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Crowdsourcing based terminal positioning using multidimensional data clustering and interpolation

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***Abstract*—Recent years can be characterized by the rapid increase of mobile device usage in people's lives. Contemporary mobile devices are equipped with many sensors and have high computational and processing capabilities. In a crowdsourcing systems, mobile users participate constructively in specific information handling. Data collected by crowd of mobile devices and stored in a database may help offering new services such as operator's radio quality evaluation and tracking of users. In this paper, we focus on mobile positioning by clustering and interpolating data to match fingerprints to positions. Our method is trained during the offline phase and parameters are periodically updated to track possible changes in propagation environment.**

I. Introduction

IN RECENT years a new field of research in radio communication technologies was born taking benefit from wisdom of mobile crowds [1]. In crowdsourcing a large group of users or crowd participate in service gathering, enhancement or evaluation, information sharing and passing in a professional or a social network. Many crowdsourcing applications have been designed so far, and some of them require provision of location information, with different level of accuracy. The traditional way to retrieve mobile location is GPS positioning but its drawback is activating GPS on mobile phone which is power consuming and it does not work well in indoor environment. The actual challenge for crowdsourcing location based techniques, is how to estimate mobile position using only collected statistics and network parameters.

Our paper deals with mobile user location based on crowdsourcing data collected with the use of smartphones. Various techniques exist in literature, the most common is fingerprinting based positioning. Another positioning method is lateration technique, lateration technique depends mainly on propagation model which changes from one area to another, network parameters may also change: transmitted power, antenna parameters, the environment also may changes when there is a new buildings and new trees, some special events may also change model parameters.

Techniques that use mapping between fingerprints and mobile location were also studied and such methods as: $k-$nearest neighbors $k-$NN, neural network and support vector machine (SVM) were applied in order to approximate the location of mobile user [4].

In this work, we investigate the possibility of mobile position determination based on information collected from cellular networks and WLANs. The main idea is based on data clustering and multidimensional interpolation, the use of clustering is justified by the fact that similar fingerprints could exist in different locations, mobile devices sense and retrieve network information periodically, collected data are sent to a database, where received information is organized in tables and columns.

User's position are sparse in outdoor environment and estimation of mobile position is a challenge. The proposed method takes into account the fact that equal fingerprints may occurs in different positions.

The remainder of the paper is organized as follows: in section II we described structure and pre-processing of collected data, in section III we presented the propagation model, related works are discussed in section IV. In section V we propose our method of crowdsourcing based terminal positioning. Performance evaluation and results are presented in section VI we finish by a conclusion and future works.

II. Crowdsourcing data

A. System architecture and data structure

In crowdsourcing context, mobile applications data are collected by user devices and sent to a database. The overall architecture of the application is depicted in Fig. 1. Various data are collected related to the network parameters and also fingerprints, timestamps are also recorded. To summarize, the collected information covers:

1) Received signal strength (RSS) collected from 2G, 3G, 4G serving cells and WLAN access points (AP).
2) Cell and BS identifier (CID or BSID).
3) Primary scrambling code (PSC) or physical cell identity (PCI) for LTE.
4) Timestamp.
5) GPS coordinates.
6) RSS from neighboring cells and access points.

The reference static database contains information about cellular network parameters in the region of interest:

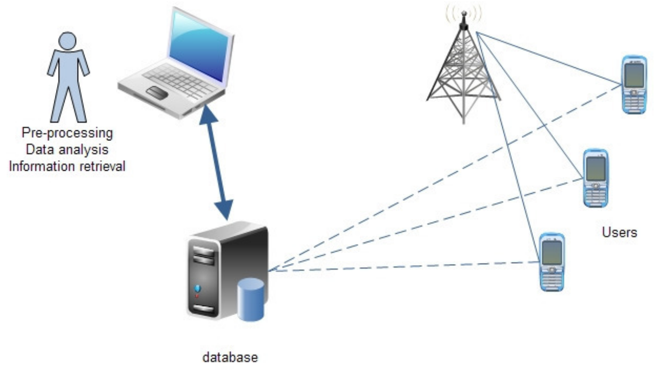

Fig. 1. General overview of a crowdsourcing system

1) Cells in the region of interest.
2) Tilt and Azimuth angle of each cell for cellular technologies.
3) Antenna height and maximum gain.
4) GPS coordinates of a base station.
5) Frequencies.
6) Cell identifier.

B. Data pre-processing

Collected data are periodically sent by mobile phone to the database, user should activate the selected technology for measurement, sometimes there are missing or wrong information. The preprocessing phase is necessary to organize data into tables, each table contain measurements relative to a wireless technology (GSM, UMTS, LTE, WLAN).

Pre-processing phase is compulsory to delete rows with non-significant or missed measurements and to match measurement with the reference database. GPS information is needed in the training phase only. To solve the problem of UTM coordinates, we can refer to conversion method in [3] to use Cartesian coordinate system. For example lateration technique based on fingerprints data uses Euclidean distance.

III. Propagation model

We assume the log-distance shadowing model [5], [9] in most cases of outdoor scenario, spatial received power correlation is also considered [6]. Vector of received power P from K transmitters at a specific position (x, y) is given by:

$$P = \bar{P} + \alpha S(x, y) + \Gamma U \tag{1}$$

Where, P is $K \times 1$ vector of received power at user side, $\bar{P} = P_{TX} + G_{TX}(\theta, \phi) - L_{feeder} - L_c - 20log_{10}(f)$ is the received power at one meter from the transmitter. G_{TX}, P_{TX} and L are: antenna gain, transmitted power and feeder attenuation respectively, and:

$$S(x, y) = \begin{bmatrix} -10\log_{10}(d_1) \\ -10\log_{10}(d_2) \\ \cdots \\ -10\log_{10}(d_K) \end{bmatrix} \tag{2}$$

is the vector of log of distance between location X and each transmitter's location, each element of the vector is given by: $d_i = \sqrt{(x-\alpha_i)^2 + (y-\beta_i)^2}$ for $i = 1 \ldots K$, where (α_i, β_i) is the position of transmitter i. Γ is the result of Cholesky decomposition of the covariance matrix R of the shadowing channel, R is given by:

$$R = \Gamma^T \Gamma \tag{3}$$

U is a vector of normal distribution with mean zero and identity covariance matrix. Elements of U are statistically independent. Many others models based on environment characteristics are reported in the literature. In our work, collected RSS at each user position are assumed to be the mean value of power in equation 1, $RSS = \bar{P} + \alpha S(x, y)$. Statistical properties of the shadowing model are not covered by this paper.

IV. Related works

In outdoor scenario, received power depends on several parameters such as: network configuration, propagation environment, mobile orientation and user's velocity, complexity of exploiting fingerprints information from crowdsourcing data increases when one or more parameters are missing or erroneous. lateration and radio map techniques assume knowledge of network parameters and also radio models. Many propagation models exist in literature, and choice of the right model depends on the environment. In many research works we assume shadowing model with known parameters such as propagation exponent and shadowing variance.

Geolocalization methods of mobile users range from geometrical approaches such as lateration techniques using Cartesian coordinates [8], time and angle of arrival at a given position, to data analysis approach using matching methods between fingerprints and associated positions:

1) Lateration based: In lateration technique, we assume the shadowing propagation model with known parameters, hence, we estimate the distance between current position and transmitter position, the number of received signals should be at least 3, by solving a set of K linear equations, mobile position $X = (x, y)^T$ is estimated as:

$$\hat{X} = (A^T A)^{-1} A^T b \tag{4}$$

Where, A and b are defined as:

$$\begin{cases} A_{i,1} = 2(\alpha_i - \sum_{j=1}^{K} w_{i,j}\alpha_j) \\ A_{i,2} = 2(\beta_i - \sum_{j=1}^{K} w_{i,j}\beta_j) \\ b_i^{(1)} = (\alpha_i^2 + \beta_i^2) - \sum_{j=1}^{K} w_{i,j}(\alpha_j^2 + \beta_j^2) \\ b_i^{(2)} = \hat{d_i}^2 - \sum_{j=1}^{K} w_{i,j}\hat{d_j}^2 \\ b_i = b_i^{(1)} - b_i^{(2)} \\ \sum_{j=1}^{K} w_{i,j} = 1 \\ \hat{d_i}^2 = 10^{-\frac{P_i(d)-P(d_0)}{5\alpha}} \end{cases} \tag{5}$$

This method is known as linear least square (LLS) [7], weighting coefficients $w_{i,j}$ are set to $\frac{1}{K}$. Other techniques based on distance estimation such as nonlinear least square (NLS) and Differential RSS techniques are applied when information on transmitted power and antenna parameters is missing [9].
Geometrical method has some limitations because propagation channel is subject of fast and slow fluctuations that vary from location to another, hence affects positioning accuracy. It is possible to exploit the lateration method in the future in crowdsourcing concept.

2) Neural network based: Neural network is commonly used in pattern recognition in signal processing, in mobile positioning it is used to map received RSS P and associated positions X in a given region [10], during training phase, layer's parameters are tuned in order to minimize the global mean square error MSE. Neural network techniques used in literature are MLP (multi-layer perception) and ANN (artificial neural network). Simulation results obtained for indoor environment are good in terms of accuracy. The disadvantage is the computational complexity of the method.
3) Radio coverage map based: During planning phase of radio network, coverage and quality maps should be traced and stored in a database. Strength of the signal received by a mobile phone from nearby base stations is compared to reference points in the radio map. The reference points are usually organized into rectangular or hexagonal grids. This technique is not adapted to the variation of radio propagation channel and parameters changes.

Localization methods are evaluated based on accuracy and algorithmic complexity. When collected data are sparse in space, previous methods seem to be less accurate because there is not enough points to determine model parameters in each area and we may face the problem of appearance of the same fingerprints (SF) in different positions.

V. Proposed method

In our proposed method we start by subdividing data into two sets, the first one used to perform data clustering using collected information and built up functions that fit well each cluster in order to overcome spatial data sparsity problem, the second set is used to perform tests. Fig. 2 summarizes our approach.

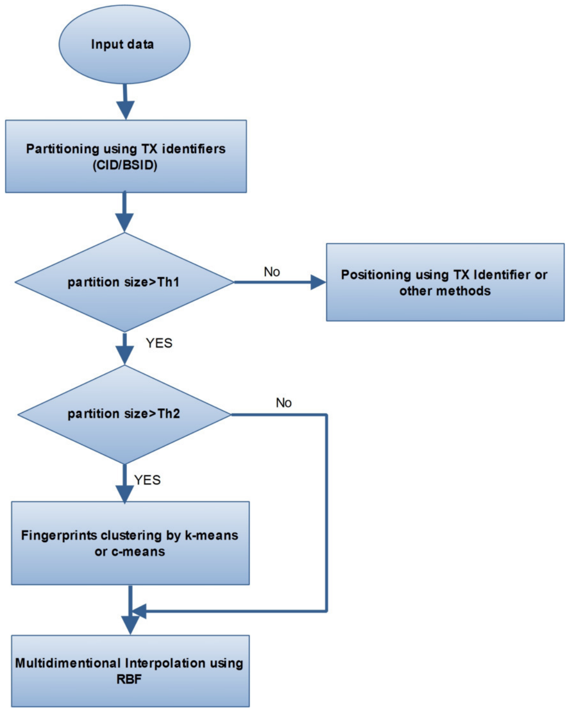

Fig. 2. proposed method

Many clustering techniques are used in literature, such as $k-$means, $c-$means, multimodal classification. First, we cluster collected data based on their CID or BSID, to guarantee that samples belong to one geographical area. Let P_i be the vector of received power in a given position $X = (x, y)^T$, number of element in P_i may change from position to another, depends on sensitivity of the mobile terminal. Clustering using cell identifier or base station identifier is an alternative to determine location area of mobile user, if we consider identifier of more than one cell, we can enhance precision.

After classification of user positions into small regions of interest, we will focus on data interpolation assuming compactness of input data in each cluster, clustering using both transmitter identifier and RSS may reduce the similar fingerprint problem and enhance then positioning accuracy. We look for function f that fits well all points inside a specific class. For example in [7] interpolation using polynomial regression was applied. Our method assumes the use of radial basis function (RBF) with Gaussian kernel.

A. Data clustering

Clustering or data partitioning, is the way of grouping data based on some parameters or criteria, for example, received power, CID or BSID, frequency.

1) Network parameters based:

- Frequency: frequency of the received signal can give information about location of serving cell, if we know frequency plan of region of interest each cell is characterized by its frequencies, but frequency plan may change when needed, hence this method is not good from crowdsourcing point of view.
- Cell identifier or base station identifier: knowledge of CID/BSID increase location accuracy of mobile user, if we consider more than one signal we can approximate better the mobile position, generally, values of CID and BSID are fixed, CID/BSID is considered also as spatial clustering.
- The strongest signals: The number of received signal K in a given position may change from area to another, the RSS vector contains the power of the serving cell/transmitter and the candidate cells or the neighboring cell.

2) Fingerprint based clustering:

$k-$Means: $k-$Means is an unsupervised clustering algorithm taking as input multidimensional data and as input N centroids. Each input fingerprint P_i, power vector of received signal strength, is assigned to the cluster with center C_j as:

$$C_j = \arg\min_{C_l} ||P_i - C_l||^2 \tag{6}$$

Cluster centers C_j are computed by iterative process, the new center of each cluster is the centroid of the old cluster.

Fuzzy $C-$Means: Is a modified version of $K-$means, was proposed by James Bezdek [11], where each sample may belong to a cluster with some membership degree, the mathematical formulation of FCM is given by:

$$\begin{cases} \arg\min\limits_{C_j,U} \sum\limits_{i=1}^{M}\sum\limits_{j=1}^{K} u_{i,j}^m ||P_i - C_j||^2 \\ \sum\limits_{j=1}^{K} u_{i,j} = 1 \\ m > 1 \end{cases} \tag{7}$$

Optimization is performed using the differentiation with respect to U, C and λ_i of:

$$\xi(U,C) = \sum_{i=1}^{M}\sum_{j=1}^{K} u_{i,j}^m ||P_i - C_j||^2 - \sum_{i=1}^{M} \lambda_i (\sum_{j=1}^{K} u_{i,j} - 1) \tag{8}$$

λ_i are the Lagrangian multipliers relative to each condition, cluster centers and weights are computed using iterative algorithm.

B. Class definition

Each data class is represented by a vector V containing: the number of sensed signals K, cell identifier CID/BSID and fingerprint centroid C_j.

$$V = \{CID, K, C_j\}$$

CID may contain two or three identifiers of transmitters. From cellular network point of view, we know that location area with one CID vector, where more than two signals co-exists, are unique, but we can not generalize this assumption in cell's borders. If we increase the number of identifiers that characterize one area, it is possible to reduce the cluster and hence enhance positioning accuracy. Before using interpolation, each measurement is assigned to its corresponding class V, for more accuracy we can use more than one cell for CID clustering.

C. Multidimensional data interpolation

Multidimensional interpolation is a mathematical tool that fit some input data with dimension $N \times K$ to output data with dimension $N \times 2$, Interpolation problem is equivalent to solving set of linear equations in order to determine parameters of interpolating function [12]. In positioning radial basis function was used for indoor localization in [13] where RSS fingerprints are fitted with corresponding positions, mathematical formulation of interpolation is given by:

$$\begin{array}{rccc} X: & \mathbb{R}^K & \longrightarrow & \mathbb{R}^2 \\ & P & \longmapsto & f_K(P) \end{array} \tag{9}$$

Where K is the number of detected signals by the receiver at a given position. P is the input vector and X the associated position. Interpolation by radial basis function (RBF) is given by:

$$X = \sum_{i=1}^{N} W_i \phi_h(||P - P_i||) \tag{10}$$

Where ϕ_h is a radial function, h a shape parameter, and W_i are 2×1 weighting coefficients. To compute weight coefficients, it is necessary to train the network using fingerprints and associated locations.

We assume N input and output data (X_i, P_i), Equation 10 became:

$$X_j = \sum_{i=1}^{N} W_i q_{i,j} \tag{11}$$

Where $q_{i,j} = \phi_h(||P_j - P_i||)$, T_h is $N \times N-$symmetric matrix, and X is $N \times 2$ matrix. Equation 11 is equivalent to:

$$W = Q_h^{-1} X \tag{12}$$

In the case where Q_h is singular matrix, we can modify the solution by introducing small value ϵ as:

$$W_h = (Q_h + \epsilon I)^{-1} X \tag{13}$$

This case occurs when there are the same fingerprints in one cluster. If we want to fix the number of basis functions in each cluster, the weight vector is given as:

$$W = (Q_h^T Q_h)^{-1} Q_h^T X \tag{14}$$

Gaussian kernel function is used for data interpolation.

$$\phi_h(r) = \exp\left(-(hr)^2\right) \tag{15}$$

Performance of RBF interpolation depends mainly on choice of h, number of radial basis functions and also the choice of the radial norm.

D. Advantages and limitations of the proposed method

In the test phase, first we assign mobile to its cluster using one clustering technique, then, we estimate its position based on interpolation function.

In order to evaluate the accuracy of our method, we use two approaches: in the first one we compute the distance between from the estimated value of the position and a reference point, with nearest RSS vector. Let start by first order Taylor expansion of $\phi_h(||P - P_i||)$ around P_j:

$$\phi_h(r_i) = \phi_h(r_{i,j}) - 2h^2(P - P_j)^T(P_j - P_i)\phi_h(r_{i,j}) \quad (16)$$

Where P_j is the nearest neighbor to P, $r_i = ||P - P_i||$ and $r_{i,j} = ||P_j - P_i||$. The distance between the nearest point with position X_j and test point with position X, and using function interpolation of user's position, is expressed as:

$$d_{RBF} = 2h^2 || \sum_{i=1}^{N} W_i(P - P_j)^T(P_j - P_i)\phi_h(r_{i,j}) || \quad (17)$$

The second level of evaluation is to check if CID cluster of the test point and the reference point are overlapping or not. If the two clusters are not overlapping, the estimation using RBF is wrong and we have to assign a position from the training set that have similar CIDs.

If the value of the distance d_{RBF} is low, and the test cluster overlap with the reference one, the RBF interpolation approximates well the position.

When receiving low numbers of signals from transmitters, the probability of getting SF increases. We conclude that interpolation is more efficient when the number of received signals is high in one hand, in the other hand, we need more sample data to get good approximation by interpolation when the dimension of the received signal is high. The number of collected identifiers may reduce the size of the cluster. Then in the training phase, when the number of samples is high within the cluster region, accuracy increases, otherwise, we cluster the data with lower number of cell identifiers.

Differences between global interpolation and interpolation within cluster are:

- Lower complexity for interpolation within a cluster and matrix inversion do not consume memory.
- Lower number of SF for cluster based interpolation, hence good fitting properties.
- Higher error in positioning for global interpolation with some probability different from zero.

Limitations of the proposed method are:

- Samples are sparse, to overcome this problem we need more measurements and more memory to store data.
- This method should be upgraded in order to track fluctuations of propagation channel, transmitted power and network's parameters changes.

VI. Performance Evaluation

A. Measurement setup

The crowdsourcing system used for evaluation of the proposed approach consisted of application and database servers responsible for data storage and pre-processing, and a group of Android-based mobile devices. The test devices were equipped with dedicated mobile application running in the background and responsible for collecting of the measurement data during normal device operation. The background service is also responsible for communication with the application servers and periodic uploading of the measured data to the system database. The data were collected in the opportunistic manner, i.e. during everyday device usage by a group of test users, and using different devices. The range of data reported to the system covered strengths of the signals received by the device from surrounding radio access network transmitters (the set of parameters depends on the radio access technology as described in Section II) and from nearby Wi-Fi access points, as well as actual GPS-based position of the user.

B. Experimental results

During the initial tests of the system, the measured data were collected in the surroundings of Lodz University of Technology campus area using number of terminals. The locations of reference measurement points are shown in Fig. 3 and 4, measurements could be performed dependently or separately.

Fig. 3. ROI and part of experimental data positions (GSM measurements)

Fig. 4. ROI and part of experimental data positions (LTE measurements)

A selection of 80% of measurements are dedicated to find clusters and interpolate data in each cluster using radial basis functions, the remaining 20% of RSS measurements are reserved to the test phase.

Fig. 5 shows cell identity pairs from collected data, in y-axis the identifier of the strongest cell or server and in x-axis the best neighbor cell, hence each point describe a set of fingerprints, more the number of fingerprints is more the accuracy we get. In cellular network, theoritically two CIDs are sufficient to characterize a compact location area because antenna are directive, in WLAN technology antennas are generally omni-directional and at least three received signals are required for area identification. It is possible also to cluster data using three or more best cells in order to identify a location area with some serving cells. Fingerprints associated to unique CID pair are collected together. Then RSS vectors are clustered based on their dimensionality, dimension K of received RSS vary from 2 to 7.

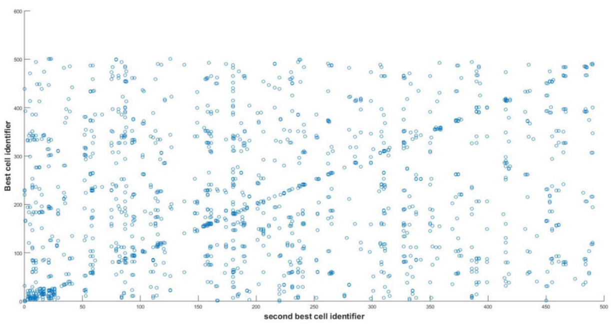

Fig. 5. CID based clustering

Clustering using k-means or FCM will be applied only when the number of fingerprints in each fixed (CID, K) set is huge, the splitting of data into smaller clusters may reduce the complexity in the interpolation phase.

Table I shows the number of samples for each signal dimension. The fitting error increase with the number of existing SF pairs in the training sequence, it is obvious that for global fitting method the error is higher than for clustered method.

TABLE I
DISTRIBUTION BASED ON K

K	Total samples
7	87296
6	55294
5	17813
4	3982
3	225
2	35

In total we have 416 pairs of cell identifiers (CID), retrieved from the collected data, an average number of fingerprints in a CID cluster equal to 348.4. In order to increase accuracy of location area, we can also use triplets of CIDs, in this case the size of the area will be further reduced.

When the number of fingerprints is between $Th2 = 50$ and $Th2 = 10$ for given pairs we use interpolation technique after CID clustering. When the number of fingerprints is higher than $Th2$, we create new sub-clusters using c-means or FCM, then we use interpolation. Table II show the distribution of cluster's size Fig. 6 shows three GSM clusters of size 52, 55 and 171 respectively: Clusters with sample size higher than $Th2$ are subdivided into subsets using $k-$means or FCM, furthers studies will be focused on how to tune thresholds and also in which case we should use one or the other of the clustering algorithm in order to get more accurate results.

TABLE II
DISTRIBUTION BY CLUSTER SIZE

cluster size ≥ 51	$10 \leq$ cluster size ≤ 50	cluster size ≤ 9
201	143	72

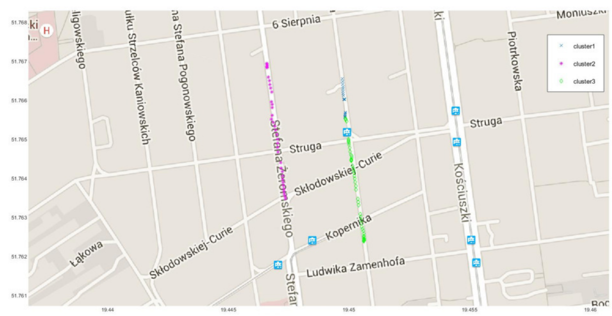

Fig. 6. GSM clusters

After the clustering phase, we determine the interpolation function assigned to each cluster using RBF. We compare in the table III the fitting error between the proposed method and interpolation only method.

TABLE III
ERROR OF FITTING

cluster based RBF	Global RBF
$8.9357.10^{-10}$	$9.03111.10^{-10}$

Increasing the number of cell identifiers per each cluster may adds more accuracy comparing to the case when using only a pair of CI, but number of samples will be low and interpolation error will increase too.

From measurements we can notice that, a test point could be assigned a position in a different cluster while using global interpolation technique, as we discussed in the limits and advantages paragraph, we can detect this error and assign a new position to the test point based on CID only, in this case we may gain in terms of accuracy. Our method requires many measurements to train and extract associated parameters for each cluster, as we introduce the SF problem, we may also define the same position problem SP and how to solve it. In future we plan to consider such issues as network parameters tackling as a result of tilts modification, transmitted power and azimuth changes using correlation between measured information with its corresponding cluster. Crowdsourcing adds more consistency to positioning, In our method we add clustering using transmitter identifier with comparison to lateration techniques which based on propagation model, our approach is more realistic and can track possibles changes that occurs in propagation channel. Lateration technique assumes knowledge of APs positions and also transmitter's parameters. Our method can outperform also radio map based technique as many changes may happen in the network after the initial deployment.

Disadvantages of our method is the updating policy of the database. Any change of radio network parameters induces possible changes in received power, and old value of saved RSS will be useless.

VII. Conclusion and future works

This paper deals with crowdsourcing data analysis with special emphasis on localization. Statistical information from data collected by smartphone can be exploited for user localization, approach using techniques like lateration depends on propagation model and the model vary in space and time. We start our work by data partitioning into small or compact area using cell identifier of received signals, if the cardinality of partition is higher than a given threshold, associated RSS fingerprints are clustered into each region using $k-$means or $c-$means methods. Adding clustering may reduce the same fingerprint problem SF that can occur in radio propagation scenario. The second step of the training process was multidimensional interpolation using RBF with Gaussian kernel to estimate the user's position. Clustering and interpolation increase positioning accuracy, in global interpolation method, the probability of similar measurement in two different locations increase with collected data, hence it is possible to get a bad estimate of the position, due to the channel fluctuation it is possible also to get two different fingerprints for the same position. The proposed method, can be updated each time we have new training data, it is possible also to store new sub area and update parameters of interpolation function. As future works, we focus to exploit more correlation techniques between fingerprints and transmitter's identifiers and tracking techniques.

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