considered with a variable number of the reference points. Fig. 4 clearly shows that both versions, WkNN-PCA and WkNN-MDS, achieve significantly better localization error than the WkNN algorithm, especially when a smaller number of reference points is considered. In the case with 2 reference points, WkNN-PCA shows the best performance. The increase in the number of the reference points obviously deteriorates localization error when the methods of distance data transformation are used. The case when a pre-processing is included is presented in Fig. 4. Due to the very similar performances between the NG and RoNN pre-processing steps, only the results when the RoNN method is applied are presented. Besides the obvious similarities in the behavior of the localization errors in Fig. 3 and Fig. 4, the significant difference should be noted. Namely, the error curves steepness is higher when both PCA and MDS are used. As a result, a localization error of the methods with the pre-processing in comparison to the case without this step, becomes lower when the number of reference points is small, e.g. 2, and the accuracy is poorer when the number of reference points increases.

Experiments were also conducted in order to study the effect of the number of accessible APs on the localization accuracy. The authors varied a number of access points from 3 to 5. Fig. 5 portrays the CPF of localization error with and without included PCA step. The figure clearly demonstrates two facts: 1) the accuracy of localization is much higher when the PCA transformation step is included; and 2) the accuracy of localization is always better when the number of APs increase.

![Figure 2](image270x534to540x642.png)

**Figure 2.** Cumulative error probability of 1.2 m for the weighted k-NN (WkNN) method with 3 APs and \(k=2,\ldots,5\).
VI. CONCLUSION

In this paper, authors have investigated the enhanced weighted k-nearest neighbor method in indoor fingerprint-based localization. In the localization algorithm two additional processing steps are introduced: a) the pre-processing of collected received signal strength measurements in order to find most representative prototype vectors needed for the radio map forming of the deployment area; b) during the on-line location estimation the signal strength vector space and spatial coordinates are transformed and mapped using dimension reduction techniques. Two techniques of data reduction are investigated in this framework: PCA and MDS method. The results of the experimental evaluation show that either of the proposed steps can significantly improve the localization accuracy of the estimation process. The increase in the number of available access points has positive effect on the localization accuracy, while the increase of reference points has the opposite effect.

This research can be continued in several directions. First, the impact of courser-grid placement of reference points on the performances of the proposed processing steps in the location fingerprinting will be investigated. Furthermore, the authors will explore localization performances for the tracking of moving wireless sensors and incorporation of its trajectory information into the location estimation procedure.

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