IMPACT OF RADIO MAP SIMULATION ON POSITIONING IN INDOOR ENVIRONTMENT USING FINGER PRINTING ALGORITHMS

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ABSTRACT

In the paper the use of radio map modeling approach for a fingerprinting based indoor positioning will be discussed. The paper will describe different propagation models used for a radio map simulation together with the theory of deterministic localization algorithms. In the paper deterministic algorithms from Nearest Neighbor family will be used together with previously proposed rank based fingerprinting algorithm. Impact of used propagation model for radio map simulation on the performance of fingerprinting algorithms will be investigated. The radio map was simulated on the model of Department of Telecommunications and Multimedia at University of Zilina using Radioplan RPS software. Afterwards real world positioning was performed using described algorithms to evaluate impact of radio map simulation on these algorithms.

Keywords: radio map, simulation, fingerprinting algorithms.

INTRODUCTION

In the recent time, positioning in the indoor environment becomes extremely interesting field. This is mainly caused by the fact, that large number of location based services emerged in the outdoor environment where position can be estimated using GNSS (Global Navigation Satellites Systems). On the other hand, utilization of LBS (Location Based Services) in indoor environment still represents new opportunities for service providers [1]. This is given by the fact, that it is not possible to use GNSS systems in the indoor environment, due to high signal attenuations and multipath propagation. Therefore, development of indoor positioning systems can open new markets to such service providers.

Based on this fact, large numbers of positioning systems for use in the indoor environment was proposed. These systems can be based on different principles such as audio signals, image processing, various magnetic field based sensors and radio networks. From all of these, systems based on radio networks are the most popular. This is mainly caused by the fact that in most cases commonly used devices like smart phones can operate in such systems. Large number of systems based on Bluetooth [2], ZigBee [3], cellular networks [4], UWB (Ultra Wide Band) [5] and Wi-Fi [6, 7] emerged in recent time. Among these Wi-Fi is based are the most common, since WLAN (Wireless Local Area Networks) are almost ubiquitously deployed in the indoor environment.

Currently, the most popular indoor positioning systems that utilize Wi-Fi networks are based on radio signal fingerprinting approach. Main advantages of these systems are possibility to use standard hardware without any modification and also the fact that fingerprinting positioning systems seems to be immune to multipath propagation. Immunity to multipath propagation is extremely important feature, since multipath phenomenon is especially strong in the indoor environment.

On the contrary, the disadvantage of fingerprinting positioning systems is need of calibration phase, which can be time consuming. The calibration phase is required to be performed in the whole area, where the positioning system will be deployed. During this phase measurements of the radio signal properties are performed on known positions – reference points. All the measurements are sent to the radio map database which is stored at the localization server.

In this paper we will focus on possibilities of radio map simulation for positioning based on fingerprinting algorithms. In order to evaluate impact of radio map simulation on performance of positioning system, we decided to use simulated radio map for a position estimation using different deterministic fingerprinting algorithms.

The rest of the paper will be organized as follows; in the next section theoretical background in fingerprinting and radio signal propagation modeling will be described. Section 3 will describe simulation and measurement scenarios; achieved results will be presented and discussed in Section 4. Section 5 will conclude the paper and present some ideas for a future work.

Theoretical background

In this section theoretical background needed for the experiments will be described. Firstly it is important to describe signal propagation models that were used in the process of the radio map creation. The second part of this section will describe algorithms, which were used in the positioning system to estimate position of mobile device.

Propagation models

Propagation models used for radio map creation are described in this subsection; both models are implemented in Radioplan RPS software tool that was used for a simulation of radio map [8].

3D Ray tracing

Ray tracing propagation model is based on geometrical optics. The ray is assumed to be direct, unless it hit the surface of the obstacle. In such case the ray is reflected and the direction of reflected ray is given by the

Shnelliu's law. Attenuations caused by the reflections are given by thickness of the obstacle, its material characteristics and frequency of the radio signal [9].

Advantage of this model is that large amount of information is used for estimation of received signal strength. The radio signal is assumed to be propagated from the transmitter to receiver by multiple paths and each path has different signal strength. This may result to the higher complexity and demands on computational power.

Ray tracing techniques can be divided into ray launching and ray imaging. Computationally more effective solution for high number of reflections is the ray launching method. In this method, rays are emitted homogenously in all directions from a unit sphere centered on transmitter antenna. Only those rays that intersect imaginary detection area at the receiver antenna after a number of reflections and diffractions lower than threshold are counted into the received signal. The basic rule is that the higher the number of rays the lower the detection error, however, it is important to accurately define the detection area. In case that the area is too small or too big, the detection gap is increased or rays that should not be received are detected [10].

COST231 Multi-Wall Model

In contrast to ray tracing approach, the COST 312 Multi-Wall Model (MWM) estimate Received Signal Strength (RSS) based on direct path between the transmitter and the receiver and is given by [11]:

$$L = L_0 + 20\log_{10}(d) + k_f\left[\frac{k_f+2}{k_f+1} - b\right]L_f + \sum_{i=1}^{k_w} k_{wi}L_{wi}$$

where L_0 denotes 40.2 dB for 2.4GHz frequency band, k_f stands for the number of penetrated floors d is the distance between transmitter and receiver, b is used to empirically fit the nonlinear effects of the number of floors, L_f represents the loss between adjacent floors, k_w gives the number of different wall types, k_{wi} and L_{wi} are number and attenuations of walls of i-th type respectively.

Fingerprinting algorithms

In the paper we deal with deterministic algorithms from the fingerprinting framework. The basic assumption used in the deterministic framework is that RSS is not random and depends only on the position of the mobile device.

Basically, the fingerprinting approach is performed in two main stages, the first – calibration phase is performed in the area where positioning system is to be deployed. The second stage, called online or positioning stage is in fact the operation of the positioning system itself. During this stage different devices may request estimates of their position. The position is estimated, based on measurements performed on the device, in the localization server using different localization algorithms.

Offline phase

During the calibration phase the radio map is constructed by collection of fingerprints in the area, where the positioning service is to be deployed. Fingerprints consist of measured radio signal property linked with position where it was collected. The most common radio signal property that is measured is RSS, however other measurements are also possible e.g. RTT (Round Trip Time), ToA (Time of Arrival) and SIR (Signal-to-Interference Ratio). The fingerprints are then sent to the radio map database in the following form:

$$S_j = (\alpha_1, ..., \alpha_{N_j}, c_j, \theta_j) \qquad j = 1,2,..., M$$

where N_j is the number of APs in the communication range at the j-th reference point, M stands for the number of reference points, α_i are RSS values, c_j denotes coordinates of j-th reference point and parameter vector θ_j can contain any additional information that may be used in the localization phase.

This stage of fingerprinting framework represents the main drawback of fingerprinting method, since it may be time consuming and it is necessary to be performed in the area of localization. In this paper we will use simulation of radio propagation instead of traditional on-site calibration measurements.

Nearest Neighbor Family Algorithms

In the online or positioning stage of fingerprinting framework, the mobile device measures given radio signal property and send the measurements to the localization server. The localization server uses one of the implemented algorithms in order to estimate the position of mobile device. Used algorithms can be divided to two main groups – deterministic algorithms and probabilistic algorithms. In the literature it was shown that algorithms from both frameworks achieve very similar results [12].

Algorithms from the Nearest Neighbor (NN) family are one of the most common algorithms used in the fingerprinting positioning. In contrast to the probabilistic algorithms, the main advantage of NN algorithms is that there is no need of accurate probabilistic model to describe the area of positioning. Therefore it is possible to extend the area where the positioning service is about to be provided, without any additional effort. The estimator used to guesstimate the position of the mobile device can be written as:

$$\hat{x} = \sum_{i=1}^{M} \omega_i \cdot c_i \Big/ \sum_{i=1}^{M} \omega_i$$

where ω_i represents a weighting factor, that has to be non-negative. In the most of the applications the weights are given as the inverted value of the distance between RSS vectors from the positioning phase and vectors stored in the radio map database. Currently the most widespread solution is to use the Euclidean distance, but other distance measures can be used and resulting in results [13].

If the estimator in the formula (3) keeps the K highest weights and sets the others to zero, the algorithms is labeled as the WKNN (Weighted K-Nearest Neighbors) method. In case that estimator uses WKNN with all

VOL. 10, NO. 15, AUGUST 2015 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

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weights set to $\omega_i = 1$ it is entitled as KNN (K-Nearest Neighbors) method [7]. Furthermore the simplest mode, where $K = 1$, is named the NN (Nearest Neighbor) method. Obviously it was found that WKNN and KNN methods achieve better results as the NN method, specifically when the parameter K is set to 3 or 4 [12].

RBF Algorithm

In the previous paper [14] we had proposed the RBF (Rank Based Fingerprinting) algorithm, which is a modification of deterministic KNN algorithm. In the algorithm preprocessing of measured data was introduced in order to reduce impact of device parameters on accuracy of estimated position. The algorithm use rank vectors instead of RSS values to estimate position of the mobile device as can be seen from the Figure-1.

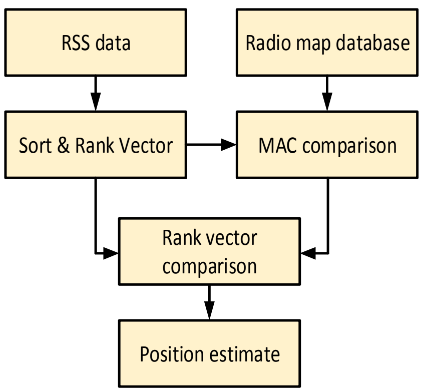

Figure-1. Principle of the RBF algorithm.

In the RBF the algorithm firstly sort APs in the range from the AP with the highest RSS value to AP with the lowest RSS. Rank vector X is created by adding rank to each AP based on the position in sorted vector in the following manner: the value equal to 1 is given to the first (i.e. strongest) AP, the second strongest AP has rank 2, etc. The rank of AP in fact represents its position in the sorted vector.

Rank vectors Y_i are created afterwards, based on information from the radio map database. Process of the rank vector creation is using MAC address comparison, so APs with the same MAC addresses have the same rank values. In contrast to vector X, in vectors Y_i the rank values do not have to represent the position of APs in the sorted vector [14].

After the rank vectors from both database and measurements are created the algorithms compute similarity between them. The RBF algorithm utilizes the Spearman's footrule [15], which given by:

$$d_i = \sum_{j=1}^{n} \left| x_j - y_{ij} \right|$$

where x_j represents the rank of j-th element in vector X, similarly y_{ij} stands for the rank of j-th element in vector Y_i and n is given by the number of elements in vectors X and Y_i.

In the last step the position of the mobile device is estimated using (3). Similarly to NN algorithms, the weights ω_i are given as inverted value of Spearman's footrule in case that RBF is used. Implemented algorithm keeps K highest weights and sets others to 0, therefore, RBF represents a modified version of WKNN algorithm.

Simulation and measurement scenario

This section describes scenarios proposed in order to evaluate impact of radio map simulation on the localization accuracy of different fingerprinting algorithms. In this section, firstly the simulations performed in the Radioplan RPX software will be described. The second part of the section will be dedicated to description of real world testing scenario, which was performed at the Department of Telecommunication and Multimedia at the University of Zilina.

Simulation of Radio Map

The simulations were performed using the accurate model of the Department of Telecommunications and Multimedia at the University of Zilina. The model can be seen in Figure-2.

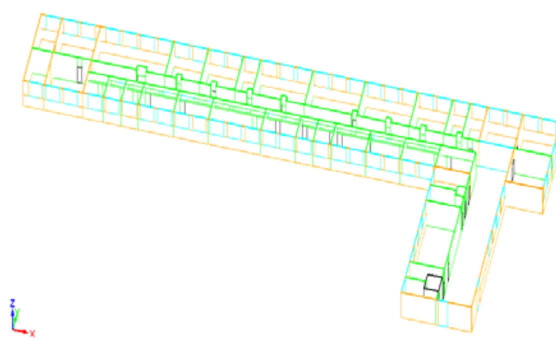

Figure-2. Model of the area where the positioning was performed.

In the simulation both models described in previous section were used to create radio map. We decided to use both models, because their cornerstones are based on different assumptions. The 3D ray tracing propagation model estimates the RSS based on multipath propagation, in contrast to COST231 MWM, which estimates the RSS only from direct path of the radio signal.

In the simulation we decided to use 6 APs, which were placed in the area in order to cover most of the department with a radio signal. Reference points were chosen in grid with 2m spacing as can be seen in Figure-3.

ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

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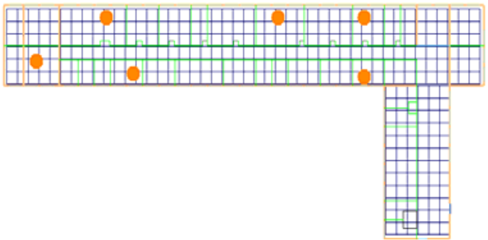

Figure-3. Simulation scenario setup.

The orange points in the figure represent positions of the APs and reference points are defines by the intersections of the blue lines. Results of the simulation were stored in the radio map and used for the positioning using real world measurements.

Real World measurements

The measurement scenario was set up in correlation with the simulation scenario. There were 6 APs placed at the area of localization, and their positions were the same as in simulation.

In order to reduce impact of signal fluctuations on the position estimate signal averaging was performed at the mobile device. The average RSS can be defined as:

$$\overline{RSS} = \frac{1}{N_s}\sum_{i=1}^{N_S} RSS_i$$

where RSS_i represents i-th RSS sample and N_S is given by the number of RSS measurements. In our scenario we used 20 RSS samples to calculate the average RSS value.

In the experiment 50 position estimations were performed on different positions in the area. Positions were estimated by the localization server that utilized radio maps from both propagation models at the same time. Therefore, the results were achieved under the same conditions.

Achieved Results

In this section achieved results are shown and discusses. Firstly, the results achieved when the radio map was created using 3D Ray tracing model. During the localization phase all the described algorithms were used. The achieved results can be seen in the Figure-4.

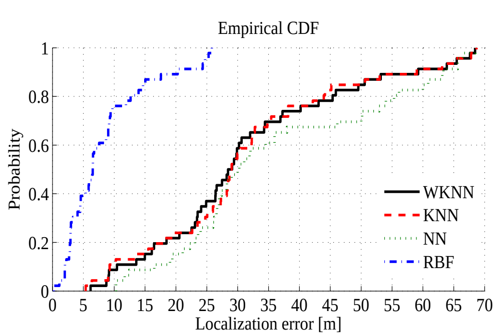

Figure-4. Localization error achieved when 3D Ray tracing model was used.

From the figure it is clearly seen that RBF algorithm achieved significantly lower localization error when compared to the traditional NN algorithms. In addition it can be noted that all three traditional NN algorithms achieved very similar results. The statistical description of achieved results can be found in the Table-1.

Table-1. Localization errors achieved when 3D Ray tracing model was used.

Algorithm used	Mean error [m]	Median error [m]	Standard deviation [m]	95% error [m]
RBF	8.38	6.52	6.85	24.83
WKNN	31.64	28.77	16.29	65.91
KNN	31.52	28.91	16.26	65.80
NN	36.18	30.13	17.32	65.82

From the table it can be seen how significantly better the accuracy achieved by the RBF algorithm is. It can be noted that both mean and median localization errors are more than three time lower for RBF when compared to other algorithms. From the traditional algorithms the best results were achieved by the WKNN algorithm; however the difference with KNN is not significant.

Similarly the results achieved when radio map created using COST231 MWM model was used can be seen in the Figure-5.

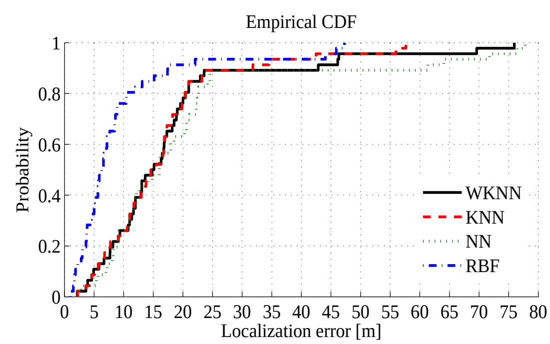

Figure-5. Localization error achieved when COST231 MWM model was used.

It can be noted that, similarly to results achieved with radio map created using 3D ray tracing, RBF algorithm achieved the highest accuracy. However it is important to note that results achieved by the traditional deterministic algorithms seem to be slightly better. The statistical description of achieved results can be seen in the Table-2.

Table-2. Localization errors achieved when COST231 MWM model was used.

Algorithm used	Mean error [m]	Median error [m]	Standard deviation [m]	95% error [m]
RBF	9.44	6.43	10.69	44.43
WKNN	18.04	14.96	15.24	50.98
KNN	16.74	15.04	11.77	45.18
NN	20.48	16	18.72	72.70

From the results it can be seen that mean error achieved by the RBF algorithm is again significantly lower when compared to traditional algorithms. When compared do KNN the mean error is almost two times lower, in addition to that median error it is approximately 2.5 times better than results achieved by the NN and WKNN algorithms.

In case that radio map was created using COST231 MWM model, the best results among the traditional algorithms was achieved by KNN algorithm. When this algorithm was used the mean localization error was more than 1m and 3m lower compared to WKNN and NN, respectively. Also the difference in 95% error achieved by KNN algorithm is significantly lower when compared to WKNN and NN algorithms.

From the previously presented results it is clear that the most appropriate algorithm to be used with simulated radio map is the RBF algorithm. Therefore, the comparison of CDF error achieved by RBF algorithm for the radio map created using both propagation models is shown in Figure-6.

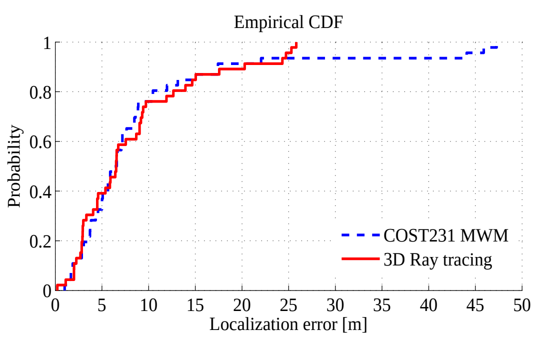

Figure-6. Results achieved by RBF with both models used for radio map construction.

From the results in the figure it can be seen that RBF algorithm performed very similar in both cases. However, it is important to note that there was significantly lower number of outliers when 3D Ray tracing propagation model was used to simulate the radio map.

In comparison to real world results published in [14] achieved accuracy of all algorithms was lower, however, this may be caused by the fact that relatively low number of APs was used in the scenario presented in this paper. In the current scenario there were spots with only 2 or 3 APs were in the range, which may have negative impact on accuracy of position estimates.

CONCLUSIONS

In the paper impact of radio map modeling on positioning in the indoor environment was investigated. Two propagation models based on different principles were used to construct the radio map instead of traditional on-site calibration measurements.

From the achieved results it is clear that traditional NN family algorithms are significantly affected by the simulation of radio map. The achieved localization error is extremely high and such results cannot be used in the real applications. However, previously proposed RBF algorithm achieved promising results. Therefore, propagation models seem to work correctly in combination with the RBF algorithm.

In the future we would like to give more focus on testing and evaluation of positioning system, which will utilize signal propagation modeling for creation of radio map. Such system may help to easily deploy indoor positioning system and open new market for service providers.

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