Spatial Sparsity Based Indoor Localization in Wireless Sensor Network for Assistive Healthcare

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***Abstract*—Indoor localization is one of the key topics in the area of wireless networks with increasing applications in assistive healthcare, where tracking the position and actions of the patient or elderly are required for medical observation or accident prevention. Most of the common indoor localization methods are based on estimating one or more location-dependent signal parameters like TOA, AOA or RSS. However, some difficulties and challenges caused by the complex scenarios within a closed space significantly limit the applicability of those existing approaches in an indoor assistive environment, such as the well-known multipath effect. In this paper, we develop a new one-stage localization method based on spatial sparsity of the x-y plane. In this method, we directly estimate the location of the emitter without going through the intermediate stage of TOA or signal strength estimation. We evaluate the performance of the proposed method using Monte Carlo simulation. The results show that the proposed method is (i) very accurate even with a small number of sensors and (ii) very effective in addressing the multi-path issues.**

***Index Terms*— Time of Arrival (TOA), Received Signal Strength (RSS), Sparsity, Compressive Sensing (CS).**

I. Introduction

Indoor localization has been a long-standing and important issue in the areas of signal processing and sensor networks that has raised increasing attention recently [1][10]. As the number of elderly people grows rather quickly over the past few decades and continue to do so [15], it is imperative to seek alternative and innovative ways to provide affordable health care to the aging population [16]. A compelling solution is to enable pervasive healthcare for the elderly and people with disabilities in their own homes, while reducing the use and dependency of healthcare facilities. To this aim new technology and infrastructure must be developed for an in-home assistive living environment. One of the key demands in such an assistive environment is to promptly and accurately determine the state and activities of an inhabitant subject. The indoor localization provides an effective means in tracking the position, motions and reactions of a patient, elderly or any person with special needs for medical observation or accident prevention.

In assistive healthcare applications, the individual may wear a small device that could emit a radio frequency (RF) signal for localization. This emitter(s) propagates a signal and several pre-mounted wireless sensors located in known positions receive that signal. The sensors estimate the location of the emitter after sharing some data and performing some processing.

The classic approach to localization methods is to first estimate one or more location-dependent signal parameters such as time-of-arrival (TOA), angle-of-arrival (AOA) or received-signal-strength (RSS). Then in a second step, the collection of estimated parameters is used to determine an estimate of the emitter's location. However, the systems based on AOA need multiple antennas or a scannable antenna that are usually costly [3]. The methods based on signal strength measurement (RSS) require a costly training procedure and complex matching algorithms and also the positioning accuracy for these methods is limited by the large variance in indoor environments [4][10]. The methods based on time-of-arrival (TOA) are usually very accurate. However, the accuracy of the classic TOA based methods usually suffers from massive multipath conditions in indoor localization, which is caused by the reflection and diffraction of the RF signal from objects (e.g., interior wall, doors or furniture) in the environment [1].

In this paper, we exploit spatial sparsity of the emitter on the x-y plane and use convex optimization theory to estimate the location of the emitter directly without going through the intermediate stage of TOA estimation. It is obvious that in emitter location problems, the number of emitters is much smaller than the number of all grid points in a fine grid on the x-y plane. Thus, by assigning a positive number to each one of the grid points containing an emitter and assigning zeros to the rest of the grid points, we will have a very sparse grid plane matrix that can be reformed as a *sparse vector*. In this context, a *sparse vector* is a vector containing only a small number of non-zero elements [11]. Since each element of this grid vector corresponds to one grid point in the x-y plane, we can estimate the location of emitters 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 (e.g in compressive sensing problems) to approximate it with ℓ_1-norm minimization, which is a convex optimization problem and also achieves the sparse solution very well [11]. 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 delay relationship between the signals transmitted from the grid point and the signals received by the sensors.

In [12], the authors suggested a two-stage source localization method based on time-difference-of-arrival (TDOA) in a multipath channel exploiting the sparsity of the multipath channel for estimation of the line-of-sight component. In this method, the sensors don't need to know the information on the specific transmitted symbols but, they require knowledge of the pulse shape of the transmitted signal. In [13], the authors suggested a compressive-sensing based distributed target localization. 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 just using its own received signal. Also, each sensor computes its own location estimation of the emitter that is not necessarily equal to other sensors' estimations. However, in our method the signal will be estimated in the sensor network using all received signals for unknown signal cases to achieve more accurate results.

Contrary to classic methods, in this paper we estimate the location of the emitter 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.

In Figure 1(a), we can see a typical apartment. Figure 1(b) shows the same apartment with four receiver sensors mounted at the corners. Figure 1(c) shows a simple case for multipath scenario. In this figure, the solid lines present the direct path and dashed lines shows the reflected paths. However, given the extremely complex nature of the reflections within such a closed environment and the tremendous difference in the reflection rates for different building materials, it is impossible to conclude a rather perfect multi-path reflection model for the indoor circumstance. However, it is well agreed that the strength of reflected signals deteriorate after each reflection. Moreover, the TOA based localization systems usually suffer from first-order reflections since they generate the side-lobes very close to the main peak in the correlation stage used in traditional TOA based methods. Thus, the models like in figure 1(c) seem reasonable for the purpose of research.

In our method, we also don't need to have any time synchronization between emitter and receivers since the method is implicitly based on time *difference* of arrival (TDOA) between receivers.

The proposed localization method can be also implemented for three-dimensional model. In this approach, the height of the worn device (emitter) from the floor can be also estimated. Thus, the system can detect if the patient falls on the floor because of unconsciousness or any other reasons.

We evaluate the performance of the proposed method by Monte Carlo computer simulations. The simulation results show the accurate localization and high performance of this method even in multipath conditions, with low SNRs and with small number of sensors; this provides a significant advantage over using TOA, RSS or other single-stage methods.

Figure 1. (a) A typical apartment layout. (b) Four sensors mounted in the corners. (c) A simple case for multipath scenario. The solid line is direct path and dashed lines are reflected paths.

II. Problem Formulation

Suppose that an emitter transmits a signal and L sensors 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 $s(t)$ is the transmitted signal, α_l is the complex path attenuation, τ_l is the signal delay and $w_l(t)$ is a white, zero mean, complex Gaussian noise. Assume that each sensor collects N_s signal samples at sampling frequency $F_s = 1/T_s$. Then we have

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

$$\boldsymbol{s} \triangleq [s(t_1)\,,\quad s(t_2)\,,\quad \ldots\quad ,\quad s(t_{Ns})]^T$$

$$\boldsymbol{r}_l \triangleq [r_l(t_1)\,,\quad r_l(t_2)\,,\quad \ldots\quad ,\quad r_l(t_{Ns})]^T$$

$$\boldsymbol{w}_l \triangleq [w_l(t_1)\,,\quad w_l(t_2)\,,\quad \ldots\quad ,\quad w_l(t_{Ns})]^T$$

where $\boldsymbol{r}_l$ is the vector containing N_s samples of the received signal by lth sensor, $\boldsymbol{s}$ is N_s samples of the transmitted signal 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.

$$\boldsymbol{D} = \begin{bmatrix} 0 & & & 1 \\ 1 & 0 & & \\ & \ddots & \ddots & \\ 0 & & 1 & 0 \end{bmatrix} \quad , \quad \boldsymbol{D}_l = \begin{bmatrix} 0 & & & 1 \\ 1 & 0 & & \\ & \ddots & \ddots & \\ 0 & & 1 & 0 \end{bmatrix}^{n_l}$$

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

Now, we assign 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 an emitter and zero for the rest of the grid points. Thus, the signal vector received by l^{th} sensor 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 emitter is located in the grid point (x,y) and the summations are over all 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 assistive healthcare systems, we can easily assume that the transmitted signal $\boldsymbol{s}$ is known by the receiver sensors. However, in other applications when the signal is not known for receivers, we can consider the transmitted signal $\boldsymbol{s}$ as a *deterministic unknown* signal. Then, for each grid point, we estimate the transmitted signal using the Minimum Variance Unbiased estimator (MVU) as

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

where $\hat{\boldsymbol{s}}_n$ is the MVU estimate for the transmitted signal from grid point n. We define the matrix $\boldsymbol{\Gamma}_n$ as the delay operator w.r.t all L sensors, assuming that the received signal comes from the grid point n (there is an emitter at grid point n):

$$\boldsymbol{\Gamma}_n \triangleq \begin{bmatrix} \alpha_{1,n} \boldsymbol{D}_{1,n} \\ \alpha_{2,n} \boldsymbol{D}_{2,n} \\ \vdots \\ \alpha_{L,n} \boldsymbol{D}_{L,n} \end{bmatrix}_{LN_s \times N_s}$$

Then, we can define $\boldsymbol{\theta}_n, n \in \{1, 2, \ldots, N\}$ as an $LN_s \times 1$ vector containing all signals received by all L sensors when the emitter is in grid point n as

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

If we arrange all vectors $\boldsymbol{\theta}_n$ for n:1...N as the columns of a matrix $\boldsymbol{\Theta}$ as

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

then we have

$$\boldsymbol{r} = \boldsymbol{\Theta} \times \boldsymbol{z} + \boldsymbol{w} \tag{8}$$

$$\boldsymbol{r} \triangleq [\boldsymbol{r}_1^T \quad \boldsymbol{r}_2^T \quad \ldots \quad \boldsymbol{r}_L^T]^T{}_{LN_s \times 1}$$

$$\boldsymbol{z} \triangleq [z_1 \quad z_2 \quad \ldots \quad z_N]^T{}_{N \times 1},$$

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. Now, we can solve our problem by forming a *BPIC* (*Basis Pursuit with Inequality Constraints*) *problem* [14] 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 *BPDN* (*Basis Pursuit Denoising*) *problem* [14] 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

We examined the performance of the proposed method using Monte Carlo computer simulation with 500 runs each time for various numbers of sensors (from 3 to 8 sensors). We simulated the massive multipath conditions in a typical apartment shown in Figure1(a). The sensors are mounted at x-y locations (0,0) , (0,10) , (10,0) , (10,10) , (0,4) , (4,10) , (10,6) , (6,0) respectively and the location of the target has been chosen randomly. In this simulation, we used a BPSK signal with carrier frequency of 1 GHz. The sampling frequency is 200 MHz and the number of samples is equal to 256. We run this simulation one time for SNR = 0dB and another one time for SNR = 10dB.

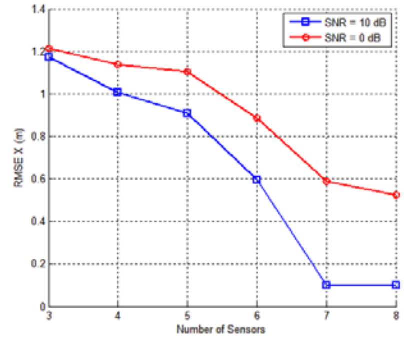
Figure 2 shows the RMS Error vs. number of sensors for estimating the location of the target in (x, y) plane. As we expected, the accuracy gets better by increasing the number of the sensors. However, the results show that the proposed method has very good performance even for small number of sensors (3 sensors). Thus, we have this possibility to use small number of sensors to reduce the complexity and expenses of the system.

Furthermore, the system works very well in the presence of multipath reflections and in noisy environments with low SNRs and it means that even with low transmitted power (to keep the worn device small with long battery life), we can achieve a high localization accuracy.

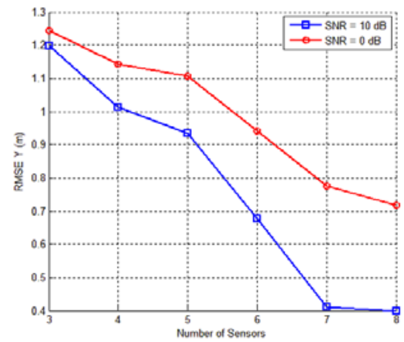
IV. Conclusion

The indoor localization is a very beneficial tool in assistive healthcare environment when tracking the location, behavior and reactions of the patient is required for medical observation, symptoms identification or accident prevention. Existing methods are susceptible to performance degradation due to the likely occurrence of multipath reflections in an indoor setting.

To combat the degradation due to multipath we developed a one-stage localization method based on spatial sparsity of the target(s) in the grid plane. In this method, we assign a non-zero number to each one of the grid points containing an emitter (target) and zero to the rest of the grid points. Thus, the vector formed from these numbers will be a sparse unknown vector that we aim to estimate. Since each element of this vector corresponds to one grid point in the grid plane, we can estimate the location of emitters by extracting the position of non-zero elements of the sparsest vector that satisfy the delay relationship between transmitted signals and received signals. We evaluated the performance of the proposed method using Monte-Carlo simulation (with 500 runs each time). The simulation results show that the proposed method has very good performance even with small number of sensors and for low SNRs. 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 scenarios.



(a)



(b)

Figure (1): RMS Error for X and Y (meter) versus Number of sensors.

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