Improving WLAN-Based Indoor Mobile Positioning Using Sparsity

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***Abstract*— Growing demand for Indoor Localization and Navigation, and the increasing importance of Location Based Services (LBS) necessitates methods that can accurately estimate the position of mobile devices in environments where GPS does not work properly. In this paper, we propose a novel localization method that uses spatial sparsity to improve indoor mobile positioning. The simulation results show the high performance of the proposed method and its robustness to multipath conditions compared to other existing methods. The proposed method has less complexity, less cost and higher robustness to configuration changes compared to common methods such as RSS Fingerprinting approaches.**

I. Introduction

Accurate indoor localization for mobile users is an important and challenging issue in the areas of signal processing and wireless sensor networks that has received increasing attention recently [1]-[21]. Poor performance of the GPS-based methods in indoor environment (as well as sometimes in urban environments) and the large demand for Location Based Services (LBS) have motivated researchers to design new and feasible methods to carry out indoor positioning. Recent advances in smartphones and their growing role in human life encourage service providers to use it as tool to provide indoor positioning and location-based services using the Cellular Networks and/or Wireless Local Area Network (WLAN) infrastructures.

Existing indoor localization systems usually use a wireless communication technology and measure location-dependent parameters to estimate the position. The proposed wireless communication systems include the cellular network (such as GSM) [4], WLAN (such as Wi-Fi) [5],[6],[18], RFID [7], [8], Bluetooth [9][10], [11], Ultrasound [12], Infrared [13], [14] and etc.

Indoor location is challenging due to the complicated propagation characteristics such as multipath [15]. The classic approach to positioning methods is to first estimate location-dependent signal parameter(s) such as time-of-arrival (TOA), time-difference-of-arrival (TDOA), received-signal-strength (RSS) and etc. Then in a second step, the collection of these estimated parameters is used to estimate the location using statistical methods, triangulation or fingerprinting methods [22]. Although TOA/TDOA provides the best accuracy in free-space, its classical two-stage approach yields poor location accuracy in the presence of the massive multipath conditions typically found in indoor localization environments [21]. Because of this, RSS is the most widely applied method; even though it is also impacted by multipath much work has been done to develop means to mitigate such degradations through so-called "Fingerprinting". Fingerprinting is a popular method based on comparing the RSS measurements to a previously prepared RSS Map of the desired area. In some recently published papers, various methods such as Compressive Sensing have been suggested to use to reduce the amount of off-line samples and/or on-line measurements [23]. Nonetheless, the fingerprinting approach is not without its own disadvantages; it requires a costly and time consuming training procedure, requires a complex map generating and matching algorithms, it requires creating and storing a database for the area of coverage and any changes in physical features of the environment or any changes in the configuration of the WLAN access points necessitates updating the database [16],[17], [19], [20].

In this paper, we proposed a novel TOA-based positioning method exploiting spatial sparsity of the mobile device on the x-y plane (or x-y-z space) that can largely mitigate the impact of the indoor multipath environment. We use convex optimization theory to estimate the location of the mobile directly without going through the intermediate stage of TOA estimation. The goals of this method are to improve the overall accuracy of the positioning compared to classic RSS methods, reduce the complexity and cost and also increase the robustness to configuration changes compared to Fingerprinting, and increase the robustness to multipath conditions compared to classic two-stage TOA/TDOA based methods.

If we divide the location space to fine enough grid points, then the number of mobiles to be localized is much smaller than the number of all grid points. Thus, imagine a sparse grid matrix that has a positive number at each one of the grid points containing an emitter (i.e implant) and zeros in the rest of the grid points; this can be reformed as a *sparse vector*. We can estimate the location of the targets by extracting the position of non-zero elements of the sparsest vector that satisfies the delay relationship between transmitted signals and received signals.

In principle, sparsity of the grid vector can be enforced by minimizing its ℓ_0-norm which is defined as the number of non-zero elements in the vector. However, since the ℓ_0-norm minimization is an NP-hard non-convex optimization problem, it is very common to approximate it with ℓ_1-norm minimization, which is a convex optimization problem and also achieves the sparse solution very well. Thus, after formulating the problem in terms of the sparse grid vector, we can estimate this vector by pushing sparsity using ℓ_1-norm minimization on the grid vector, subject to the TOA relationship between the transmitted and received signals at the grid point and the wireless access points (APs). By solving this minimization problem, the position of the non-zero elements of the sparse grid plane matrix will always be the best estimation for the location of the mobile targets.

In cases when the transmitted signals are not known, we can estimate the signal using the Minimum Variance Unbiased estimator (MVU). In [25], the authors proposed a general target localization method based on compressive sensing. In this method, each sensor approximates the transmitted signal by its own received signal mapped to each one of the grid points. This idea helps to reduce the amount of data transmission in the sense of distributed localization but it lowers the quality of the estimation since each sensor estimates the transmitted signal only based on its own received signal. For the purpose of mobile positioning in the case when the signal is unknown, we will estimate the transmitted signal in the sensor network using *all received signals* by MVU estimator to achieve a higher accuracy.

The method can be implemented in two forms: (1) a Handset-Based form (where the localization process is carried out in the mobile) and (2) a Network-Based form (where the localization process is completely implemented in the network and then the results will be sent to the mobile). As mentioned above, contrary to classic methods, we estimate the location of the target directly without going through the intermediate stage of TOA estimation. We will see this method is very robust and very effectively deals with multipath, which is a very serious problem in indoor localization due to the many reflections from furniture and walls. The multipath makes it appear on each channel that there are multiple sources – however, the apparent sources are not consistent across all the channels and the sparsity constraint acts to discount the effect of the multipath [24]. In our method, we don't need to have time synchronization between Mobile device and WLAN access points since the method is implicitly based on time *difference* of arrival (TDOA) between received signals.

II. Problem Formulation

Here, we talk about Network-Based form of localization when the mobile device transmits the signal as emitter and WLan access points (APs) receive the transmitted signal as receiver sensors. It is easily possible to extend the results for Handset-Based form when the mobile plays the receiver role. Suppose that an emitter transmits a signal and L sensor receivers receive that signal. The complex baseband signal observed by the lth sensor is

$$r_l(t) = \alpha_l s(t-\tau_l) + w_l(t) \tag{1}$$

where α_l is the complex path attenuation, $s(t)$ is the transmitted signal, τ_l is the signal delay in seconds and $w_l(t)$ is a white, complex Gaussian noise. If we convert the equations to discrete time format, we can assume that each AP collects N_s signal samples at sampling frequency $F_s = 1/T_s$. Then we have,

$$\boldsymbol{r}_l = \alpha_l \boldsymbol{D}_l \boldsymbol{s} + \boldsymbol{w}_l \tag{2}$$

where $\boldsymbol{s} \triangleq [s(t_1),\ s(t_2),\ \dots,\ s(t_{Ns})]^T$ is N_s samples of the transmitted signal, $\boldsymbol{r}_l \triangleq [r_l(t_1),\ r_l(t_2),\ \dots,\ r_l(t_{Ns})]^T$ is the vector containing N_s samples of the received signal by lth AP, $\boldsymbol{w}_l \triangleq [w_l(t_1),\ w_l(t_2),\ \dots,\ w_l(t_{Ns})]^T$ is the noise samples vector and $\boldsymbol{D}_l$ is the time sample shift operator by $n_l = (\tau_l / T_s)$ samples. We can write $\boldsymbol{D}_l = \boldsymbol{D}^{n_l}$ where $\boldsymbol{D}$ is an $N_s \times N_s$ permutation matrix defined as $[\boldsymbol{D}]_{ij} = 1$ if $i = j+1$, $[\boldsymbol{D}]_{0,N-1} = 1$ and $[\boldsymbol{D}]_{ij} = 0$ otherwise.

To simplify the notations, we assume that we are interested in estimating the location of the mobile in the two-dimensional (x-y) plane. It is easily possible to expand the localization problem to the three-dimensional case.

Now, we allocate a number $z_{x,y}$ to each one of the grid points (x,y). Assume that $z_{x,y}$ is one for the grid points containing a mobile device and zero for the rest of the grid points. Thus, the signal vector received by l^{th} sensor (l^{th} AP) will be,

$$\boldsymbol{r}_l = \sum_x \sum_y z_{x,y} \alpha_{l,x,y} \boldsymbol{D}_{l,x,y} \boldsymbol{s} + \boldsymbol{w}_l \ , \tag{3}$$

where $\boldsymbol{D}_{l,x,y}$ is the time sample shift operator w.r.t sensor l assuming that the mobile device is located in the grid point (x,y). The summations are over all possible grid points in the desired (x,y) range. Now, if we reform all of the grid points in a column vector and re-arrange the indices, we will have,

$$\boldsymbol{r}_l = \sum_{n=1}^{N} z_n \alpha_{l,n} \boldsymbol{D}_{l,n} \boldsymbol{s} + \boldsymbol{w}_l . \tag{4}$$

In cases when the transmitted signal is not known, we can consider the transmitted signal $\boldsymbol{s}$ as a *deterministic unknown* signal. Then, we can estimate the signal using the Minimum Variance Unbiased estimator (MVU) [24] as following:

$$\hat{\boldsymbol{s}}_n = \frac{1}{L} \sum_{l=1}^{L} \alpha_{l,n}^{-1} \boldsymbol{D}_{l,n}^{-1} \boldsymbol{r}_l \tag{5}$$

We define the matrix Λ_n as delay operator w.r.t all L sensors (all APs), assuming that the received signal comes from the grid point n (in other words, assuming that there is a mobile device at grid point n):

$$\Lambda_n \triangleq \begin{bmatrix} \alpha_{1,n} \boldsymbol{D}_{1,n} & \alpha_{2,n} \boldsymbol{D}_{2,n} & \cdots & \alpha_{L,n} \boldsymbol{D}_{L,n} \end{bmatrix}_{N_s \times LN_s}$$

Then, we can define $\boldsymbol{\theta}_n, n \in \{1, 2, \dots, N\}$ as an $LN_s \times 1$ vector including all signal samples transmitted from grid point n (when the mobile device is in grid point n) captured by all L sensors as,

$$\boldsymbol{\theta}_n \triangleq \Lambda_n \times \boldsymbol{s} \tag{6}$$

In the case when the signal is unknown, we can replace $\boldsymbol{s}$ in (6) by $\hat{\boldsymbol{s}}_n$ from equation (5). Now, if we arrange all vectors $\boldsymbol{\theta}_n$ for n:1...N as the columns of a matrix $\boldsymbol{\Theta}$ as,

$$\boldsymbol{\Theta} = [\boldsymbol{\theta}_1 \quad \boldsymbol{\theta}_2 \quad \dots \quad \boldsymbol{\theta}_N]_{LN_s \times N} \quad , \tag{7}$$

where $\boldsymbol{\Theta}$ is the matrix containing the signals transmitted from all possible grid points observed by all L access points. Then we have,

$$\begin{aligned} &\boldsymbol{r} = \boldsymbol{\Theta} \times \boldsymbol{z} + \boldsymbol{w} \qquad (8) \\ &\boldsymbol{r} \triangleq [\boldsymbol{r}_1^T \quad \boldsymbol{r}_2^T \quad \dots \quad \boldsymbol{r}_L^T]^T_{LN_s \times 1} \\ &\boldsymbol{z} \triangleq [z_1 \quad z_2 \quad \dots \quad z_N]^T_{N \times 1}, \end{aligned}$$

where $\boldsymbol{r}$ is the vector of all L received signals, $\boldsymbol{z}$ is the sparse vector of z-values assigned to each grid point and $\boldsymbol{w}$ is the noise. To estimate the mobile position, we need to find the sparsest vector $\hat{\boldsymbol{z}}$ that is well-suited to the equation (8). To do that, we can minimize the cost in equation (8) and maximize the sparsity (by minimizing ℓ_1-norm) at the same time to end up with a sparse solution. We can solve this problem by forming a *Basis Pursuit with Inequality Constraints* (*BPIC*) *problem* [26] as following:

$$\begin{cases} \hat{\boldsymbol{z}} = \arg\min \|\boldsymbol{z}\|_1 \\ s.t \quad \|\boldsymbol{\Theta} \times \boldsymbol{z} - \boldsymbol{r}\|_2 \le \varepsilon \end{cases} \tag{9}$$

or regularized *Basis Pursuit Denoising* (*BPDN*) *problem* [26] as:

$$\hat{\boldsymbol{z}} = \arg\min \|\boldsymbol{\Theta} \times \boldsymbol{z} - \boldsymbol{r}\|_2 + \lambda \|\boldsymbol{z}\|_1 \tag{10}$$

where $\|.\|_p$ is the ℓ_p-norm defined as $\|v\|_p = \sqrt[p]{\sum_i |v_i|^p}$.

III. Simulation Results and Conclusion

To evaluate the performance of the proposed method, we run Monte Carlo computer simulation with 500 runs each time for various numbers of access points (from 4 to 16 APs) and various SNRs (0dB , 10dB and 20dB). We simulated the massive multipath conditions in a typical $10m \times 10m$ building. The APs are mounted at x-y locations (0,0), (10,0), (0,10), (10,10), (0,6), (6,0), (10,6), (6,10), (0,4), (4,0), (10,4), (4,10), (4,6), (6,4), (6,6), (4,4) respectively and the location of the mobile has been chosen randomly. Note that the mobile position is not necessarily placed exactly on a grid point. In other words, the target may be located in the area between two grid points (actually, the assumption that the target is located exactly on a grid is very ideal case that rarely happens). Thus, when the target is not placed on a grid point, in the best case when the algorithm finds the closest grid point to the target position, we still have an error in localization. However, we can always reduce this error by choosing a finer grid. To decrease the computation load in grid search, we can employ an iterative algorithm to shrink the search area and increase the grid resolution for the new area of interest in each step.

Fig. 1 shows the RMS Error vs. number of access points. As we expected, the accuracy gets better by increasing the number of the receiving sensors. The results show that the proposed method has very good performance even with low SNRs and with small number of access points; this provides a significant advantage over classic two-stage TOA and RSS methods. The results also indicate that, in contrary to the classic TOA based methods, the proposed approach is a very effective and robust tool to deal with multipath issues.

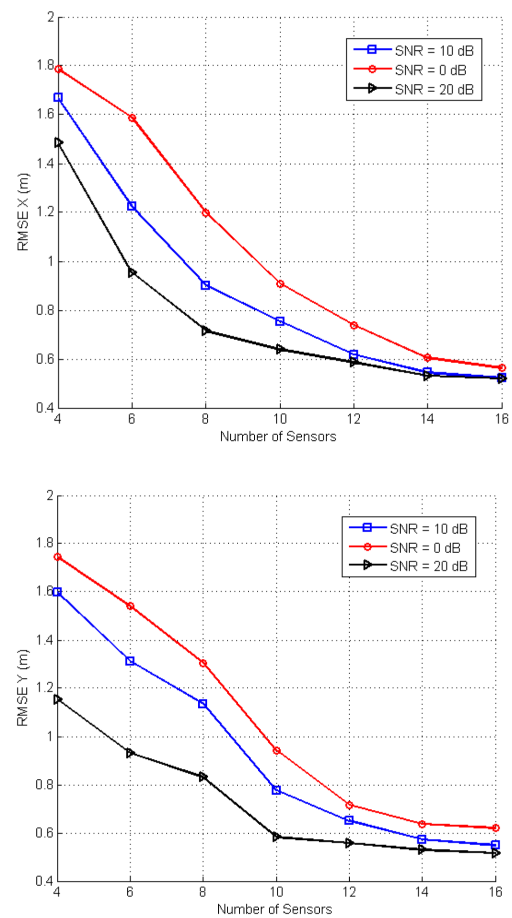

Fig. 1. RMS Error for X and Y location (in meters) versus Number of Access Points.

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