Performance Investigation of the RBF Localization Algorithm

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Abstract. *In the present paper the impact of network properties on localization accuracy of Rank Based Fingerprinting algorithm will be investigated. Rank Based Fingerprinting (RBF) will be described in detail together with Nearest Neighbour fingerprinting algorithms. RBF algorithm is a new algorithm and was designed as improvement of standard fingerprinting algorithms. Therefore exhaustive testing needs to be performed. This testing is mainly focused on optimal distribution of APs and its impact on positioning accuracy. Simulations were performed in Matlab environment in three different scenarios. In the first scenario different numbers of APs were implemented in the area to estimate the impact of APs number on the localization accuracy of the Rank Based Fingerprinting algorithm. The second scenario was introduced to evaluate the impact of APs placement in the localization area on the accuracy of the positioning using fingerprinting algorithms. The last scenario was proposed to investigate an impact of the number of heard APs and distribution of the RSS values on the accuracy of the RBF algorithm. Results achieved by the RBF algorithm in the first and second scenarios were compared to commonly used NN and WKNN algorithms.*

Keywords

Indoor positioning, localization, rank based fingerprinting, simulations.

1. Introduction

The basic requirement for Location Based Services (LBS) [1], [2], is knowledge of the mobile device position. This can be achieved in many different ways. Global Navigation Satellite Systems (GNSS), like GPS (Global Positioning System) or GLONASS (Global Navigation Satellite System) are widely used, and these systems work very well in the outdoor environment, especially in areas with a clear view to the satellites. However in a dense urban environment GNSS can suffer from the high signal attenuations and reflections, which can seriously degrade accuracy of the position estimate. The situation is even worse in the indoor environment, as GNSS signals are mostly too weak to be received at all.

These drawbacks of GNSS have motivated the development of positioning algorithms that use signals from existing or newly deployed radio networks. These algorithms use different properties of the radio signals. Measurements of RSS (Received Signal Strength) and ToA (Time of Arrival) are most common in the indoor environment. The work presented in this paper deals with the RSS measurements. Advantage of RSS consists in the ability of every device operating in radio networks to measure this parameter without additional modifications. Indoor positioning systems can be based on a different wireless technologies, for example Bluetooth (IEEE 802.15), [3], UWB (Ultra Wide Band), [4] and WiFi (IEEE 802.11), [5], [6], [7], [8], [9], [10], [11], [12]. This work deals with WiFi signals, because WiFi is the most common technology in the indoor environment and it is supported by a wide range of devices, e.g. cell phones, PDAs, tablets and laptops.

Most indoor positioning systems based on WiFi use some kind of fingerprinting algorithms. In the fingerprinting algorithms, measured RSS values stored in a database (known as a radio map) are compared to RSS values measured by the mobile device during the localization process. A basic difficulty here is that because of hardware and software differences between the different devices (even devices of the same make and model), the RSS reported by the mobile device may differ from the RSS in the database, and this can significantly degrade the positioning accuracy [6], [7]. One approach to deal with this issue is to calibrate the RSS scale and bias for the each device. This can be done for example using a self-calibration learning algorithm as proposed in [6]. Another solution was for this issue is to calibrate used devices in the anchor room as proposed in [7].

In the previous work [13], we proposed a novel fingerprinting positioning algorithm that uses only the rankings of the APs instead of the RSS values and is called Rank Based Fingerprinting (RBF) algorithm. Since rank information is invariant to any monotonic increasing transformation (bias and scale), the algorithm's performance seems to be less affected by the change of the mobile device. Differences in bias and scale are given by different hardware and software equipments of use devices. It can be caused for example by different gains of receivers and antennas.

In this paper we will investigate the impact of the number of Access Points (APs) and their placement on localization accuracy of the RBF algorithm. We will try to find the optimal solution for APs placement to achieve higher localization accuracy. Impact of the number of APs will be also investigated to find the optimal number of APs for localization in the real world environment. Results achieved by RBF algorithm for the different number and different placement of the APs will be compared to traditional fingerprinting algorithms. We will also take a closer look on the distribution of the localization error in the test area and try to find what lies behind the higher error in some parts of the area. The rest of the paper is organized as follows. In the next section related work in the area of fingerprinting localization algorithms used in simulations will be described. Section three will introduce used a simulation model and describe simulation scenarios. Achieved simulation results will be shown and discussed in section four and section five will conclude the paper and propose some of the ideas for the future work.

2. Related Work

In this section fingerprinting algorithms used in the simulations will be described. In general, fingerprinting algorithms consist of two phases [12]. The first phase is the offline phase (also called calibration phase), [9]. In this phase, the radio map database is created and stored in the database at the localization server. The second phase is called online phase [11]. In this phase position of the mobile device is estimated using one of the fingerprinting algorithms. In this paper deterministic NN and WKNN algorithms were used as a comparison to the RBF algorithm in the simulations.

2.1. Radio Map

Radio map is built during the offline phase. Area where localization services will be offered is divided into small cells during this phase. Each cell is represented by one spot, called Reference Point (RP). In the all reference points the RSS values from all the transmitters in the range - fingerprint is measured for the certain period of time [9]. Principle of the radio map creation can be seen in Fig. 1. Element of radio map has the form:

$$P_a = (N_a, \vec{\alpha}_{ab}, \theta_a);\ a = 1, 2, ..., M, \tag{1}$$

where N_a is identification of a-th reference point, M is the number of all RPs, $\vec{\alpha}_{ab}$ is the vector of RSS values and parameter θ_a obtains additional information which can be used during the localization phase. Radio map can be modified or preprocessed before the online phase to reduce memory requirements or computational cost of used localization algorithm.

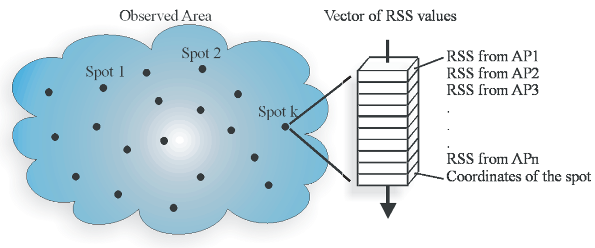

Fig. 1: Radio map creation.

2.2. NN Family Localization Algorithms

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

$$\hat{x} = \frac{\sum\limits_{a=1}^{M} \omega_a P_a}{\sum\limits_{a=1}^{M}}, \tag{2}$$

where P_a is the position of a-th reference point, ω_a represents the weight of a-th reference point and M is the number of RPs in radio map.

Weighting factors can be calculated as the inverted value of Euclidean distance between the RSS vectors from the online and radio map. The estimator (2), which keeps the K biggest weights and sets the others to zero, is called the WKNN (Weighted K-Nearest Neighbor) method. WKNN with all weights $\omega_a = 1$ 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 $K = 4$ [9]. On the other hand, NN method can achieve almost the same results as KNN and WKNN methods in case, that the density of a radio map is high enough.

2.3. Rank Based Fingerprinting Algorithm

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

In the RBF algorithm (Fig. 2), the RSS values measured in the online phase from different APs are sorted from strongest to weakest in the first step. Then ranks are assigned to APs based on their position in the sorted vector $\vec{x}$. 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 the position of the AP in sorted vector from the online phase. The sorted vector of APs detected in the online phase is in the next step compared to vectors stored in the radio map.

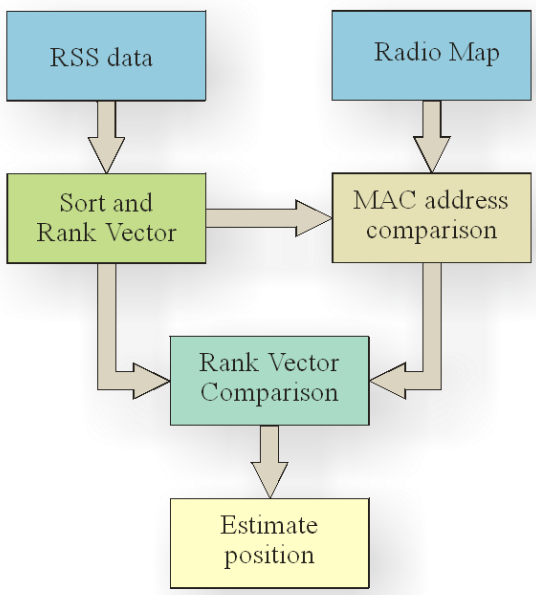

Fig. 2: Block diagram of RBF algorithm.

In this step MAC (Media Access Control) addresses of APs in sorted the vector from online phase are compared to MAC addresses stored in the sorted vectors of AP in the radio map database. Based on comparison of MAC addresses rank vectors $\vec{y}_M$ are created from the data stored in the radio map database. When MAC addresses of the APs in online and offline phases are the same, same rank values are assigned to them. This means that the rank of the AP from the radio map does not represent the position of AP in a sorted 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 the last step of the RBF algorithm, previously computed rank vectors are compared to the vector from online phase using Spearman's footrule [15]:

$$D_F = \sum_{c=1}^{h} |\vec{x}_c - \vec{y}_c| \,, \tag{3}$$

where $\vec{x}_c$ is the rank of c-th element in vector $\vec{x}$, y_c is the rank of c-th element in vector $\vec{y}$ and h is the number of elements in vectors $\vec{x}$ and $\vec{y}$. The K reference points with the smallest difference are used to calculate the estimated position using the weighted average formula (2). In proposed algorithm weights are given by similarity between rank vectors from online and offline phase.

3. Simulation Model and Scenarios

In this section the simulation model created in the Matlab environment to evaluate localization performance of indoor localization algorithms based on the fingerprinting will be briefly described. Simulation model was previously minutely described in [16]. Simulation scenarios used to achieve the results shown in this paper will be described.

3.1. Simulation Model

In the simulation model the RSS is modeled by two independent parts: path-loss and immediate variations of signal strength. Path-loss is based on multi-floor-and-wall propagation model (MFW), [17].

$$L_{MFW} = L_0 + 10\, n \log(d) + \sum_{i=1}^{I} \sum_{k=1}^{K_{wi}} L_{wik} + + \sum_{j=1}^{J} \sum_{k=1}^{K_{fj}} L_{fjk}. \tag{4}$$

The MFW model considers the nonlinear relationship between the cumulative penetration loss and the number of penetrated floors and walls. Total loss L_{MFW} in distance d can be computed from equation 4, where L_0 is the path loss in the distance of 1 m in dB, n is power decay index, d is the distance between transmitter and receiver in meters, I is the number of walls types, K_{wi} is the number of traversed walls of category i, L_{wik} is attenuation due to wall type i and k-th traversed wall in dB, J stands for a number of floor types, K_{fj} is the number of traversed floors of category j and L_{fjk} represents attenuation due to the floor of the type i and k-th traversed floor in dB. Immediate variations of signal strength could be caused by objects motion at observed area. These variations influence RSSI measurements and add measurement error. Behavior of the variations was derived from experimental measurements. Measurement error is simulated using random variable with lognormal distribution.

3.2. Simulation Scenarios

In all scenarios the localization process was performed at an area of 512 square meters. Reference points were chosen in a grid with the 2 m distance between them. Localization area can be seen in Fig. 3. In the figure the lines represents walls of the building and the dots show positions of the reference points. Position of mobile device was chosen from the area randomly with the uniform distribution.

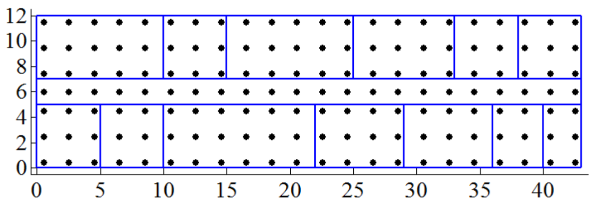

Fig. 3: Localization area.

Each fingerprint is created by measuring of 20 RSS samples for the each AP in the very short time on all reference points. The average received signal strength was calculated from these measurements to eliminate the signal fluctuations. Simulations were performed with the 1000 independent trials, i.e. for the 1000 positions of the mobile device. In the simulations $K = 4$ was used for WKNN algorithm. In the RBF algorithm, the number of used RPs to estimate the position of the mobile device was set to 2. Parameter K for both RBF and WKNN algorithms was chosen based on results achieved in previous simulations.

In the first scenario, the number of APs on the area was changed from 4 up to 12 to evaluate the impact on localization accuracy of the fingerprinting algorithms. In this scenario APs were placed randomly, in the area with the same configuration for every number of APs and also in all trials.

In the second scenario, impact of AP placement on the localization accuracy was investigated. In this scenario APs were placed in the area in 4 different shapes (Fig. 4) - random, symmetric, square and triangle, to evaluate the impact of AP placement and find the optimal solution.

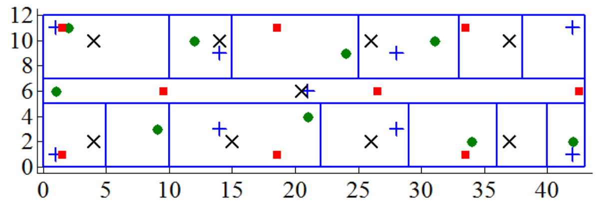

Fig. 4: Shapes of AP placement in the second scenario.

In the figure, green dots represent random placement of APs, blue crosses show positions of APs in the symmetric shape, black × show positions of APs in the square shape and red squares represent positions of APs in the triangle shape.

In the third scenario, position of mobile device was generated in the grid thru the whole localization area with a step of 0,5 m. In this scenario, the distribution of localization error over the area was investigated. Simulations were performed in 100 individual trials for each position of the mobile device. Impact of the number of the APs in the range and distribution of the RSS values from APs on the achieved accuracy was investigated in this simulation scenario.

4. Simulation Results

In the first simulations, impact of the number of APs distributed on the localization area was evaluated. Results achieved in this simulation are shown in Fig. 5.

From Fig. 5 it can be seen that number of APs in the localization area has an impact on localization accuracy of all fingerprinting localization algorithms. According to achieved results in this simulation, RBF algorithm seems to be less affected by changing the number of APs compared to the traditional algorithms. On the other hand, NN and WKNN algorithms seem to be more affected, if the number of APs is lower than 9. In case that the number of APs is 9 and higher the performance of algorithms used in simulations seems not to be significantly affected.

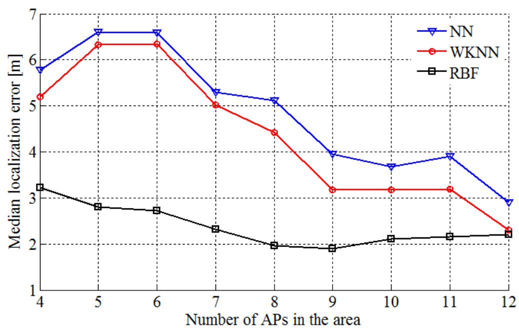

Fig. 5: Impact of the number of APs.

It can be seen that RBF algorithm achieved the best results in all cases. When number of APs is lower than 9 this difference is more obvious, since median localization error achieved by RBF algorithm is more than 50 % lower compared to WKNN algorithm. When number of APs is higher than 8, the difference in median localization accuracy between WKNN and RBF localization algorithms decrease to approximately 30 %. These results prove that the localization accuracy of the RBF algorithm is less affected by the number of APs in the range, compared to NN and WKNN algorithms.

On the basis of achieved results it is possible to choose optimal number of APs equal to 9, since further increase of the number of APs does not provide significant improvement of the localization accuracy. When optimal number of APs was found in the previous simulation, the second scenario was proposed to find optimal shape of APs placement in the area to further improve localization accuracy. In this scenario, number of APs was equal to 9. Achieved results are depicted in Fig. 6.

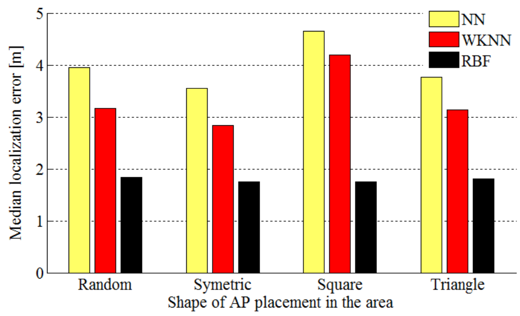

Fig. 6: Impact of the shape of APs.

From the figure it can be seen that shape of APs placement does not have an impact on the accuracy of RBF localization algorithm. Achieved results for the RBF algorithm are almost the same for all investigated cases. Small differences in the results for RBF algorithm are probably caused by differences in random positions of the mobile device than by the differences in APs positions. From the results it can be seen that shape of APs placement has more significant impact on classical fingerprinting algorithms. These algorithms achieved the best results with symmetric shape of APs, and in the other hand the worst results when APs were placed in square shape. RBF algorithm seems to be immune to shape of APs placement in the localization area. This simulation proves that RBF localization algorithm is more stable and accurate compared to NN and WKNN algorithms.

Further investigation of localization accuracy of the RBF algorithm was performed for random placement of APs. In Fig. 7 and Fig. 8 mean localization error over the localization area and distribution of the number of APs in the range are shown. Blue dots in Fig. 7 represent positions of APs in the localization area. From the figures above it can be seen that localization error is not affected by the number of APs in range. It can be seen that in the area, where a lower number of APs was in the range, the same localization accuracy as on the rest of the area was achieved. On the other hand, localization error was higher in the area where the maximum number of APs was in range (lower right corner in Fig. 7).

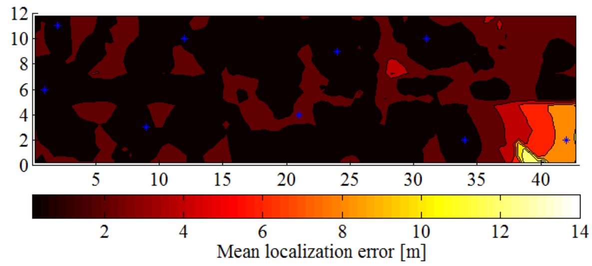

Fig. 7: Distribution of mean localization error in the area.

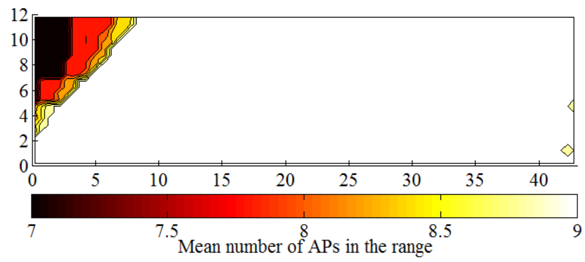

Fig. 8: Distribution of the number of APs in range.

In the next simulation we decided to take a closer look on the impact of the RSS values on the accuracy of the RBF algorithm. In the first step, the distribution of the average RSS value from all APs in the range for the each point in the area was investigated. Achieved results are shown in Fig. 9.

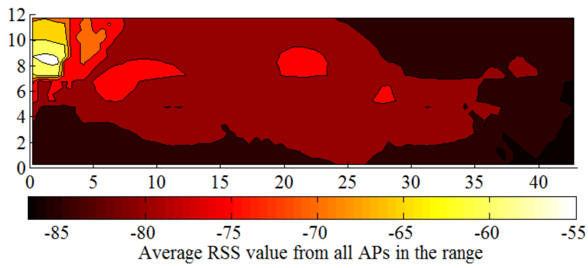

Fig. 9: Distribution of mean RSS values from all APs in the range.

From the achieved results it can be seen that average RSS values are the lowest in the area where the highest localization error was achieved. It is also clear that localization accuracy in the area where the average RSS values were the highest is not significantly increased. Based on this fact we decided to take a closer look on the numbers of APs divided into three groups:

- APs with low RSS value ($RSS < -85\ dBm$),
- APs with medium RSS value ($-85\ dBm < RSS < -65\ dBm$),
- APs with high RSS value ($RSS > -65\ dBm$).

Achieved results for the APs with low RSS values are shown in Fig. 10.

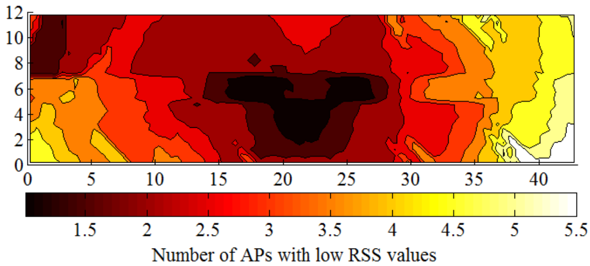

Fig. 10: Distribution of APs with RSS values lower than −85 dBm.

From the results it can be seen that in the area where the highest localization error was achieved, high number of APs with low RSS values were in the range. The results for the APs with medium RSS values are shown in Fig. 11.

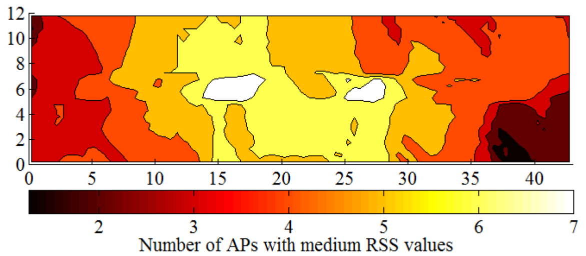

Fig. 11: Distribution of APs with RSS values in range from −85 dBm to −65 dBm.

It can be seen that in the lower right corner low number of APs with the medium RSS values were in the range. It is important to notice that number of APs with the medium RSS values in the range is much higher everywhere else in the area. Results achieved for the last group of the APs are shown in Fig. 12.

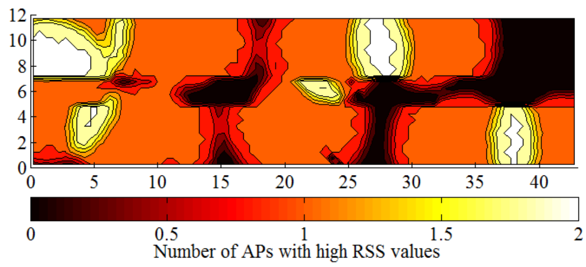

Fig. 12: Distribution of APs with RSS values higher than −65 dBm.

From these results it can be seen that number of APs with high RSS values in the range does not have a significant impact on localization accuracy. This is proven by the fact that achieved accuracy in the upper right corner of the area was the same as in the other parts of the area, even when there were not APs with the high RSS values.On the basis of the results achieved in this scenario it seems that localization accuracy is given by the number of APs with low and medium RSS values. If the number of APs with the low RSS is high and number of APs with the medium RSS values is low, then the localization error is significantly increased. The number of APs with high RSS values significantly influences the accuracy of RBF algorithm. This is due to the fact that the low RSS values are much more affected by the fluctuations and noise compared to medium and high RSS values. From the results it is clear that, when the number of APs with the high and medium RSS values is lower than 50 % of all APs in the localization area, the localization accuracy is significantly decreased. In this case localization error increased to 200–300 % of the average localization error. The lowest accuracy of the RBF algorithm was achieved when only less than 34 % of APs has high or medium RSS values. This error was 600 % higher compared to average localization error in the area.

5. Conclusion and Future Work

In this paper, the exhaustive investigation of RBF algorithm was performed. The impact of the number of APs and APs placement in the localization area on localization accuracy was investigated using simulations. Simulations were performed in Matlab environment. According to achieved results, it can be seen that RBF localization can achieve much better results, compared to WKNN algorithm. In case that number of APs in the area is not enough high, localization error achieved by RBF algorithm is 50 % lower compared to localization error achieved by WKNN algorithm. In case that number of APs in the area is higher RBF algorithm still outperforms WKNN algorithm, but difference decrease to approximately 30 %.

From results achieved in the second simulation scenario it seems that RBF fingerprinting algorithm is not strongly affected by shape on which APs are placed in the localization area. RBF algorithm achieved best results from used localization algorithms in all cases. Small differences in accuracy were more probably caused by differences in measured RSS samples in the simulations, than by changes in the shape of APs placement in the localization area. On the other hand, NN and WKNN algorithms achieved best results for symmetric shape of APs placement in the area. It can also be seen that NN and WKNN algorithms are more affected by shape of APs placement in the area. Achieved results showed that recently developed RBF algorithm can achieve more accurate results compare with commonly used NN and WKNN algorithms. It is also clear that RBF algorithm is more stable and is less affected by the number of APs in the localization area. Localization accuracy of RBF algorithm is not affected by shape of APs placement as well. This parameter also seems to have an impact on NN and WKNN algorithms, since the difference in median localization error between the best and the worst case is over 1 m.

Extensive investigation of the accuracy achieved by the RBF algorithm over the localization area has shown, that algorithm achieved the same level of accuracy even in areas, where number of APs in the range was lower. Higher localization errors were achieved in an area, where RSS values from a large number of APs in range were lower than −85 dBm. Results of this simulation show that RBF algorithm is immune to the varying of the number of APs in range. On the other hand, its accuracy is highly affected when RSS values from APs are low, due to changes in ranks caused by high RSS fluctuations. In the future the RBF algorithm will be implemented to the WifiLOC positioning system and real world experiments will be performed to validate results achieved in the simulations. Based on the achieved results algorithm for removal of APs with negative impact on the localization accuracy will be developed and tested.

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