Using of GSM and Wi-Fi Signals for Indoor Positioning Based on Fingerprinting Algorithms

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Abstract. *In the paper framework for indoor positioning utilizing Wi-Fi and GSM signals is introduced. Nowadays, indoor positioning is a very attractive topic for researchers, since accurate and reliable positioning system can unlock new market to service providers. In this paper we will analyse the use of Wi-Fi and GSM signals and their combination for the fingerprinting based positioning in the indoor environment. Performance of positioning system in terms of accuracy was analysed using simulations. In the simulations the position of the mobile device was estimated in three ways, when only GSM signals were used, when only Wi-Fi signals were utilized and when a combination of both signals was used. Three positioning algorithms from the Nearest Neighbour (NN) family were used in the simulations. Simulations were performed in the simulation model created in MATLAB environment.*

Keywords

GSM, indoor localization, positioning, simulation, Wi-Fi.

1. Introduction

In the recent years research in the area of positioning systems becomes an interesting topic. This is caused by two factors-development of location based services [1], [2] and [3] and significantly increased use of smart devices. Most of the smart devices are capable to estimate the position of the mobile user in an outdoor environment using at least one of Global Navigation Satellite Systems (GNSS), generally GPS. However GNSS systems are not developed to perform well in an indoor environment [4] and [5]. Thus many research teams work on indoor positioning using radio networks.

Most of research teams working on the topic of indoor positioning using radio networks deals with Wi-Fi signals [6]. Main advantage of this approach is that Wi-Fi networks are used in almost every building and most of the smart devices are equipped with Wi-Fi transmitter. However using Wi-Fi signals for positioning also have drawbacks. Positioning systems based on Wi-Fi can be easily influenced by adding new Access Points (APs) into the area or by altering APs settings or adding new APs with the same MAC address and SSID [7] etc.

In the recent paper [8], we focused on indoor positioning system based on GSM signals since GSM signal should be more stable and should not be so easily affected by attacks, when compared to Wi-Fi signals. On the other hand, GSM signals have lower difference between minimum and maximum RSS (Received Signal Strength) values in the area compared to Wi-Fi, due to the fact that GSM Base Transceiver Stations (BTS) are further away and the signal is less attenuated due to use of lower frequency band. This may lead to the higher localization errors.

In this paper we will investigate possibility to use combination of Wi-Fi and GSM signals for localization based on fingerprinting framework. In the proposed solution the signals from GSM should improve positioning accuracy of Wi-Fi based system by adding some extra information about the environment. Our goal is to develop modular positioning system which could be used in various environments and can outperform previously developed WiFiLOC [9] positioning system.

In the paper results from simulations performed to compare basic Wi-Fi and GSM based positioning with the system that utilizes signals from the both networks will be presented. Achieved results will be compared based on statistical analysis of achieved localization error. Traditional deterministic fingerprinting algorithms will be used in simulations to estimate the position of the mobile device using Wi-Fi, GSM and signals from both networks.

The rest of the paper will be organized as follows; in the Section 2. fingerprinting localization framework will be shown, simulation model and simulation scenario will be introduced in Section 3. , in Section 4. achieved results will be shown and discussed and Section 5. will conclude the paper.

2. Fingerprinting Localization Framework

Fingerprinting localization framework is widely used in indoor positioning systems based on radio networks. Main advantage of the fingerprinting approach is the fact that it seems to be immune to the multipath propagation [10], which is significant in the indoor environment.

Function of fingerprinting localization algorithms can be divided into two phases [11], in the first phase calibration measurements are performed over the localization area and radio map is created. During the second phase position of mobile device is estimated, using one of localization algorithms and calibration data stored in the radio map.

2.1. Radio Map

Radio map is created during the calibration or off-line phase. Radio map is represented by the database of Reference Points (RPs) together with RSS measurements collected during the calibration process [12].

Firstly area where position of mobile device will be estimated is divided into small cells. Each cell is represented by one reference point. At each reference point RSS measurements are performed and collected data are then stored in the database, as follows:

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

where P_j represents fingerprint at j-th reference point, M is number of reference points, N_j represent identification of the reference point, p_j represents position of reference point and consists of its coordinates, α_{ji} is the vector of the RSS measured at j-th reference point from i-th transmitter, and θ_j can obtain any additional information needed during the position estimation process.

2.2. Deterministic Algorithms

In the deterministic algorithms, the state P is assumed to be a non-random vector. This means that the RSS measurements at each reference points are not random, but depends on the position of reference point. Main objective of the localization algorithm is to compute the estimate $\hat{x}$, which is combination of reference point coordinates p_j, stored in the radio map [13], given by:

$$\hat{x} = \frac{\sum_{j=1}^{\mathbf{M}} \omega_j \cdot p_j}{\sum_{i=1}^{\mathbf{M}} \omega_i}, \tag{2}$$

where ω_i and ω_j represents nonnegative weights, which are computed as inversed value of Euclidean distance between RSS vector measured during positioning and RSS vector stored in the database for i-th reference point [14].

The estimator Eq. (2), which keeps the K highest weights and sets the others to zero is called the WKNN (Weighted K-Nearest Neighbor Method) [15]. WKNN with K highest weights $\omega_i = 1$ is called the KNN (K-Nearest Neighbor) method [16]. The simplest method, where $K = 1$, is called the NN (Nearest Neighbor) method [17].

KNN and the WKNN can perform better than the NN method, particularly with parameter values $K = 3$ and $K = 4$ [18]. On the other hand NN algorithms can outperform KNN and WKNN algorithms when radio map density is high.

3. Simulation Model and Scenario

This section will provide detailed information about simulation model created in MATLAB environment and simulation scenario, which was used to analyze fingerprinting positioning utilizing GSM and Wi-Fi signals.

3.1. Simulation Model

Simulation model used for testing of GSM-based fingerprinting localization was developed as modification of previously introduced simulation model for indoor positioning using Wi-Fi signals [19].

In the model the signal propagation is modeled using Multi Wall and Floor (MWF) propagation model [20]. The MWF propagation model is based on the assumption that attenuation of the same type of wall is decreased with the number of signal transitions thru the wall of given type. In the model the mean attenuation value LMWF in distance between transmitter and receiver d can be calculated using:

$$L_{MWF} = L_0 + 10n \log\left(\frac{d}{d_0}\right) + \sum_{i=1}^{I}\sum_{k=1}^{K_{wi}} L_{wik} + \sum_{j=1}^{J}\sum_{k=1}^{K_{fj}} L_{fjk}, \tag{3}$$

where L_0 is path loss at distance $d_0 = 1$ m in dB (given by Friis transmission equation), n is power decay index, I is number of walls types, K_{wi} is 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 number of floor types, K_{fj} is number of traversed floors of category j and L_{fjk} represents attenuation due to floor type j and k-th traversed floor in dB. Parameters of MWF model were chosen based on analysis provided in [20].

The second propagation model was implemented for GSM signals and BTS positions were defined in the simulation model. In the simulation model we assumed 7 BTS in the area. We assumed ideal signal propagation for each BTS, thus area covered by each BTS is assumed to be hexagonal. Radius of each hexagon is 1 km thus the distance between 2 BTS is 2 km. Positions of BTS in simulation model are depicted in the Fig. 1.

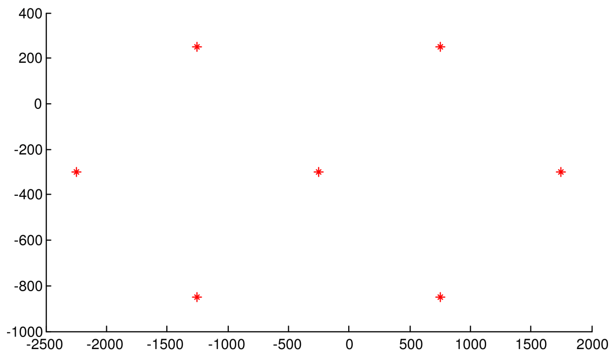

Fig. 1: Positions of GSM BTS in the simulation model.

We have implemented AMATA radio propagation model to evaluate path loss of GSM signals. AMATA propagation model is modification of ITU propagation model and allows calculating of signal propagation losses in indoor environment [21]. Propagation loss L is given as:

$$L = 20\log_{10} f + 10n_0 \log_{10} d + L_{out} + X_a + L_F, \tag{4}$$

where f represents frequency of the GSM signal in MHz, n_0 is path loss exponent after isolation of the internal wall effect, d is distance from the transmitter in m, L_{out} is attenuation loss factor of outer wall and L_F represents (multi)floor attenuation. X_a is the multi internal wall attenuation loss factor, which is given by:

$$X_a = 0.0075H^4 - 0.18H^3 + 1.1H^2 + 2.9H, \tag{5}$$

where H is the number of separated walls of standard brick type. Equation above applies for up to 11 indoor walls in the measurement process. It is also important to notice that signal attenuations after penetrating of 8 walls become relatively weak to measure.

In the simulation model random variables are added to the computed propagation losses to simulate signal fluctuations presented in the real world environment. These fluctuations were simulated by the random variable with lognormal distribution with 0 mean and standard deviation of 5 dB. We decided to use lognormal distribution based on previous results, in which high correlation between real world and simulation results was proved.

3.2. Simulation Scenario

Simulation scenario was proposed to evaluate impact of different wireless technologies and their combination on the performance of the fingerprinting based positioning system from the accuracy point of view. Radio map was created by generating of 20 RSS samples from each transmitter in the communication range at each reference point. Before the fingerprints were stored in the radio map, RSS samples were averaged in order to reduce fluctuations of RSS signals.

In the simulations we assumed only 2D environment, e.g. one floor building, therefore attenuations caused by floors in propagation models Eq. (3) and Eq. (4) can be neglected.

Simulations were performed with 10000 independent position estimation trials. In each trial, position of mobile device was randomly (uniform distribution) chosen from the localization area. Localization area with reference points separated by 2 m can be seen in Fig. 2.

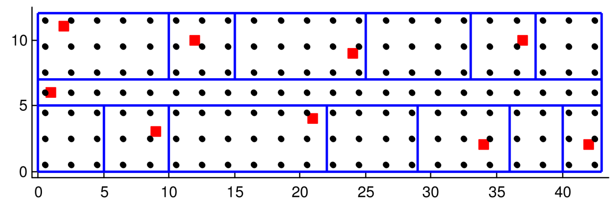

Fig. 2: Localization area.

In the Fig. 2, the blue lines represent walls of the building and black dots represent positions of the reference points in the area. Positions of APs used in simulations are represented by red squares. The area was covered by signals from 9 Wi-Fi APs placed inside the building and by signals from 7 GSM base stations placed outside the building (as can be seen in Fig. 1 and Fig. 2).

All RSS measurements were affected by random variable with lognormal distribution to simulate real world fluctuation of RSS, which can be caused by shadowing and multipath propagation. In the simulation model 20 samples of RSS from all transmitters (Wi-Fi and GSM) was measured during each positioning and average RSS value was computed to reduce impact of RSS fluctuation.

During each trial, position was estimated using all three algorithms described in the previous section - NN, KNN and WKNN. Position was estimated for three cases, in the first case only Wi-Fi measurements were used, in the second case only GSM measurements were used and in the third one both measurements were used to estimate position of the mobile device. The KNN and WKNN algorithms K was set to 3 and 4 respectively, in case that measurements form Wi-Fi and combination of Wi-Fi and GSM was used for the position estimation. In the case when only GSM measurements were utilized K was set to 7 for both KNN and WKNN algorithms. Based on previous results these settings should provide the most accurate results [8] and [22].

4. Simulation Results

In this section results achieved in simulations will be shown and discussed. Firstly, comparison of impact of used radio signals on algorithm performance was investigated. Results achieved for NN algorithm are shown in Fig. 3. In the figure the CDF of achieved localization error is depicted.

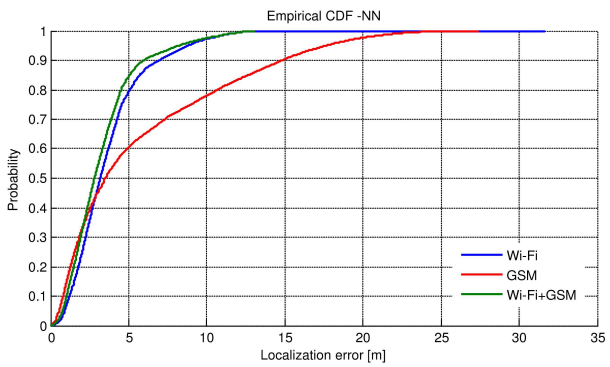

Fig. 3: Localization error of NN algorithm.

From the figure it can be seen that the highest accuracy was achieved by the combination of Wi-Fi and GSM signals. It can also be seen that GSM based localization achieved similar results to the other cases in 50 % of position estimates, however the other 50 % of position estimates was affected by extremely high error. In the Fig. 4, the CDF of positioning errors achieved by KNN algorithm is shown.

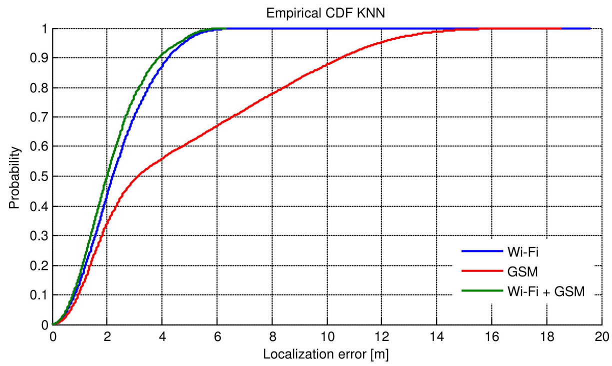

Fig. 4: Localization error of KNN algorithm.

From the figure it can be seen that, similarly to NN algorithm, combination of Wi-Fi and GSM signals improved accuracy of the position estimates of KNN algorithm. From the figure it is clear that GSM based localization has significantly lower accuracy in 60 % of estimates. CDF of localization error achieved by WKNN algorithm is depicted in Fig. 5.

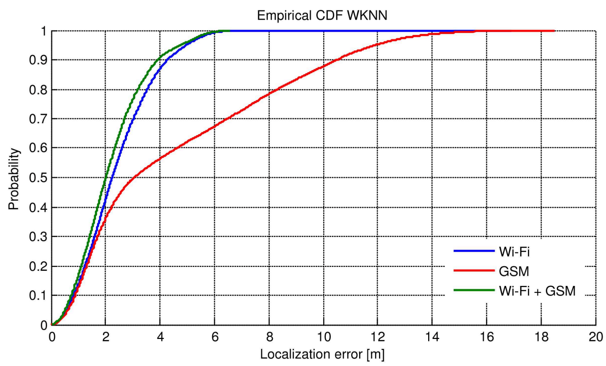

Fig. 5: Localization error of WKNN algorithm.

From the figure above, it is clear that, similarly to NN and KNN algorithms, achieved errors were significantly lower when Wi-Fi signals were used. Moreover, it can be seen that accuracy of WKNN algorithm was improved by use of both Wi-Fi and GSM signals in the process of position estimation.

From the Fig. 4 and Fig. 5 it can be seen that positioning accuracy of WKNN algorithm is almost the same compared to KNN algorithm. This is given by small differences in weights used in WKNN algorithm, which were calculated from Euclidean distance between RSS samples. Therefore, there cannot be high difference in the performance of these algorithms.

Moreover, from the presented figures it can be seen that positioning accuracy achieved by KNN and

WKNN algorithms is significantly higher when compared to the one achieved using NN algorithm. This is given by the fact that NN algorithm gives additional localization error, since it estimates position only as a position reference point with the highest weight. On the other hand, in both KNN and WKNN algorithms the positions of reference points are averaged, thus position can be estimated anywhere in the area.

In the Tab. 1 comparison of statistical measures of achieved localization errors for all three algorithms with utilization of Wi-Fi and GSM signals combination is shown. From the previous results it is clear that combination of Wi-Fi and GSM signals allows to achieve higher accuracy of position estimates, thus results for separate Wi-Fi and GSM based localizations are not shown. From the results in the table it can be seen that KNN and WKNN algorithms achieved very similar results, and are able to significantly outperform NN algorithm. It can be seen that average localization error was for more than 1m lower when KNN and WKNN algorithms were used. When we take a look at 95 % error, the error achieved by NN algorithm is two times higher compared to KNN and WKNN algorithms.

Tab. 1: Localization error of algorithms when both Wi-Fi and GSM signals were used.

	Localization error [M]			
	Mean	**Median**	**STD**	**95 %**
NN	3.3	2.81	2.27	8.23
KNN	2.18	2.01	1.22	4.64
WKNN	2.21	2.02	1.26	4.79

For better analysis of the achieved results, CDF of localization error achieved by the three algorithms is depicted at Fig. 6.

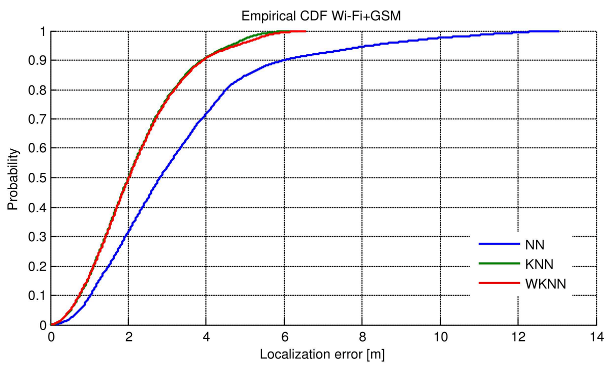

Fig. 6: Comparison of algorithms when both Wi-Fi and GSM signals were used.

From the results in the figure it can be seen that KNN and WKNN algorithms performed in the same way. The only difference between these two algorithms is only in the 10 % of highest localization errors, where KNN algorithm outperformed WKNN algorithm, by reducing error of highest outliers. This may be given by the fact that the reference point with highest weight has relatively high error. This fact can be observed on the performance of NN algorithm, since this algorithm uses only reference point with the highest weight.

5. Conclusion and Future Work

In the paper indoor fingerprinting localization system utilizing combination of Wi-Fi and GSM signals was introduced and tested using simulations. Proposed localization system uses deterministic algorithms NN, KNN and WKNN to estimate position of mobile device in the localization area.

The impact of the radio signals used to estimate position of mobile device, on the localization accuracy was tested in simulations. Simulation model was created in MATLAB environment, as modification of previously used simulation model for Wi-Fi based positioning [19].

From the achieved results it is clear that combination of Wi-Fi and GSM signals can outperform positioning using only one type of these radio signals. It is important to note that GSM based positioning does not achieve performance of Wi-Fi based positioning. However from the results it is clear that additional RSS samples from GSM network can help to improve positioning accuracy of Wi-Fi based positioning.

From the analysis of results achieved by different algorithms in combination with both Wi-Fi and GSM signals it can be stated that NN algorithm was outperformed by both KNN and WKNN algorithms. Mean localization error achieved by NN was 50 % higher compared to KNN and WKNN algorithms. In addition 95 % error of NN algorithm was who times higher compared to KNN and WKNN algorithms. This is partially given by the nature of the used algorithms.

In the future we will implement proposed localization framework into the modular localization system [23] and test its performance in the real world environment. Real world experiments will be performed in order to analyse conditions where stand alone GSM or Wi-Fi positioning can be outperformed by use of signals from both systems. Modular positioning system should perform in all kinds of environment-indoor, outdoor and dense urban, and always choose the most appropriate localization module.

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