SEQUENTIAL ACOUSTIC ENERGY BASED SOURCE LOCALIZATION USING PARTICLE FILTER IN A DISTRIBUTED SENSOR NETWORK

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ABSTRACT

A sequential source localization method using particle filter is presented to estimate and track multiple-target locations. This method is designed to make use of acoustic signal measured at multiple acoustic sensors randomly deployed in a wireless distributed sensor network. By using the particle filter, non-Gaussian probability density function of the target locations are represented by a discrete set of "particles". The positions of these particles are propagated sequentially using known state transition equation, and updated using new location estimates via the observation equation. Compared to a previously proposed Maximum Likelihood source localization algorithm, this new approach is computationally effective and more robust to parameter perturbation.

1. INTRODUCTION

Source localization is an important application in the distributed sensor network system. The objective is to estimate the positions of the moving targets within a sensor field monitored by a sensor network. Most localization methods depend on three types of physical variables measured by or derived from sensor readings for localization: time delay of arrival (TDOA)[1], direction of arrival (DOA)[2] and received signal strength[3].

For wireless distributed sensor network applications, energy (intensity) based source localization method is an appropriate choice since it will reduce the computation burden as well as communication bandwidth [3]. In addition, the coarse time interval for computing each new energy reading will also much relieve the burden of accurate time synchronization among sensors using wireless communication channel.

A maximum likelihood (ML) source localization method using acoustic energy readings in the wireless sensor network was presented in [3]. Compared to the existing acoustic energy based source localization methods, ML method delivers more accurate results and offers the enhanced capability of multiple source localization. However, ML method has several limitations. Specifically, ML method is sensitive to the parameter perturbation and the computational complexity is high for multi-target location estimation. These limitations can be addressed by applying particle filtering.

Particle filter was applied in video conference speaker localization application to filter out the spurious speaker location induced by reverberation [4]. In this paper, we will apply a particle filter to determine the source locations in the wireless sensor network. Using the particle filter, the prior and posterior likelihood of the source states are effectively represented by a set of particles. This set of particles is sequentially propagated by particle filtering based on the state transition model and is updated upon receiving the new measurement. It eliminates the requirement of a comprehensive search over the whole location space and filters out the spurious locations caused by the strong background noise such as wind gust.

2. SEQUENTIAL SOURCE LOCALIZATION

2.1. Sequential Bayesian Estimation

In a sequential Bayesian estimation framework, the state vector at time t, denoted by $\boldsymbol{\alpha}_t$, is estimated using observations at time t, $\mathbf{x}_t$, and previous state estimate $\boldsymbol{\alpha}_{t-1}$ at time $t-1$ in a sequential manner. It is assumed that the state transition equation

$$\boldsymbol{\alpha}_{t+1} = f_t(\boldsymbol{\alpha}_t, \mathbf{w}_t) \tag{1}$$

and the observation equation

$$\mathbf{x}_t = g_t(\boldsymbol{\alpha}_t, \mathbf{v}_t) \tag{2}$$

are known. The *pdf* of the system excitation $\mathbf{w}_t$ and measurement noise $\mathbf{v}_t$ are also assumed to be known.

Define $\mathbf{X}_{t-1} = \{\mathbf{x}_i :, i = 1, ...t-1\}$ to be the observation sequence made up to time $t-1$. The sequential

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Bayesian estimation estimates $\mathbf{x}_t$ in two steps: a *prediction* step and an *update* step. During the *prediction* step, the a posteriori probability of $\boldsymbol{\alpha}_t$ based on $\mathbf{X}_{t-1}$, denoted by $p(\boldsymbol{\alpha}_t|\mathbf{X}_{t-1})$ is predicted from the following Bayes equation

$$p(\boldsymbol{\alpha}_t|\mathbf{X}_{t-1}) = \int p(\boldsymbol{\alpha}_t|\boldsymbol{\alpha}_{t-1})p(\boldsymbol{\alpha}_{t-1}|\mathbf{X}_{t-1})d\boldsymbol{\alpha}_{t-1} \quad (3)$$

where $p(\boldsymbol{\alpha}_t|\boldsymbol{\alpha}_{t-1})$ is the state transition *pdf* that can be estimated from the system model.

Once the observation $\mathbf{x}_t$ is made, the *update* step will update the a posteriori probability of the state vector using the Bayes rule:

$$p(\boldsymbol{\alpha}_t|\mathbf{X}_t) = \frac{p(\mathbf{x}_t|\boldsymbol{\alpha}_t)p(\boldsymbol{\alpha}_t|\mathbf{X}_{t-1})}{p(\mathbf{x}_t|\mathbf{X}_{t-1})} \quad (4)$$

2.2. Particle Filter/Bootstrap Filter

Sequential Bayesian estimation has no analytical solution when the model is non-linear or the noise is non-Gaussian. Particle filter was proposed to solve the generalized non-linear or non Gaussian sequential estimation [5] using sequential Monte-Carlo simulation.

During each step of the sequential estimation, the particle filter predicts and updates a set of L discrete samples of the state vector $\{\boldsymbol{\alpha}_t(i)\}$ using sequential importance sampling (SIS) algorithm and use these particles to approximate the a posteriori density function $p(\boldsymbol{\alpha}_t|\mathbf{X}_t)$. As the number of samples becomes large, these samples effectively provide an equivalent representation of the required *pdf*.

3. SEQUENTIAL SOURCE LOCALIZATION AND TRACKING USING PARTICLE FILTERING IN DISTRIBUTED SENSOR NETWORK

3.1. System Model

Define

$$\boldsymbol{\alpha}_t = [\boldsymbol{\alpha}_t^{(1)} \ \boldsymbol{\alpha}_t^{(2)} \ \ldots \ \boldsymbol{\alpha}_t^{(K)}]$$

as the state vectors of the K sources at time t, where

$$\boldsymbol{\alpha}_t^{(k)} = [\boldsymbol{\rho}_k(t) \ \mathbf{u}_k(t) \ \mathbf{a}_k(t)]^T$$

is the state vector of the k^{th} acoustic source at time t, $\boldsymbol{\rho}_k(t)$ stands for the location of source k at time t, $\mathbf{u}_k(t)$ is the velocity of source k at time t and $\mathbf{a}_k(t)$ is the acceleration of the source k at time t. For simplicity, we assume a linear state transition model and source movement is independent between each other.

$$\mathbf{a}_k(t) = \mathbf{w}(t) \quad (5)$$

$$\mathbf{u}_k(t) = \mathbf{u}_k(t-1) + \mathbf{a}_k(t)T \quad (6)$$

$$\boldsymbol{\rho}_k(t) = \boldsymbol{\rho}_k(t-1) + \mathbf{u}_t(t-1)T + \frac{1}{2}\mathbf{a}_k(t)T^2 \quad (7)$$

where T is the time interval and $\mathbf{w}(t)$ is assumed to be uniformly distributed on $[-W_{max} \ W_{max}]$. W_{max} is the maximum acceleration rate.

3.2. Acoustic Energy Based Source Localization Model

Previously [3], we proposed a maximum likelihood estimation based method to localize acoustic sources. Our method is based on an acoustic energy attenuation model that has been validated through real world experiment [3] [6]:

$$y_i(t) = \gamma_i \sum_{k=1}^{K} \frac{s_k(t)}{\| \boldsymbol{\rho}_k(t) - \mathbf{r}_i \|^2} + \varepsilon_i(t) \quad (8)$$

where K is the number of targets (assumed to be known), $y_i(t)$ is the acoustic energy received by the i^{th} sensor at time t. $\varepsilon_i(t)$ is a perturbation term that summarizes the net effects of background additive noise and the parameter modeling error. γ_i and $\mathbf{r}_i$ are the gain factor and location of the i^{th} sensor respectively, $s_k(t)$ and $\boldsymbol{\rho}_k(t)$ are the energy emitted by the k^{th} source (measured at 1 meter from the source) and its location during the t^{th} time interval. N is the number of sensors in the activated region. We have analyzed [3] the probability distribution of $\varepsilon_i(t)$ and concluded that it can be modeled well with an $i.i.d.$ Gaussian random variable when the time window T for averaging the energy is sufficiently large. The mean and variance of each $\varepsilon_i(t)$ can be empirically estimated from constant false alarm (CFAR) detector. Based on this model, we derived a negative log-likelihood function [3]

$$\ell(\boldsymbol{\theta}_t) \propto \|\mathbf{x}_t - \mathbf{H}_t\mathbf{s}_t\|^2 \quad (9)$$

where $\boldsymbol{\theta}_t = \left[\ \boldsymbol{\rho}_1^T(t) \quad \cdots \quad \boldsymbol{\rho}_K^T(t) \quad s_1(t) \quad \cdots \quad s_K(t) \ \right]^T$ is the vector of unknown parameters. $\mathbf{x}_t$ is a vector of normalized energy reading $y_i(t)$. $\mathbf{H}_t$ is a matrix in which each element is a function of the gain factor γ_i, unknown source location $\boldsymbol{\rho}_i(t)$, noise variance $\sigma_i(t)$ and known sensor location $\mathbf{r}_i$. $\mathbf{s}_t$ is a vector of source energy $s_i(t)$.

In [3], we have shown that, once the source locations $\left[\ \boldsymbol{\rho}_1^T(t) \quad \cdots \quad \boldsymbol{\rho}_K^T(t) \ \right]^T$ is found, the source energy vector $\mathbf{s}_t$ can be estimated by

$$\mathbf{s}_t = \mathbf{H}_t^{\dagger}\mathbf{x}_t \quad (10)$$

where $\mathbf{H}_t^{\dagger}$ is the pseudo-inverse of $\mathbf{H}_t$

Substituting above equation into the log likelihood function, we obtain an equivalent log likelihood function that is proportional to the projection energy, i.e.:

$$-\ell(\boldsymbol{\theta}_t) \propto \{\mathbf{x}_t^T\mathbf{P}_t\mathbf{x}_t\} = \mathbf{x}_t^T\mathbf{U}_t\mathbf{U}_t^T\mathbf{x}_t = \|\mathbf{U}_t^T\mathbf{x}_t\|^2 \quad (11)$$

where $\mathbf{P}_t = \mathbf{H}_t(\mathbf{H}_t^T\mathbf{H}_t)^{-1}\mathbf{H}_t^T = \mathbf{U}_t\,\mathbf{U}_t^T$ is a projection matrix, and $\mathbf{U}_t$ is the matrix of the left singular vectors of the $\mathbf{H}_t$ matrix. Hence, the likelihood of the measurement given a particular source location subspace,i.e., given the i^{th} sample state, can be estimated as:

$$q_i = p(\mathbf{x}_t|\boldsymbol{\alpha}_t^\star(i)) = \eta e^{\mathbf{x}_t^T\mathbf{P}_t(\boldsymbol{\alpha}_t^\star(i))\mathbf{x}_t} \tag{12}$$

Here, the measurement set $\mathbf{x}_t$ is the normalized energy measurements. $\mathbf{P}_t$ is a function of $\boldsymbol{\alpha}_t^\star(i)$, which is the i^{th} prior sample for the K source states. η is defined to normalize the posterior probability, i.e.,

$$\eta = \sum_{i=1}^{L} e^{\mathbf{x}_t^T\mathbf{P}_t(\boldsymbol{\alpha}_t^\star(i))\mathbf{x}_t} \tag{13}$$

To reduce the degeneracy phenomenon of particle filtering, the particles are resampled according to the weights denoted as (12). To improve the resampling efficiency, we sort the sample sequence (the set of particle) by their weights q_i in descending order. Resampling is then performed using the sorted sample sequence.

3.3. Region Division

To save computation power and communication bandwidth in wireless sensor network, the localization algorithm is triggered on demand. The entire sensor field is divided into several smaller overlapping sub-regions. The overlapping sub-regions is applied because the energy of the sources located at the boundary of the region will contribute to the energy readings of some sensors placed in the neighborhood region. Since energy decays with the square distance from the source, 10 meter overlapping boundary is sufficient.

In each sub-region, we define one manager sensor node and other nodes are defined as detection nodes. Detection node detects target using CFAR algorithm and calculates the energy readings individually and sends these information to the manager node. The manager node will perform region fusion detection and localization and tracking algorithm based on the information received from all detection nodes in the sub-region.

Since the sub-region has smaller size and less sensors, the communication burden is reduced. The sub-region is activated if the tracking algorithm announces that the targets will move into another sub-region. Then, the current sub-region manager node will send this information to the manager node of the next sub-region. The corresponding sub-region is activated. And the current sub-region will go to sleep.

3.4. Number of Sources

In this proposed method, it is assumed that the number of acoustic sources is known in advance before the localization algorithm is applied. Indeed, the proposed method can be extended to the situation of unknown number of the targets, using a classical generalized likelihood ratio test (GLRT) or weighted subspace fitting method [7]. Yet, these two methods require high computation. They are not suitable for sensor network application where the power supply is limited. In stead, in sensor network application, we use other methods to estimate the number of targets. If the sources are well-separated and sensors are densely deployed over the sensor field, the number of sources can be determined by finding the number of peaks of the energy profile. When several targets are very closely positioned, the number of energy profile peaks may be unable to indicate the number of sources correctly. However, since sequential source localization and tracking algorithm keeps the individual velocity for each target, the closely positioned targets can still be distinguished by their different velocities. The only unresolvable targets are those targets that appear in the subregion at the same time and they keep closely all the time with the same moving direction. Yet, in such situation, it is still safe to treat these multiple targets as a single target because physically, they look like a single target.

4. SIMULATION

Simulations have been conducted to compare the performance of sequential acoustic energy based source localization algorithm using particle filter to the previously proposed ML algorithm. We use (8) to generate the acoustic energy readings of a 2-D sensor field of size 100×100 square meters. The sensors are randomly deployed as Fig.1, where the whole sensor field is divided into four overlapping smaller subregions. Two targets move from positions (-50,-50) and $(50, -50)$ to positions $(50, 50)$ and $(-50, 50)$ respectively with the initial velocity of 20 m/s for each target. The velocity and acceleration for the two targets are changed according to our state transition model. The source energy for target 1 measured at 1 meter distance is set as $s_1 = 10000$. The source energy for target 2 is set as $s_2 = 1.2s_1$. The background noise level is set as $\sigma_i = 3$ for all sensors in the sensor field. The number of particles is chosen to be 500. Note that for a 100×100 square meters sensor field, ML estimation using the projection solution and multi-resolution search for two target location estimation with an initial grid size of 8 needs a search of $12^4 = 20736$ times. Therefore, using the particle filter dramatically reduces the computational complexity. In the simulation, a random noise with high strength is occasionally produced at a random position in the sensor region. 500 repeated trials are simulated for each sequential running point. Estimation mean as well as estimation bias and variance are shown in Figs. 2 and 3. Note that very high noises are randomly added to simulate the spurious sources, the estimation bias

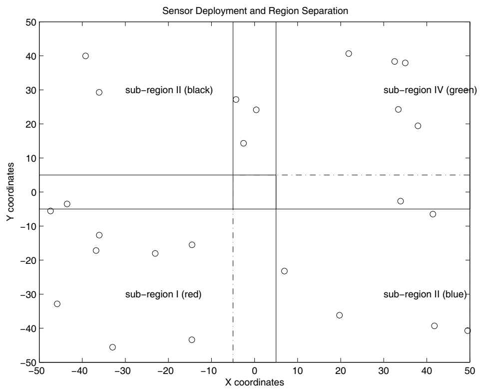

Fig. 1. Sensor Placement for Target Localization Estimation Simulation

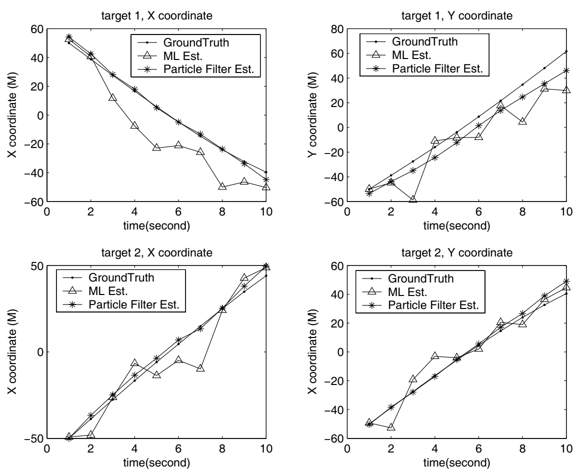

Fig. 2. Ground Truth and Location Estimation Mean using Particle Filter and ML estimation, 500 Trials for Each Simulation Point

and variance are large when ML estimation algorithm is applied. The figures show that, using particle filter, the effects of the measurement perturbation caused by the occasional strong noise are effectively filtered out. The localization results estimated by the particle filter demonstrates much higher accuracy than the ML algorithm.

5. CONCLUSION

Sequential acoustic energy based source localization using particle filter has been presented. The algorithm represents the required *pdf* as a set of random samples. Using the prior-likelihood function and post-likelihood function, the particle filter propagates and updates the set of random samples, eliminates the requirement of a comprehensive search over the whole location space and filters out the spurious location. Hence, it is more robust to parameter perturbations

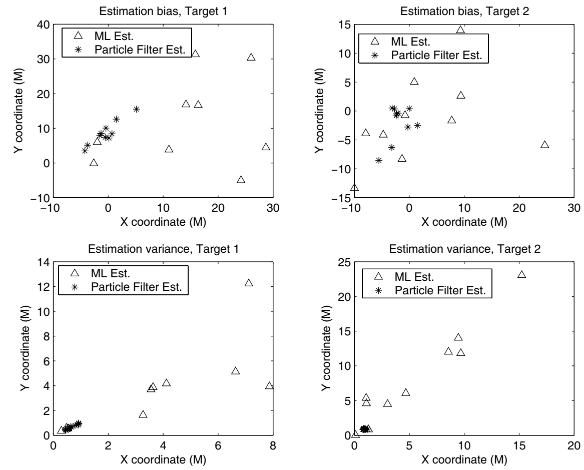

Fig. 3. Estimation Bias and Variance using Particle Filter and ML estimation, 500 Trials for Each Simulation Point. Strong random noises are occasionally added at random positions in the sensor field to simulate the spurious sources

and more computationally efficient.

6. REFERENCES

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