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Optimization of Rank Based Fingerprinting Localization Algorithm

J. Machaj, P. Brida
Department of Telecommunications and Multimedia
Faculty of Electrical Engineering, University of Zilina
Zilina, Slovakia
{juraj.machaj, peter.brida}@fel.uniza.sk,

***Abstract*— This paper deals with optimization of the Rank Based Fingerprinting (RBF) algorithm, which was previously proposed by the author. Results achieved in the real world experiments shown that RBF algorithm can achieve more accurate position estimate compared to some of traditional fingerprinting algorithms. Accuracy of the RBF algorithm seems to be less affected by change of device and small signal fluctuations since algorithm is based on assumption that bias and scale of measured RSS data will not affect rank of the APs. Optimization algorithm that significantly reduces computational complexity of the RBF algorithm will be introduced. Function of the algorithm was investigated in the simulations and real world experiments. Achieved results show that proposed optimization algorithm can significantly decrease computation complexity, especially when radio map database is high enough. Achieved results show that proposed optimization algorithm allows use of the RBF algorithm in applications, where the position estimate must be calculated in a very short time e.g. tracking and navigation applications.**

Keywords- optimization; Rank Based Fingerprinting; indoor positioning; localization

I. INTRODUCTION

In the last decade large number of LBS (Location Based Services) was developed [1], [2]. These services become extremely popular between the users and became part of their daily life. Since basic requirement for LBS is accurate position estimate these systems were at the beginning mainly developed for the indoor environment where position can be estimated using one of GNSS (Global Navigation Satellite Systems). In the last few years there was a higher demand on the development of the LBS for the indoor environment. Main problem here is position estimation, since GNSS can not be used due to high signal attenuations caused by the structure of a building [3].

The fact that GNSS can not be used in the indoor environment caused that novel localization systems and algorithms were developed by many research teams. Most popular way to estimate position in the indoor environment is use of radio networks. This is caused by the fact that almost every device, on which LBS are used, needs wireless connection to the internet or to the service provider. Large number of the localization systems was developed [3], [4]. These systems are based on wireless technologies like Wi-Fi [5], [6], GSM [7], Bluetooth [8], ZigBee [9] and UWB [10].

Wi-Fi seems to be most feasible network technology from the economy point of view, since transmitters are already implemented in the large number of devices, network components are quite cheap and Wi-Fi networks are almost ubiquitous in the indoor environment. Most popular positioning approach in combination with the Wi-Fi networks is fingerprinting positioning [5]. The main advantage of the fingerprinting positioning approach seems to be immunity to the multipath propagation of a radio signal. On the other hand the disadvantages of the fingerprinting approach are need of the offline (calibration) phase and influence of device change. During the offline phase the radio map is created at the area where positioning will be performed. Radio map is database which consists of reference points positions and RSS (Received Signal Strength) values measured on each of the reference points from all the surrounding APs. Even higher disadvantage is that accuracy of the fingerprinting localization systems is affected by the change of hardware and software of used devices. Hardware change is given by the fact that there are receivers and antennas with different gains implemented in devices. Software change is mainly given by the different scale in which RSS are measured.

In the previous work [11] we have proposed novel fingerprinting algorithm RBF (Rank Based Fingerprinting) that does not use measured RSS values directly, but use rank of the APs based on RSS values. This algorithm is based on the assumption that the rank of a given AP will be less affected due to device change compared to measured RSS value. From the results achieved in the real world measurements the accuracy of RBF was higher and less affected by a change of the used device compared to NN and WKNN algorithms. The drawback of the proposed RBF algorithm is computational complexity, due to need of preprocessing of measured data and creation of the rank vectors, which are used during the position estimation process. Computational complexity is an important parameter in dynamic application such as navigation or tracking, when position must be estimated in the shortest time possible. In this paper optimization algorithm developed to decrease

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computational complexity of the RBF algorithm will be introduced and will be tested in the simulations and real world measurements.

The rest of the paper will be organized as follows; in the next section related work in the area of fingerprinting localization will be described. Proposed optimization algorithm for the radio map reduction will be introduced in the section 3. In the section 4 simulation and measurement scenarios will be described. Achieved results will be shown and discussed in the section 5 and section 6 will conclude the paper and propose some of the goals for the future work.

II. Related Work

In this section fingerprinting algorithms used in simulations and measurements will be described. In general, fingerprinting algorithms consist of two phases. First phase is the offline phase (also called calibration phase). In this phase, the radio map is created and stored in the database [11]. Second phase is called online phase, mobile device position is estimated using one of fingerprinting algorithms in this phase. In the measurements deterministic WKNN algorithm was used as comparison to the RBF algorithm.

A. Radio map construction

Radio map is built during the offline phase. Area where localization services will be offered is divided into small cells in this phase. Each cell is represented by one spot, called Reference Point (RP) [12]. In these points RSS values from all transmitters in range – fingerprint is measured for certain period of time and stored in database. Principle of radio map creation can be seen in Fig. 1. Element of radio map has the form:

$$P_j = (N_j, \alpha_{ji}, \theta_j) \qquad j = 1,2,\dots,M , \tag{1}$$

where N_j is number of j-th reference point, M is the number of all RPs, α_{ji} is the vector of RSS values and parameter θ_j obtains additional information used in localization phase. Radio map can be modified or preprocessed before the online phase to reduce memory requirements or computational cost of used localization algorithm.

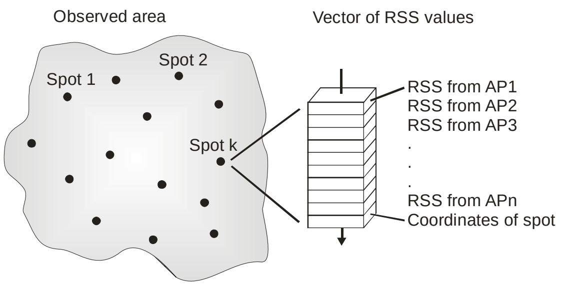

Figure 1. Radio map creation.

B. NN family localization algorithms

Deterministic framework is based on assumption that RSS values on each position represents non-random vector. Estimate of mobile device position $\hat{x}$ can be calculated using:

$$\hat{x} = \sum_{i=1}^{M} \omega_i \cdot P_i \Big/ \sum_{i=1}^{M} \omega_i , \tag{2}$$

where P_i is position of i-th reference point, ω_i represents weight of i-th reference point and M is number of RPs in radio map [13].

Weights can be calculated as inverted value of Euclidean distance between RSS vectors from online and offline phase. The estimator (2), which keeps the K biggest weights and sets the others to zero, is called the WKNN (Weighted K-Nearest Neighbor) [13] method. WKNN with all weights $\omega_i = 1$ is called the KNN (K-Nearest Neighbor) method. The simplest method, where K = 1, is called the NN (Nearest Neighbor) [14].

WKNN and KNN methods perform better than the NN method, particularly when values of parameter K are K = 3 or K = 4 [15]. On the other hand, NN algorithm can achieve almost the same results as KNN and WKNN algorithm in case that radio map density is high enough [12].

C. Rank Based Fingerprinting algorithm

The main difference between conventional fingerprinting algorithms and the RBF localization algorithm is the way in which measured data in offline and online phases are compared and used to estimate position [11]. In classical fingerprinting algorithms, vectors of RSS values measured in online and offline phase are directly compared to each other.

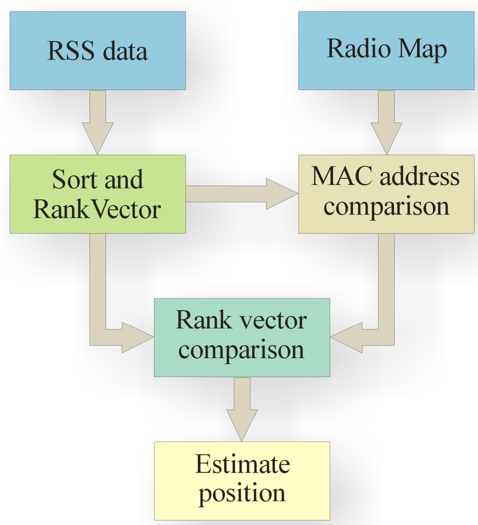

Figure 2. Block diagram of RBF algorithm.

In the RBF algorithm (Fig. 2), the RSS values measured in the online phase from different APs are first sorted from strongest to weakest. Then ranks are assigned to APs based on their position in the sorted vector. To the first AP in sorted vector rank value 1 is assigned, to second AP is assigned value 2 and so on – rank value in fact represents position of the AP in sorted vector. The sorted vector of APs detected in the online phase is then compared to vectors stored in the radio map.

In this step MAC (Media Access Control) addresses of APs in sorted vectors from online phase are compared to MAC addresses stored in sorted vectors of AP in radio map database. Based on comparison of MAC addresses ranks are assigned to the vectors from the radio map database. When MAC addresses in online and offline phases are the same, same rank values are assigned to them. In this case rank of the AP from offline phase does not need to represent position of AP in vector. In case that one (or more) of the APs from the online phase is not found in the database, the rank vector created from the radio map is padded with 0, to achieve the same length as the rank vector from the online phase.

In last step of RBF algorithm previously computed rank vectors are compared to the vector from online phase using one Spearman's footrule distance:

$$D_F = \sum_{k=1}^{n} \left| x_k - y_k \right|, \qquad (3)$$

where x_k is the rank of k-th element in vector X, y_k is the rank of k-th element in vector Y and n is the number of elements in vectors X and Y [16].

The K reference points with smallest difference are used to calculate the estimated position $\hat{x}$ using the weighted average formula (2). In proposed algorithm weights are given by similarity between rank vectors from online and offline phase.

D. *WifiLOC positioning system*

The WifiLOC positioning system is a system with decentralized architecture, using mobile device assistance [17]. The position estimate is calculated at the server implemented in the network architecture based on measurements performed by the mobile device. Architecture of the WifiLOC positioning system is shown in the Fig. 3.

The localization server can be divided into the database server and the web server. Radio map database is stored in the database server, together with additional databases which can store data about the area needed during the positioning. The web server is used for the communication with the client application and manages localization requests from the clients.

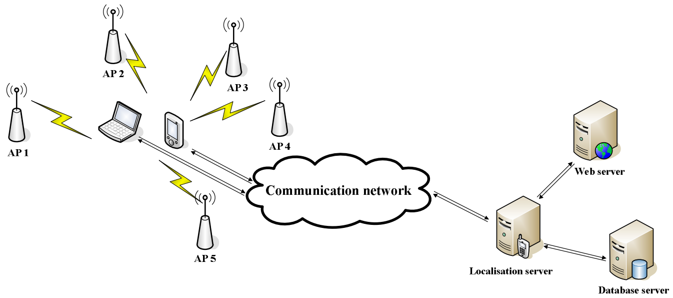

Figure 3. Flowchart of the proposed algorithm

Network access points does not to bee modified and clients does not need to connect to the APs in the range, since measurements needed for the position estimation are performed in passive mode. This helps to implement the positioning system into the areas where wireless connection is provided by the different service providers.

The mobile device can be represented by any type of mobile terminal (cell phone, PDA, laptop, …) equipped with IEEE 802.11 transmitter. Client application is developed in the Java SDK (Standard Develeopment Kit) and can be easily implemented on mobile devices based on different operation system platforms.

III. RADIO MAP REDUCTION ALGORITHM

In this section the proposed optimization algorithm for radio map reduction will be introduced. Optimization algorithm for radio map reduction was proposed to decrease computational complexity of the RBF localization algorithm and allow use the RBF algorithm in the dynamic LBS. Algorithm is developed based on assumption that computational complexity is given mainly by the number of reference points in the database. Computation complexity is higher due to preprocessing of measured data stored in the radio map database.

The proposed algorithm is used to extract a group of reference points from the database to decrease computational complexity. Basic idea is to exclude reference points if their position is far from the position of the mobile device. Proposed algorithm needs some additional data about the area. It is important to add identifications to the reference points based on the room in which they are located. It is also important to create a database with positions of the doors between the rooms. These data can help to extract reference points from the correct area and to decrease achieved localization errors.

Proposed optimization algorithm can be divided into two main parts. First part is adaptive algorithm for range estimation and the second part is part of reference point extraction. Flowchart of the proposed algorithm is shown in the Fig. 4.

A. *Adaptive algorithm for range estimation*

Adaptive algorithm for range estimation (Fig. 4, right side) was proposed to evaluate range, from which reference points will be used in positioning process. Algorithm uses previous position estimates to calculate range in which next position should be located. When only one position of mobile device is known (during the second position estimation), range is given by the maximum range value. This value was set to 20 m and it is chosen as value higher than the maximum error achieved in the previous real world measurements.

In next positioning processes the range is given by the time between two previous positioning estimations, distance between two previous position estimates and time elapsed from the last positioning. In the first step the speed of the device v [ms^{-1}] is calculated using:

$$v = \frac{d}{t_n - t_{n-1}}, \tag{4}$$

where d [m] is the Euclidean distance between previous two position estimates and t_n and t_{n-1} in [s] are times of position estimation of the last two positioning steps. Achieved speed is compared to limit value $v_{max} = 5.5\ ms^{-1}$ which is given by the speed of runner. When the speed is lower than the limit value range can be estimated using:

$$r = v \cdot t_a, \tag{5}$$

where r is estimated range and t_a is the time from the last position estimation process. Range is than compared to minimal range, which is equal to double of the grid distance between reference points.

In case that position estimate is the same for the last two positioning steps, range is given by the previous range estimate by decreasing the range. In the last step the range estimate is compared to minimum range, which is given by the distance between reference points. In case that estimated range is lower as the minimum range value, the minimum value will be used.

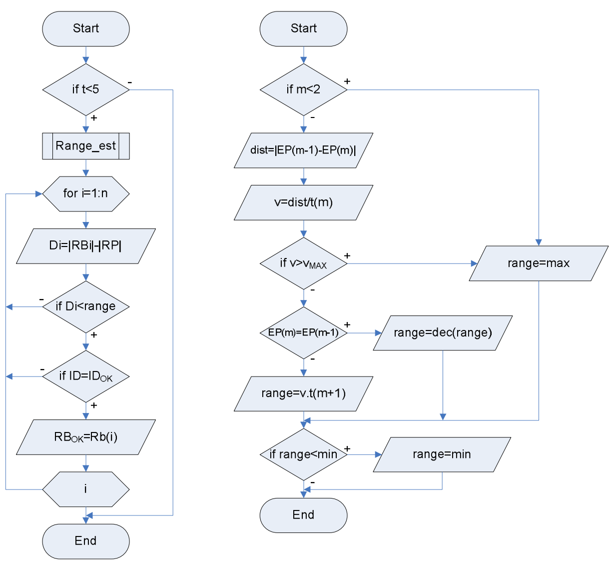

Figure 4. Flowchart of the proposed algorithm.

B. Reference points extraction algorithm

Reference point extraction algorithm is used to extract reference points from the radio map database. Extracted reference points will be used during position estimation. Extraction is performed based on the range calculated in the range estimation algorithm and informations about the area. In the first step the algorithm extracts from the radio map database all the reference points which are within the rage r from the last position estimate.

When all the reference points within the range are extracted algorithm choose points which are in the same room as previous position estimate. In case, that some of the extracted reference points are in other rooms, algorithm calculates the distance from the last position estimate to the doors between the two given rooms and the reference point. If the calculated distance is lower than the range estimate the reference point will be used during the position estimate.

IV. Simulations and Measurements Scenarios

Function of the proposed optimization algorithms was in the first step investigated in the simulations. Simulation model was created in the Matlab environment. In the simulation the Multi Wall and Floor (MWF) propagation model was used to calculate the average RSS values. These RSS values were affected by the random number with the lognormal distribution to simulate fluctuation of RSS measurements in the real world. Area where the positioning process was simulated is shown in the Fig. 5.

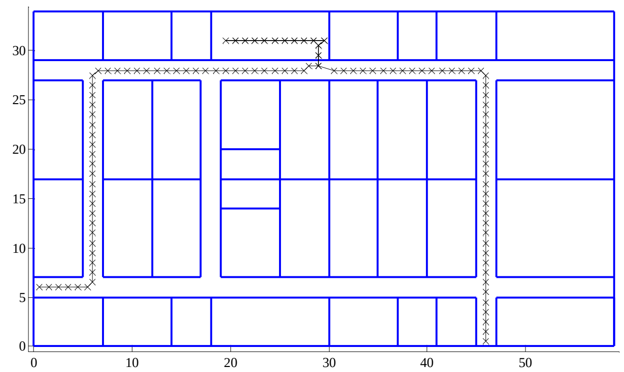

Figure 5. Area in the simulations.

The simulation scenario was proposed to evaluate impact of the two main parameters which affects the size of a radio map. Positioning process was simulated on the track which consists of the 125 points (shown as black x in Fig. 5). Simulations were performed for the different number of the reference points and different number of APs covering the area.

After the simulations the optimization algorithm was implemented into the WifiLOC positioning system, developed at University of Zilina **Chyba! Nenašiel sa žiaden zdroj odkazov.**. This positioning system was used to perform real world measurements to validate the function of the optimization and its impact on the accuracy of the RBF localization algorithm. Area where the real world measurements were performed is shown in the Fig. 6.

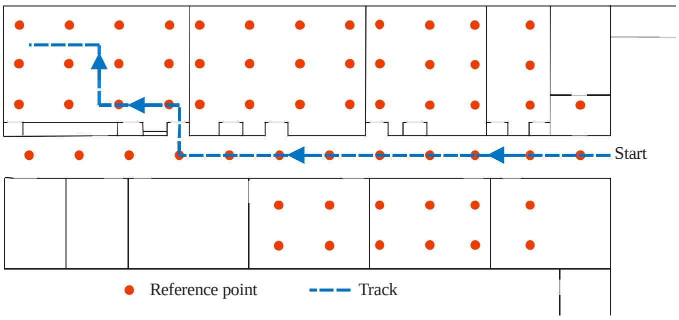

Figure 6. Area where the experiments were performed.

Performed measurements can be divided into the two scenarios. The first scenario was proposed to evaluate optimization impact on the accuracy and the complexity of the positioning system WifiLOC. Measurements in this scenario were performed during the working hours of the day, so there was large number of moving people in the area of localization. Measurements were done at the track shown in Fig. 6.

Complexity of the positioning system was measured by the time measured from the positioning data transfer to the receiving of the position estimate. Measurements were performed for three different communication technologies i.e. Wi-Fi, UMTS/HSPA and EDGE. Sequence diagram of time measurements is shown in the Fig. 7.

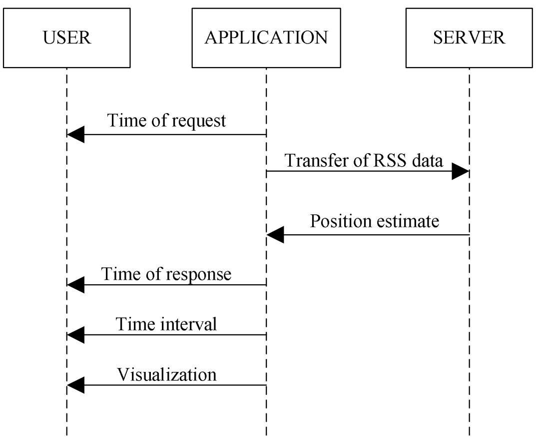

Figure 7. Sequence diagram of time measurements.

In the second scenario the accuracy of optimized RBF algorithm was tested in the different signal propagation conditions using two different devices. In this scenario measurements were performed at the same track as in previous scenario, using two devices at the same time. Measurements were performed during the working hours of a day and during the evening, when the building was almost empty. This scenario was proposed to evaluate impact of the different signal propagation conditions caused by the moving people and impact of use of the different devices on the accuracy of optimized RBF algorithm. Accuracy of optimized RBF algorithm was compared to accuracy of WKNN algorithm using the same measured data.

V. Achieved Results

In this section results achieved in the simulations and measurements will be introduced and discussed. Simulations are aimed mainly to the impact of the optimization on the computational complexity of the RBF algorithm. On the other hand measurements are aimed to evaluate impact of positioning on the localization accuracy.

A. Simulation results

In the simulation scenario the impact of the size of radio map on the complexity of RBF algorithm was investigated. In the simulation the number of APs was changed from 10 to 25 and number of reference points in the radio map was changed from 538 to 778 with step of 30. Simulations were performed on a laptop equipped with Intel Core i5 CPU (single thread used) and 4GB RAM. Achieved median of computing time for both basic and optimized RBF algorithms can be seen in the Fig. 8.

From the figure it can be seen that both number of reference points and number of APs in the area have impact on the complexity of the basic RBF algorithm. On the other hand optimized RBF algorithm has mostly the same computation complexity in all cases.

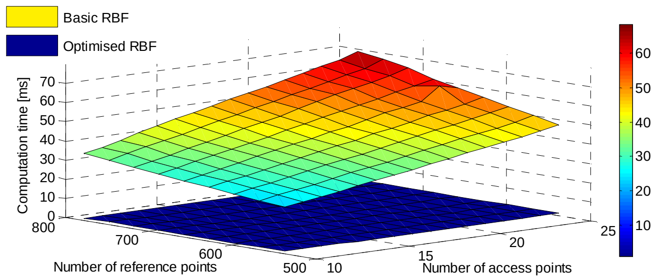

Figure 8. Impact of the number of reference points and access points on the computational complexity of optimized and basic RBF algorithms.

From the figure is clear that complexity grows linearly with both parameters of the radio map size. It can be assumed that in real world applications with higher number of reference points also the number of APs will grow, since in the new areas new APs will be in the rage.

Since complexity of the optimized RBF algorithm is changed based on the range, from which the reference points are chosen for the position estimation. In the Fig. 9 the computation times achieved in all positioning steps are shown. In this case, the number of APs was set to 10 and number of reference points in the radio map was 538.

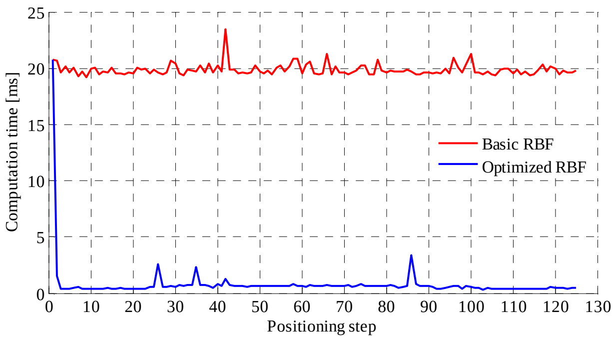

Figure 9. Impact of the optimization on the complexity of the RBF algorithm.

From the figure it can be seen that complexity of both basic and optimized RBF algorithms is the same during the first position estimation process, this is due to lack of information for the optimization algorithm. In all the next steps the computation time decrease dramatically when the optimized RBF algorithm is used. Fluctuations of the computational times shown in the figure are probably caused by the processes running in the background of the operation system.

From the results achieved in the simulations it is clear that optimization algorithm helps to significantly decrease computational complexity of the RBF algorithm in the dynamic applications. Important is the fact that complexity in the dynamic part of the localization seems to be immune to the changes of the radio map. This is due to low complexity of the optimization algorithm and low complexity of RBF in case that size of the radio map is small.

B. *Measurement results*

Real world measurements were performed at the University of Zilina campus. Radio map was created using Samsung Galaxy Tab 10.1 P7500 device. In the area total amount of 43 APs was detected, in average 10 APs were in range for each reference point. At each point of the radio map 30 samples of RSS values from APs in the range were measured. In the first scenario during the localization phase mobile device was represented by the Sony Ericsson Xperia ARC. Different device in this phase compare to offline phase was used without any additional calibration. Cumulative distribution function of the achieved localization error is shown in Fig. 10.

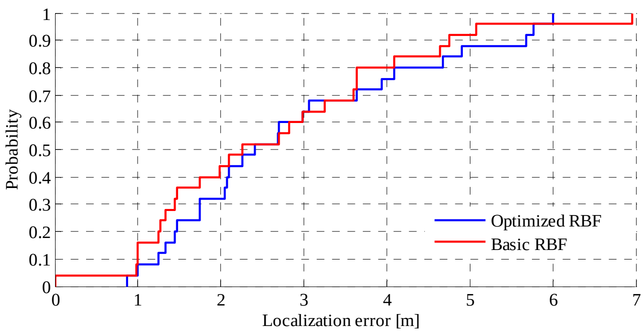

Figure 10. Impact of the optimization on the accuracy of the RBF algorithm.

From the achieved results it can be seen that localization error was slightly increased when optimized RBF algorithm was used to estimate position of mobile device compared to the basic RBF algorithm. It is assumed that the difference in achieved localization accuracy is caused by filtering out of some reference points used in the position estimation by the basic RBF algorithm.

During this scenario the delay in position estimation was also measured at the mobile device side. Achieved time delays for the different communication technologies are shown in Tab. 1.

TABLE I. POSITIONING DELAY FOR DIFFERENT TECHNOLOGIES

	EDGE	UMTS/HSPA	Wi-Fi	
Δt [ms]	1302.41	348.48	161.23	**Optimized RBF algorithm**
σ [ms]	238.64	67.9	81.79	
Δt [ms]	1353.22	380.65	193.26	**Basic RBF algorithm**
σ [ms]	242.01	68.8	82.36	

From the table it is clear that the time of positioning was slightly decreased when optimized RBF algorithm was used. The difference in position estimation delay is about 30 ms. Difference in the delays should be even higher in case that size of the radio map will be increased and more devices will send requests to the localization server. It can also be seen that the delay achieved using EDGE communication technology is much higher compared to Wi-Fi and UMTS/HSPA technologies. Since the delay achieved by the EDGE technology is higher than 1 s this technology is not feasible for the dynamic applications. High delay is caused by small transfer speed of the EDGE communication technology.

In the second measurement scenario two different devices were used during the localization phase at the same time. The same radio map as in previous scenario was used. The first device was represented by the same Samsung Galaxy Tab, which was also used during the offline phase to create radio map and Sony Ericsson Xperia ARC was again used as the second device without any additional calibration. Measurements were performed at the same time on both devices. In this scenario the localization error achieved by optimized RBF algorithm was compared to the performance of the WKNN algorithm. Achieved results can be seen in Tab. 2.

TABLE II. ACHIEVED LOCALIZATION ERROR

Device	Conditions	Localization error [m]			
		RBF		WKNN	
		Median	Max	Median	Max
Samsung	**Daytime**	3.56	9.02	3.42	9.50
	Evening	2.48	5.98	2.85	6.05
Sony Ericsson	**Daytime**	2.87	7.31	4.89	10.92
	Evening	4.97	11.47	6.60	14.01

From the achieved results can be seen that optimized RBF algorithm achieved higher accuracy compared to WKNN algorithm in all cases. When the same device was used in both online and offline phase (in table marked as Samsung) the localization accuracy achieved by WKNN algorithm was almost the same. When different devices were used the localization accuracy achieved by the optimized RBF algorithm was significantly higher compared to accuracy of the WKNN algorithm. It is clear that RBF algorithm achieved more stable results when different devices were used during the online phase of the localization process.

Interesting is a fact that the accuracy of both algorithms in the evening was higher when the same device was used in a both phases and was lower when the different devices were used. This is probably caused by the low number of detected APs during the measurements in the evening on the Sony Ericsson device, which is caused by smaller antenna gain.

From the results achieved in measurements and simulations it is clear that proposed optimization algorithm helps to significantly decrease computational complexity of the RBF algorithm. Positioning error of the algorithm is slightly higher, which can be caused by removing of some reference points which were used during position estimation in the basic RBF algorithm.

VI. Conclusion and Future Work

In the paper the optimization algorithm for a radio map reduction was proposed to decrease the computational complexity of the RBF algorithm. Function of the optimization algorithm was tested in both simulations and the real world experiments. From the achieved results is clear that the computational complexity of the RBF algorithm was significantly decreased using proposed optimization algorithm. We can conclude that the proposed optimization algorithm allows use of the RBF in dynamic applications, where the delay in the position estimation must be minimized.

The optimized RBF algorithm achieved slightly lower localization accuracy, which is caused by the fact that lower number of reference points is used during position estimation. Results shown that accuracy of the optimized RBF algorithm is slightly improved, when compared to WKNN algorithm in case that the same device was used in both online and offline phases but is significantly higher when different devices were used.

In the future work we will focus on the improvement of the algorithm from the accuracy point of view and development of the tracking and navigation system based on the RBF.

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