Distributed Lightweight Target Tracking for Wireless Sensor Networks

Sheng Wang, Xue Wang, Yong Wang and Xinyao Sun
State Key Laboratory of Precision Measurement Technology and Instruments, Department of Precision Instruments, Tsinghua University, Beijing 100084, China
E-mail: wangxue@mail.tsinghua.edu.cn

Abstract

Target tracking is an important task addressed in wireless sensor network (WSN), because the resources of WSN are limited. A distributed lightweight particle filter algorithm is proposed to achieve robust target tracking with low resource requirement in the WSN consisting of acoustic sensor nodes. In the proposed algorithm, each sensor node carries out partial particle filter with its local data and the neighbor nodes' data in distributed manner. Then local results of selected sensor nodes are fused to make final decision. To simplify the computation of particle filter, lightweight sampling and resampling schemes are introduced, where a simple range-free algorithm is adopted to restrict potential area of target's location. The experimental results verify that the proposed distributed lightweight particle filter algorithm can effectively achieve target tracking in WSN with low resource consumption. Compared to previous target localization algorithms, such as maximum likelihood estimation and centralized particle filter, the proposed algorithm has outstanding performance in accurate target tracking and low resources consumption.

1. Introduction

Wireless sensor network (WSN) always consists of a large number of sensors nodes and can collectively monitor environmental conditions. Even though fixed sensors connected by a fixed communication network protect most facilities, WSN can provide robustness, flexibility, easy deployment and additional coverage. Compared to the traditional measuring system, WSN is exactly a distributed measuring system, and it is widely used for distributed target surveillance, such as target localization and tracking [1-2].

Acoustic target localization in WSN [3-5] can be divided into three categories: time difference of arrival (TDOA) [2], direction of arrival (DOA) [3] and energy based localization [4, 5]. TDOA achieves localization by analyzing the arrival time of different sensor nodes. TDOA can provide high accuracy, but it is complex and requires time synchronization. DOA tries to acquire the direction of signal transmission, but it requires overhead hardware [2]. The energy based localization algorithms analyze the attenuation in the power of the incoming acoustic signal and uses the signal propagation model to derivate the location. It is less complex than the former two algorithms, but it always provides low accuracy. In WSN, the energy based localization algorithm is preferred, because it is easy to establish, and it also takes advantages of low requirements in sampling rate, resources consumption and time synchronization. Energy based localization algorithm can be categorized into range-based and range-free algorithms. The range-free algorithm [6, 7] does not need range hardware support and is immune to range measurement errors while providing less accurate results. The range-based algorithm [4, 8, 9] requires range hardware, but it is more accurate than range-free algorithms. In this work, we focus on energy based localization algorithm. To achieve the tradeoff between performance and consumption, we combine the range-based and range-free algorithms, where range-free algorithm provides an approximate result for the speeding up the initialization of range-based algorithm.

Essentially, range-based localization in WSN is a problem of state estimation in dynamic system. Particle filter (PF) is a well known state estimation algorithm, which is widely used for handling multimodal probability density functions and solving nonlinear non-Gaussian problems [10, 11]. However, PF suffers from some vital disadvantages, such as high computation cost and particle degradation. Generic PF cannot be afforded by single sensor node [10, 11].

To solve the above problem, this paper proposes a distributed lightweight particle filter, which implements the state estimation with the collaboration of multiple sensor nodes. Each sensor node carries out particle filter with its local data and neighbor nodes' data in distributed manner. Then local results of selected sensor nodes are fused to make final decision. To simplify the computation, each sensor node only controls the computation of a small number of particles. And lightweight sampling and resampling schemes are introduced, where a simple range-free algorithm is adopted to refine the sampling scheme.

The rest of this paper is organized as follows. Some preliminaries and assumptions are introduced in Section 2. Section 3 proposes the principle of distributed lightweight particle filter. The experimental results are given in Section 4 to illustrate the performance of the proposed algorithm, maximum-likelihood estimation (MLE) [8, 9] and centralized particle filter (CPF). Section 5 makes the conclusions.

2. Preliminaries and assumptions

2.1. Sensing model of acoustic sensor nodes

In this paper, the localization problem is constrained within two dimensions. And only single target localization is considered. Multi-target localization will be investigated in the future work. When an acoustic signal is propagating, its energy decays in a manner that is inversely proportional to the square of the distance from the source. Given N static sensor nodes and one target, the energy of received acoustic signal in *i*th sensor node at time t, $E_i(t)$, is [8]:

$$E_i(t) = \gamma_i \frac{A(t)}{\left\|\boldsymbol{p}(t) - \boldsymbol{p}_i\right\|^2} + \varepsilon_i(t), \quad i = 1, 2, \cdots, N \quad (1)$$

where, N is the number of acoustic sensor nodes, γ_i is sensor gain factor of the *i*th acoustic sensor node. $A(t)$ is the average signal energy of the target in a constant window length which is measured at 1 meter from the target. $\boldsymbol{p}(t)$ is the position vector of the target; and p_i denotes the position vector of *i*th sensor. $\|\cdot\|$ is the Euclidean distance. $\varepsilon_i(t)$ is the perturbation term that denotes background noise and modeling error, which can be approximated with an independent and identically distributed Gaussian distribution.

2.2. Principle of generic particle filter

The generic PF algorithm is based on Monte Carlo simulation and Bayesian sampling estimation theories. The sampling process is called sequential importance sampling with re-sampling (SISR) [10]. SISR consists of three steps: sampling, evaluating and resampling. In the first step, new particles are sampled. In Bayesian theory, the posterior density $p(x_k | y_{1:k})$ can be inferred from prior density $p(x_k | y_{1:k-1})$

$$p(x_k | y_{1:k}) = p(y_k | x_k) \cdot p(x_k | y_{1:k-1}) / p(y_k | y_{1:k-1}) \quad (2)$$

where

$$p(y_k | y_{1:k-1}) = \int p(y_k | x_k) p(x_k | y_{1:k-1}) \mathrm{d}x_k \quad (3)$$

Then PF uses the Monte Carlo simulation method to approximate the posterior density by N particles

$$p(x_{k-1} | y_{1:k-1}) \approx \sum_{i=1}^{N} \omega_{k-1}^i \delta(x_{k-1} - x_{k-1}^i) \quad (4)$$

The weights are nonnegative factors, and

$$\sum_{i=1}^{n} \omega_k^i = 1 \quad (5)$$

To decrease the difficulty of sampling, sequential importance sampling method samples from a known, easy-to-sample, proposal distribution $q(x_{0:k} | y_{1:k})$. And the recursive estimate for the importance weights of particle *i* can be derived as follow

$$\tilde{\omega}_k^i = \omega_{k-1}^i \cdot p(y_k | x_k) \cdot p(x_k | x_{k-1}) / q(x_k | x_{0:k-1}, y_{1:k}) \quad (6)$$

Then resampling step replaces the "bad" particles with "good" particles, and enhances the evaluation of the whole particle swarm. However, it also makes the PF algorithm suffer from sampling exhaustion problem.

The estimated state is finally approximated by

$$\hat{x}_k \approx \sum_{i=1}^{N} \omega_k^i x_k^i \quad (7)$$

2.3. General assumptions of WSN

Without loss of generality, it is assumed that the acoustic sensor nodes are densely deployed in WSN. At any time instant, each target will be detected by at least one acoustic sensor node. Each sensor node can acquire its own location by self-localization methods, such as GPS. And the sensor nodes will share their location with the neighbor nodes. Consider that the sensing field of each sensor node is a perfect circle and the sensor node is located at the centre of the circle. Different to the assumptions in some literatures [12], to simplify the hardware infrastructure, it is assumed that the sensor node only has one sensing power level. The target can continuously emit omni-directional acoustic signals in a constant energy level. And for simplicity, it is assumed that targets move with a linear state transition model and the movement of each target is independent between each other.

3. Implementation of the distributed lightweight particle filter

3.1. Centralized particle filter for localization

Define $\boldsymbol{S}_t$ as the state vector of the target at time t,

$$\boldsymbol{S}_t = \left[\boldsymbol{p}_t , \boldsymbol{v}_t , \boldsymbol{a}_t \right]^T$$

where $\boldsymbol{p}_t$, $\boldsymbol{v}_t$ and $\boldsymbol{a}_t$ are respectively, the position, velocity and acceleration vector at time t. With the assumption of linear state transition model, we have

$$\boldsymbol{v}_t = \boldsymbol{v}_{t-1} + \boldsymbol{a}_t \cdot T \tag{8}$$

$$\boldsymbol{p}_t = \boldsymbol{p}_{t-1} + \boldsymbol{v}_{t-1} T + 0.5 \cdot \boldsymbol{a}_t \cdot T^2 \tag{9}$$

where T is the time interval and $\boldsymbol{a}_t$ is assumed to be uniformly distributed on $\left[-a_{\max}, a_{\max} \right]$. Here, $a_{\max}$ is the predefined maximum acceleration rate.

Define

$$\boldsymbol{E}_t = \left[E_1(t), E_2(t) \ldots, E_N(t) \right]^T$$

A negative log-likelihood function can be derived [13]

$$-\ell(\boldsymbol{\theta}_t) \propto \left\| \boldsymbol{E}_t - \boldsymbol{H}_t A_t \right\|^2 \tag{10}$$

where

$$\boldsymbol{\theta}_t = \left[\left(\boldsymbol{p}_t \right)^T , A(t) \right]^T$$

$$\boldsymbol{H}_t = \boldsymbol{G} \boldsymbol{D}_t$$

$$\boldsymbol{G} = diag\left[\gamma_1 / \sigma_1, \gamma_2 / \sigma_2, \ldots, \gamma_N / \sigma_N \right]$$

$$\boldsymbol{D}_t = \left[1/d_1^{\,2}(t) \quad 1/d_2^{\,2}(t) \quad \cdots \quad 1/d_N^{\,2}(t) \right]^T$$

where

$$d_i^{\,2}(t) = \left\| \boldsymbol{p}(t) - \boldsymbol{p}_i \right\|^2$$

Because the energy of emitted acoustic signals can be estimated from the received acoustic signals and the source locations, the equivalent log likelihood function can be given as follows [13].

$$-\ell(\boldsymbol{\theta}_t) \propto \left\{ \boldsymbol{E}_t^{\,T} \boldsymbol{P}_t \boldsymbol{E}_t \right\} = \left\| \boldsymbol{U}_t^{\,T} \boldsymbol{E}_t \right\|^2 \tag{11}$$

where

$$\boldsymbol{P}_t = \boldsymbol{H}_t \left(\boldsymbol{H}_t^{\,T} \boldsymbol{H}_t \right)^{-1} \boldsymbol{H}_t^{\,T} = \boldsymbol{U}_t \boldsymbol{U}_t^{\,T}$$

Then, the likelihood of the measurement given the *i*th sample state, $\tilde{\boldsymbol{S}}_t^i$, can be estimated as:

$$q_i = p\left(\boldsymbol{E}_t \middle| \tilde{\boldsymbol{S}}_t^i \right) = e^{\boldsymbol{E}_t^{\,T} \boldsymbol{P}_t \left(\tilde{\boldsymbol{S}}_t^i \right) \boldsymbol{E}_t} \tag{12}$$

The importance weights, $\tilde{\omega}_t^i$, can be defined as $\tilde{\omega}_t^i = q_i$. Thus, if the number of sensors becomes large, the computation complexity of likelihood measurement will sharply increase. To solve this problem, in this paper, a distributed lightweight particle filter algorithm is proposed. The detail of the proposed algorithm is discussed in the following section.

3.2. Range-free localization based sampling

In centralized particle filter, the predicted state of each particle is drawn from the transition model. If the sampling scheme can be restricted in a accurate distribution, essentially, the convergence speed and the accuracy will be further improved.

As illustrated in Figure 1, a target is in the sensing area of three sensor nodes. And the energy results of received signals in three sensors satisfy the following relationship: $E_A(t) > E_B(t) > E_C(t)$. It is a common sense that if $E_A(t) > E_B(t)$, the distance between target and A is shorter than the distance between target and B. Thus, the potential area of the target location can be derived. It must be noticed that the number of sensor nodes receiving acoustic signals is different. If the number is 1, potential area is just the sensing area of the sensor node. If the number is 2 or 3, the potential area is determined by the selected intersection. If the number is more than 3, only 3 sensor nodes which have the largest received energy are selected.

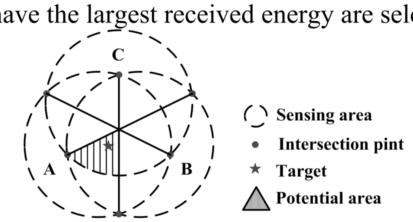


Figure 1. Potential area of target location.

With the restricted potential area, the distribution of target location can be further refined. Thus, the range-free localization based sampling scheme can be summarized as follows: Firstly, randomly generate $\boldsymbol{a}_t$ from $\left[-a_{\max}, a_{\max} \right]$, then derive the state vector, $\tilde{\boldsymbol{S}}_t^i$, according to the transition model. If the estimated target location, $\tilde{\boldsymbol{p}}_t^i$, is within the range-free localization based potential area, the sampling is successful. Otherwise, repeat the above process until a valid sample is generated.

3.3. Random resampling

Resampling is an important step for avoiding the degeneracy of the sequential importance sampling. It has been proved that the specific choice of resampling scheme does not significantly affect the performance of PF [14]. For decreasing the computation complexity, the simple random resampling scheme is designed. It is similar to the scheme proposed in [15]. At first, eliminate the particles with the weights lower than a predefined threshold ω_0 and randomly resample the new particles. Then evaluate the importance weights of new particles. Reserve the new particles with the weights larger than ω_0 and eliminate the others. Repeat the above process until the important weights of all particles are larger than the predefined threshold or the resampling times beyond a certain number. The degeneracy of the sequential importance sampling can be avoided by random resample from valid sampling area, while the diversity of particles can be guaranteed.

3.4. Distributed localization with local results

When a set of acoustic sensor nodes receive the acoustic signals, the average energy is shared with the neighbor nodes. Then each sensor node carries out particle filter with the local energy and the neighbors' energy, and acquires the local results, $\tilde{\boldsymbol{S}}_t(i)$. Then the final results are simply calculated as the average of all partial localization results.

$$\boldsymbol{S}_t = \sum_{i=1}^{N} \tilde{\boldsymbol{S}}_t(i) \tag{13}$$

where N is the number of sensor nodes that have received the acoustic signals.

The distributed computing scheme decreases the computation complexity of PF in each sensor node and increases the diversity of particles. The distributed lightweight particle filter can be summarized as.

♦ For sensor node α, ($\alpha = 1, \ldots N$)

1) Initialization: $t = 0$

Draw M' particles, $\boldsymbol{S}_0^i, i = 1, \ldots M'$, uniformly from the prior distribution of target's initial location.

2) Repeat at every time instant t:

Acquire local and N' neighbor energy results.

If $N' = 0$

Potential area is its own sensing area.

Else if $N' = 1$ or 2

Potential area is the selected intersection of the sensing areas of sensor nodes.

Else if $N' \geq 3$

Select 3 sensor nodes which have the largest received energy. Then acquire the potential area.

Endif

♦ For $i = 1, \ldots, M'$

Repeat

Sampling $\tilde{\boldsymbol{S}}_t^i$ according to the transition model

Until the estimated $\tilde{\boldsymbol{p}}_t^i$ is within potential area.

Given the energy readings vector, $\boldsymbol{E}_t$, evaluate the importance weights, $\tilde{\omega}_t^i$.

$$\tilde{\omega}_t^i = q_i = p\left(\boldsymbol{E}_t \middle| \tilde{\boldsymbol{S}}_t^i\right)$$

Normalize the importance weights ω_t^i.

Repeat

Resample the particles whose weight, ω_t^i, is below a predefined threshold ω_0 from valid sampling area.

Evaluate the importance weights, ω_t^i.

Until all importance weights are larger than ω_0 or resampling times is beyond $N_{\max}$.

Acquire the estimated target location:

$$\tilde{\boldsymbol{S}}_t(\alpha) = E\left(\tilde{\boldsymbol{S}}_t\right) = \sum_{i=1}^{M} \tilde{\boldsymbol{S}}_t^i \cdot \omega_t^i$$

♦ Calculate the average localization result.

4. Experimental results

4.1. Deployment of experiments

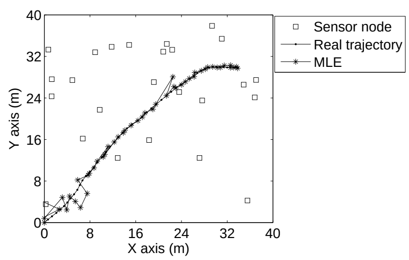
25 acoustic sensor nodes are randomly deployed in a square region of size 40*40 meters. Each node consists of an omni-directional condenser microphone, a low voltage microphone preamplifier and an 8 MHz MSP430 MCU. All sensor nodes sample acoustic signals at 1 KHz, and compute the average signal energy one time per second. A target node which is equipped with buzzers is installed on a remote-controlled toy car. The target node can move in a pre-scheduled route with a certain speed. When acoustic sensor nodes detect the target, the localization algorithm is periodically carried out by the sensor node to acquire the target location.

The experimental parameters are estimated and defined as follows. Every time, target node moves from the point of (0, 0) and the maximum acceleration is approximate to 0.2 m/s^2. And the background noise level is approximate to $\sigma_i = 1$ for all sensor nodes. The number of particles in the proposed distributed lightweight particle filter (DLPF) is set to 10 for each sensor node. 50 trials with different routes are carried out. Each trial contains 50 tracking steps (in 50 seconds). To compare the performance, MLE and CPF are also implemented on sensor nodes with the same data set of energy results. The number of particles in CPF is set to 50, and the initial value of target location in MLE is set to, (20, 20). Here, the localization error is defined as the Euclidean distance between the true target locations and the estimated ones.

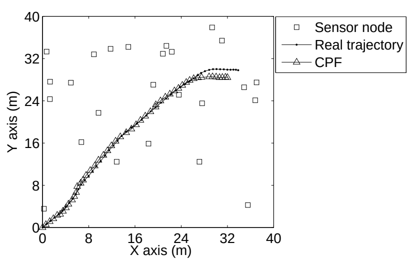
$$err_t = \sqrt{\left\| \tilde{\boldsymbol{p}}_t - \boldsymbol{p}_t \right\|^2} \tag{14}$$

4.2. Comparison of localization accuracy

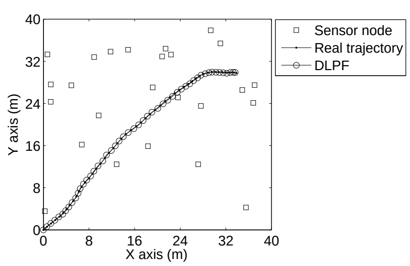
Figure 2 illustrates the tracking trajectories of three algorithms in one of 50 trials. Obviously, the tracking performance of DLPF is better than the other two algorithms since its tracking trajectory agrees with the real trajectory well. It means that the proposed DLPF can effectively achieve target tracking in the resource-constrained WSN. The tracking results also verify that CPF suffers from the problem of cumulative error. Because in the sampling step of CPF the new particles are only sampled with the transition model, the tracking error of last time instant will impact the estimation of state vector and lead to the divergence of tracking system. The localization error of MLE in early time instant is large where the acoustic sensor nodes are deployed sparsely. It verifies that the performance of MLE is largely related to the deployment of the acoustic sensor nodes. This drawback will impact the robustness of MLE and limit its application scope.



(a)



(b)



(c)

Figure 2. Tracking trajectory of (a) MLE, (b) CPF and (c) DLPF in one example of 50 trials.

To detail the performance of three algorithms, the average localization errors of 50 time instants at each trial and the ones of 50 trials at each time instant are both investigated. As illustrated in Figure 3, the localization errors of the proposed DLPF stably keep in a low level of 0.5 m, while the localization errors of CPF fluctuate at the level of 1.8 m. The performances of two particle filter algorithms are both robust against the deployment of sensor nodes and the moving routes of the target. Because the range-free localization based sampling scheme makes the particle sequence approach the real probabilistic distribution of target location, the performance of DLPF is better than CPF. Compared with two particle filter algorithms, the performance of MLE is not stable enough in the dynamic environment. As illustrated in Figure 4, two particle filter algorithms both suffer from the problem of cumulative error. But the lightweight sampling scheme can limit the bias of sampled particles. Thus, the localization errors of DLPF are nearly stable when the time instant is beyond 30th time slot, while the errors of CPF keep increasing. The results of MLE further indicate that its performance is sensitive to the initialization, because the errors are low when target moves near the initial location, (20.20).

With the above results, it can be declared that the performance of the proposed DLPF is better than MLE and CPF for target localization in constrained WSN.

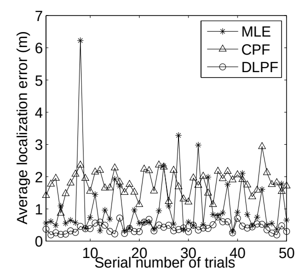


Figure 3. The average localization errors of 50 time instants at each trial

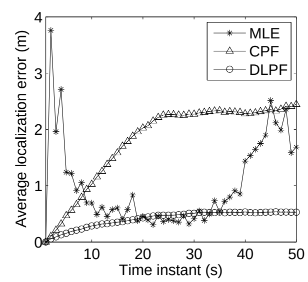


Figure 4. The average localization errors of 50 trials at each time instant

4.3. Comparison of computation time

As shown in Figure 5, the computation time of DLPF is lower than the other algorithms. The reason is that the distributed computing scheme decreases the number of energy results in each sensor node, and the restricted sampling scheme also reduces the required particles. The computation time of CPF is higher than DLPF and strongly fluctuates because the number of particles and the referenced energy results are larger than DLPF. Compared to CPF, the computation time of MLE is more stable but larger. It means that computation complexity is a big bottleneck of MLE.

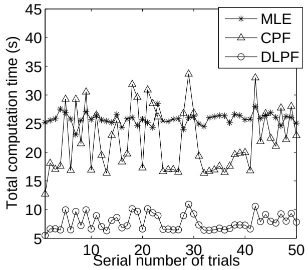


Figure 5. The total computation times of 50 time instants at each trial

5. Conclusions and future works

This paper makes efforts on target tracking in resource-constrained wireless acoustic sensor network. A distributed lightweight particle filter is proposed, which profits from the range-free localization based sampling and random resampling. The distributed computing scheme brings down the computation burden of sensor node and speeds up the convergence. A serial of localization experiments are carried out to investigate the performance of MLE, CPF and DLPF. The experimental results verify that the proposed DLPF can effectively achieve accurate and robust target localization with a low time cost in WSN.

In our future work, the impact of experimental parameters, such as the number of sensor nodes, the number of particles and background noises level, will be further investigated. The sensor nodes selection scheme for improving the accuracy and eliminating the impact of inevitable sensor nodes failure in distributed computation will also be considered.

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7. References

[1] X. Wang and S. Wang, "Collaborative Signal Processing for Target Tracking in Distributed Wireless Sensor Networks," *Journal of Parallel and Distributed Computing*, vol. 67, no. 5, May 2007, pp. 501-515.

[2] Z. Merhi, M. Elgamel and M. Bayoumi, "A Lightweight Collaborative Fault Tolerant Target Localization System for Wireless Sensor Networks", *IEEE Trans. Mobile Computing*, Accepted for future publication.

[3] V. Cevher, R. Velmurugan and J.H. McClellan, "Acoustic Multitarget Tracking Using Direction-of-Arrival Batches", *IEEE Trans. Signal Processing*, vol. 55, no. 6, Jun. 2007, pp. 2810-2825.

[4] C. Meesookho, U. Mitra and S. Narayanan, "On Energy-Based Acoustic Source Localization for Sensor Networks", *IEEE Trans. on Signal Processing*, vol. 56, no. 1, Jan. 2008, pp. 365-377.

[5] X. Wang, L. Ding and S. Wang, "Trust Evaluation Sensing for Wireless Sensor Networks", *IEEE Trans Instrumentation and Measurement*, Accepted for future publication.

[6] J. Sheu, P. Chen and C. Hsu, "A Distributed Localization Scheme for Wireless Sensor Networks with Improved Grid-Scan and Vector-Based Refinement", *IEEE Trans. Mobile Computing*, vol. 7, no. 9, Sept. 2008, pp. 1110-1123.

[7] B. Xiao, H. Chen and S. Zhou, "Distributed Localization Using a Moving Beacon in Wireless Sensor Networks", *IEEE Trans. Parallel and Distributed Systems*, vol. 19, no. 5, May 2008, pp. 587-600.

[8] X. Sheng and Y. Hu, "Maximum Likelihood Multiple-Source Localization Using Acoustic Energy Measurements With Wireless Sensor Networks", *IEEE Trans. Signal Processing*, vol. 53, no. 1, Jan. 2005, pp. 44-53.

[9] D. Blatt and A.O. Hero, "Energy-Based Sensor Network Source Localization via Projection onto Convex Sets," *IEEE Trans. Signal Processing*, vol. 54, no. 9, Sept. 2006, pp. 3614-3619.

[10] A. Doucet, "On Sequential Simulation-Based Methods for Bayesian filtering", *Technical Report*, CUED/F-INFENG/TR 310 Department of Engineering, Cambridge University, UK, 1998.

[11] X. Wang and S. Wang, "An Improved Particle Filter for Target Tracking in Sensor System", *Sensors*, vol. 7, no.1, Jan. 2007, pp.144-156.

[12] V. Vivekanandan and V.W.S Wong, "Concentric Anchor Beacon Localization Algorithm for Wireless Sensor Networks", *IEEE Trans. Vehicular Technology*, vol. 56, no. 5, Sept. 2007, pp. 2733-2744.

[13] X. Sheng and Y. Hu, "Sequential Acoustic Energy Based Source Localization Using Particle Filter in A Distributed Sensor Network", *The 2004 IEEE International Conference on Acoustics, Speech, and Signal Processing*, part III, Quebec, Canada, May 2004, pp. 972-975.

[14] R. Van der Merwe, A. Doucet, N. de Freitas, et al, "The Unscented Particle Filter", *Technical Report*, CUED/ F-INPENG/TR 380, Department of Engineering, Cambridge University, UK, 2000.

[15] L. Li, Y. Liu, L. Sun, et al. "Lightweight Particle Filters based Localization Algorithm for Mobile Sensor Networks", *The Second International Conference on Sensor Technologies and Applications*, pp. 135-140.