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EXPERIMENTAL EVALUATION OF MACHINE LEARNING ALGORITHMS FOR FINGERPRINTING INDOOR LOCALIZATION

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Abstract. *One of the most preferred range-free indoor localization methods is the location fingerprinting. In the fingerprinting localization phase machine learning algorithms have widespread usage in estimating positions of the target node. The real challenge in indoor localization systems is to find out the proper machine learning algorithm. In this paper, three different machine learning algorithms for training the fingerprint database were used. We analysed the localization accuracy depending on a fingerprint density and number of line-of-sight (LOS) anchors. Experiments confirmed that Gaussian processes algorithm is superior to all other machine learning algorithms. The results prove that the localization accuracy can be achieved with a sub-decimetre resolution under typical real-world conditions.*

Key words: *Fingerprinting, machine learning, indoor localization*

1. INTRODUCTION

We live in a world of increasing business interest in location-based applications and services, where indoor or outdoor localization or real-time tracking are common application requirements. Localization in outdoor domain is entrusted to global navigation satellite systems (GNSS) such as The Global Positioning System (GPS), and it is almost impossible to imagine any transport navigation or networks synchronization applications without GPS today, [1]. However, close to buildings, trees or indoors GPS does not perform well because

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of the weak signal and other interferences present in indoor environments such as walls and other interior components. Thus, GPS is not generally applicable for indoor localization.

Since people spend most of their time in closed environments, the indoor localization demand is increasing and becomes key prerequisite in some markets. The difficulty of modelling an indoor localization system lies in that indoor maps pay more attention to small areas, large-scale and high precision, [2]. Correlated with outdoor localization, sensing location information in indoor environments is a challenging research problem. The most important indoor localization applications are customer navigation in a mall, citizen navigation inside a public building, product localization in a supermarket and many applications in military areas, [3].

Indoor localization system is typically composed of a set of anchor nodes, placed at fixed locations in the region of interest, and a target node attached to the object or carried by the person that needs to be localized. One of the most preferred range-free methods is the location fingerprinting. The essence of the location fingerprinting is primary to set up a database of wireless signals measurements at some referent points, in the training phase. In the localization phase, the location of the target node can be determined by comparing its database wireless signals measurements. The major advantage of the location fingerprinting is providing accurate location estimations in the multipath environments, [4].

In comparison with conventional, narrowband and carrier wave radio technologies (e.g., WiFi, Bluetooth, Sub-1 GHz RF), the ultra-wide band (UWB) localization stands out as the most promising radio-based technology for indoor localization available today, [5]. The main characteristic of UWB is large bandwidth used for transmission of ultra-short pulses. The short duration of pulses ensures a good resolution in the measurement of signal time-of-flight (ToF), so the distance between two UWB transceivers can be measured with a high precision. With accurate distance data to at least three anchor nodes, the location of the target node can be calculated with a centimetre level accuracy by applying a basic range-based technique (e.g., trilateration), [6]. The accurate distance measurement can only be achieved under the line-of-sight (LOS) scenarios. In the NLOS (non line-of-sight) scenarios, the transmitted signal could only reach the receiver through penetrated or reflected paths. The problem is especially present in indoor environments of complex geometry, where mixed LOS/NLOS signals created by a number of anchor nodes exist [7].

In the localization phase, aiming to improve the localization accuracy a variety of Machine Learning (ML) algorithms are used [8]. ML algorithms are seen as a part of artificial intelligence and they are based on experiential learning. The basis of the ML algorithms is to create a model set up on sample data, in their training phase. As a result of training, they can predict or make various decisions without being explicitly programmed to do so. ML algorithms can decide on systems even with a lot of parameters, complexity or huge number of data, that is why they are powerful methods for indoor localization process, [9]. One of the main challenges in indoor localization is to find the best machine learning algorithm according to accuracy and computation time requirements, [10]. In this paper, we compare three different machine learning algorithms: k-nearest neighbours (kNN), Gaussian processes (GP) and decision tree (DT) [11]. The ML algorithms were applied on the dataset obtained from the real-world data collected in a measurement process that was carried out in a multi-room area.

This paper is organized as follows. In Section 2, we summarize related studies on fingerprinting and UWB based indoor localization. The system model and some preliminaries are introduced in Section 3. The experimental results are presented in Section 4, while the concluding remarks are given in the last Section 5.

2. RELATED WORKS

Many studies have been performed with the use of the UWB based indoor localization systems. UWB is very suitable for accuracy-critical applications, [12, 13]. In [14, 15] it is shown that the distance between two UWB devices can be measured with centimetre-level accuracy, even in complex indoor environments. Problems occur due to mixed LOS/NLOS propagation conditions which is the topic of many researches [16-18]. In [19] the LOS/NLOS problems are solved by discarding the NLOS measurements and using only LOS measurements localization estimation.

Fingerprinting is widely adopted technique for UWB localization [20, 21]. It is specially used for complex indoor environments with mostly NLOS propagation conditions, where the goal is to achieve high localization accuracy, [22-24]. Fingerprinting can be implemented using a variety of machine learning algorithms. User location and tracking system using k-nearest neighbours ML algorithm is presented in [25]. The time-efficient support vector machine algorithm for indoor positioning system has developed in [26]. In [27] the effect of machine learning techniques on accuracy of locating and tracking users in indoor environment is investigated. In [28] an indoor localization algorithm based on Naive Bayes fingerprinting is presented. An indoor localization algorithm based on the neural networks and extreme learning machine is introduced in [29]. Enhancing the performance of the indoor positioning system via the integration of different features and classification algorithms is the main goal presented in [30], where decision tree, multi-layer perceptron, and Bayesian network to improve system performances are used.

The strategy proposed in this work relies on fingerprinting and UWB localization under mixed LOS/NLOS conditions. Since the variety of ML algorithms can be used in fingerprinting process, in this paper we investigate the influence of three different ML algorithms on the localization accuracy. The experiments were performed to explore the performance of an ML algorithm under different fingerprint densities and the number of available LOS measurements.

3. SYSTEM MODEL

The proposed strategy addresses the mobile target localization problem in a complex multi-room indoor environment. We assume single target localization scheme within the context of a system for real-time 2D localization. The system is composed of: *a*) a set of N static anchor nodes, *b*) single target node, and *c*) a location server. The target node is mobile while the anchor nodes are placed at fixed and known positions in the localization environment. Distances between the target and anchor nodes are evaluated through UWB ToF ranging, [31]. The anchor nodes would be set so that at least three of them cover each point in the localization space. That means existence of at least three LOS or NLOS ToF ranging between the anchor nodes and target node. The target node collects the measured distances and then sent them to the location server, which carries out ML-based localization algorithm to estimate the current position of the target node.

The location fingerprinting method could be observed as a regression model that maps input vector to an output vector based on a training set. During the offline training phase, UWB measurement campaign is performed for building fingerprint databases.

The fingerprint database, F, is formulated as:

$$F = (d_1, l_1), (d_2, l_2), ...(d_n, l_n)$$

where d_i is the distance vector obtained during UWB measurement campaign at the i^{th} reference point with ground truth coordinates $l_i = [x_i, y_i]$.

Distance vector

$$d_i = [m_{i1}, m_{i2}, ...m_{ij}]$$

is composed of j distances, m_i, measured between the target and each of j anchor nodes. l_i is the location of the target node, expressed by $l_i = [x_i, y_i]$, the ground truth coordinates. The size of the fingerprint database is given by n, while the total number of anchor nodes is j.

We apply three different machine learning algorithms to train the fingerprint database and then use the learned model to estimate the target node location. The used set of ML algorithms includes: k nearest neighbours, Gaussian processes and decision trees. The input of the ML algorithms is target distance vector measured by the target node at an unknown location, and the output is estimated coordinates of the location.

The ML algorithm k nearest neighbours determines the position of the target node by majority voting and it is implemented in two steps, [32]. In the first step, a subset of k distance vectors in the fingerprint database that are most similar to the target distance vector is extracted. In the second step, the location of the target node is estimated by averaging the ground truth coordinates of the selected fingerprints. The Euclidean distance between distance vectors is used as a measure of similarity.

We adopt k=3 and Euclidean distance function:

$$\delta_{ZI}(l_t, l_f) = \sqrt{(x_t - x_f)^2 + (y_t - y_f)^2}$$

where $l_t = (x_t, y_t)$, and $l_f = (x_f, y_f)$ are locations of the target node and the fingerprints in the fingerprint database, respectively.

The Gaussian process assumes an unknown nonlinear random function. This method is nonparametric technique for regression, where it is capable of providing probabilities for the output. Gaussian processes are a stochastic process, such that every finite collection of random variables has a multivariate normal distribution, [33]. The distribution of a Gaussian process is the joint distribution of all those random variables, and as such, it is a distribution over functions with a continuous domain, e.g., time or space. Gaussian process models are routinely used to solve hard machine learning problems. They are attractive because of their flexible non-parametric nature and computational simplicity.

Decision Trees is a well-known and commonly used machine learning algorithm. It works with simple if-then-else decision rules and is used for both classification and regression problems. It creates a tree structure based on the data set. The tree structure consists of decision nodes, branches and leaves that represent attributes (features), conditions and classes, respectively. The decision tree is created by asking questions with true or false answers and based on their answers, the trees narrow down until the model is confident to give a prediction. The orders and content of these questions are specified by the model, [34].

4. Experimental Results

The experiment was performed in the 80m^2 indoor area with nine UWB nodes: one target and eight anchor nodes. In the experiment the UWB wireless transceiver DW1000 are used as the UWB nodes, [35]. The anchor nodes are set up on the walls 2m above the floor, while the target node is affixed to the top of a movable tripod 1m in height. Fig. 1 shows the layout of the experimental area with marked anchor positions. The fingerprint measurement campaign was done in the part of Room A, shown as a dotted area in Fig. 1. The coordinates of each dot in this area are measured manually with 10 *cm* space between dots. Maximum number of used LOS anchor in Room A was three, but in accordance with experiment that number was changed to two, one, or zero anchor. Outside of the Room A five more NLOS anchors were placed. At each reference dot in Room A, ten ranging rounds were performed and all the measured target-to-anchor distances are recorded as a location fingerprint along with the corresponding ground truth coordinates.

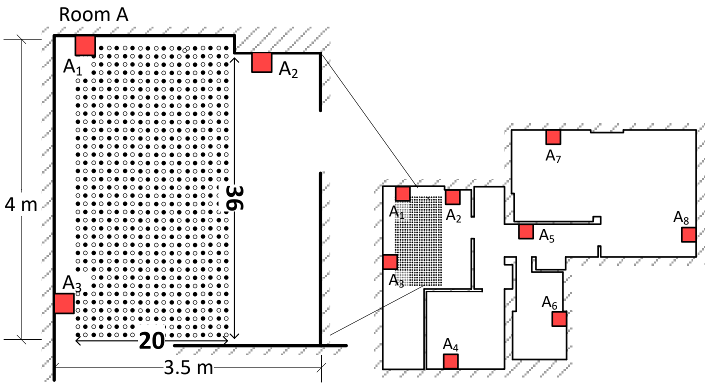

Fig. 1 The map of the experimental environment with the red boxes denote anchor nodes

We analysed the localization accuracy depending on a fingerprint density and number of LOS anchors in Room A. Five fingerprint databases of different densities are used. The maximum density of the fingerprint database was 50 *f/m*^{2} (fingerprints per square meter). We also created and used in the experiment four additional fingerprint databases with densities of: 25, 12.5, 6.25, and 3.125 *f/m*^{2}. We also changed the number of LOS anchors in Room A discarding the measured distances to one or more anchors.

The experimental results are presented in the terms of the localization error, which is defined as the Euclidean distance between the actual and the estimated location. The magnitude and uncertainty of localization errors are quantified by Mean Distance Error (MDE) and Cumulative Distribution Function (CDF) the localization error. We compare localization performance of ML algorithms: kNN, GP and DT.

The first experiment was done with three LOS anchors in Room A and the experimental results are presented in Table 1 and Fig. 2. As we can observe, the performances of all ML algorithms highly depend on fingerprint density. The ML algorithm's accuracy decreases with increasing fingerprint density. To achieve a sub-decimetre accuracy in the 3-LOS case, kNN algorithm needs a fingerprint database of density greater than 25 *f/m*^{2}, while the accuracy is slightly better for the GP algorithm and 12.5 *f/m*^{2} fingerprint density. The DT algorithm has the worst localization error, from 11.86 *cm* for a high-density fingerprint database, up to more than 36 *cm*, when a low-density fingerprint database is used.

Table 1 Statistics of localization error (in *cm*) of ML algorithms for 3-LOS case and five fingerprint densities

3-LOS	MDE of fingerprint density (f / m^2)				
ML algorithm	50	25	12.5	6.25	3.125
kNN	7.9	10.85	12.79	16.6	25.09
GP	4.78	5.25	6.4	10.23	17.27
DT	11.86	18.14	23.93	30.37	36.9

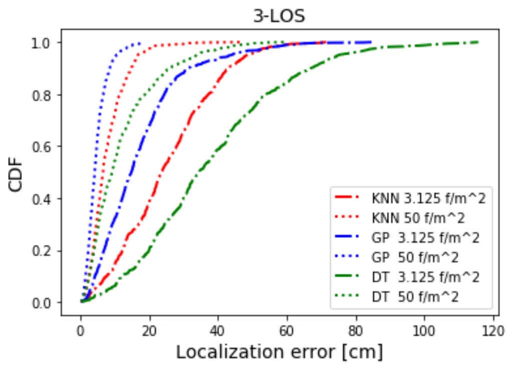

Fig. 2 CDF of the localization errors of ML algorithms for 3-LOS case and fingerprint densities of 50 f / m^2 and 3.125 f / m^2

Table 2 and Fig. 3 report the experimental results for the for the deployment scenario with two LOS anchors, while in Table 3 and Fig. 4 are presented results for one LOS case. In both cases, the results depend on fingerprint density. It can be seen that localization errors for 2-LOS case are slightly worse than in three LOS scenario. Similarly, estimating positions in 1-LOS case is not as good as in 2-LOS scenario. This is expected, given the smaller number of target-anchor distances measured under LOS conditions. The MDE difference between 2-LOS and 1-LOS cases ranges from 0.5 *cm* for kNN to 1.5 *cm* for GP and to 2.5 *cm* for the DT algorithm, for fingerprint density of 50 f/m^2. For a density of 3.125 f/m^2 the MDE difference between 2-LOS and 1-LOS cases ranges are 0.1 *cm*, 2.6 *cm* and 0.25 *cm* for kNN, GP and DT, respectively. Nevertheless, even in the 1-LOS case, the MDE of the GP algorithm is consistently lower than the other two ML algorithms.

Table 2 Statistics of localization error (in *cm*) of ML algorithms for 2-LOS case and five fingerprint densities

2-LOS	MDE of fingerprint density (f / m^2)				
ML algorithm	50	25	12.5	6.25	3.125
kNN	8.83	12.03	14.29	18.67	26.32
GP	5.98	7.44	9.14	11.94	18.73
DT	13.67	19.5	25.23	31.31	37.18

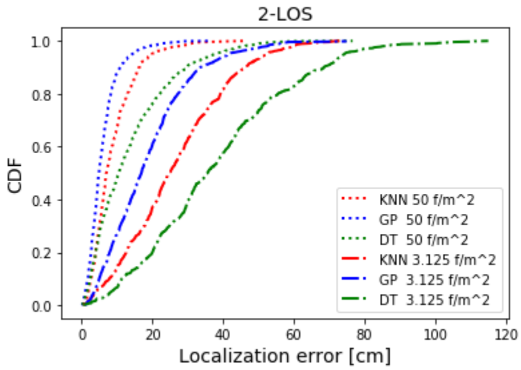

Fig. 3 CDF of the localization errors of ML algorithms for 2-LOS case and fingerprint densities of 50 $f\,/\,m^2$ and 3.125 $f\,/\,m^2$

Table 3 Statistics of localization error (in *cm*) of ML algorithms for 1-LOS case and five fingerprint densities

1-LOS	MDE of fingerprint density ($f\,/\,m^2$)				
ML algorithm	50	25	12.5	6.25	3.125
kNN	9.39	12.68	14.95	19.73	26.2
GP	7.58	9.57	11.31	13.77	21.36
DT	16.08	20.71	25.93	30.89	37.27

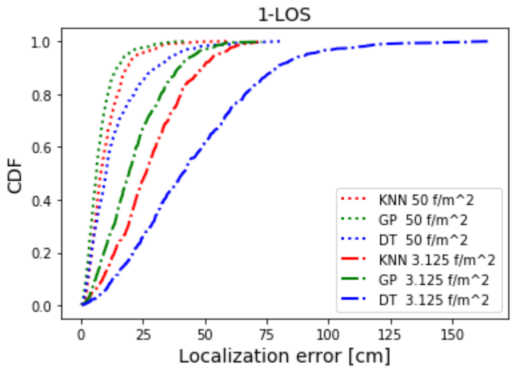

Fig. 4 CDF of the localization errors of ML algorithms for 1-LOS case and fingerprint densities of 50 $f\,/\,m^2$ and 3.125 $f\,/\,m^2$

In the 0-LOS case, in which all distances are measured under NLOS conditions, the localization error ranges from 10.8 *cm*, for a high-density fingerprint database, up to more than 39 *cm*, when a low-density fingerprint database is used. The GP algorithm has the best results among other ML algorithms for all fingerprint density, MDE ranges from 10 *cm* to 27 *cm*, for a high-density and a low-density fingerprint database, respectively.

Table 4 Statistics of localization error (in *cm*) of ML algorithms for 0-LOS case and five fingerprint densities

0-LOS	MDE of fingerprint density (f / m^2)				
ML algorithm	50	25	12.5	6.25	3.125
kNN	12.23	16.19	19.05	23.54	30.57
GP	10.88	14.44	16.65	19.5	27.03
DT	17.78	22.99	27.84	32.16	39.68

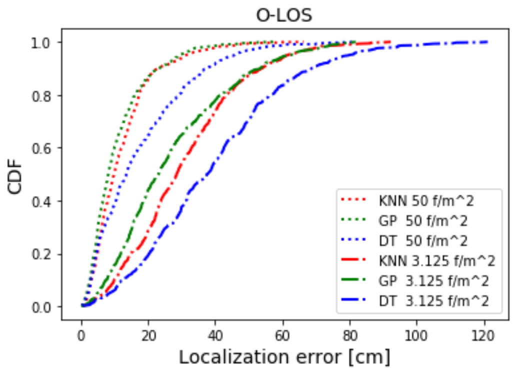

Fig. 5 CDF of the localization errors of ML algorithms for 0-LOS case and fingerprint densities of 50 f / m^2 and 3.125 f / m^2

5. CONCLUSIONS

In this paper, the fingerprinting method for indoor localization is evaluated in terms of selected machine learning algorithm under various environmental conditions. We applied three different machine learning algorithms to train the fingerprint database and then use the learned model to estimate the target node location. Our aim was to find the most appropriate ML algorithm for indoor positioning problem. Experiments confirm that GP algorithm is superior to all other ML algorithms to estimate position. Besides, kNN provides nearly the same performance when used under NLOS conditions when a high density fingerprint database is available. Since kNN is the least computationally demanding algorithm it should be considered as the first option in most real-world scenarios. In the future, the experimental results can be further improved by extending the evaluation with additional machine learning algorithms for the indoor positioning system.

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