A Self-Adaptive Particle Swarm Optimization Based Multiple Source Localization Algorithm in Binary Sensor Networks

Long Cheng,1,2 Yan Wang,2,3 and Shuai Li4

1School of Computer and Software, Nanjing University of Information Science and Technology, Nanjing 210044, China
2School of Information Science and Engineering, Northeastern University, Shenyang 110819, China
3Department of Computer and Communication Engineering, Northeastern University, Qinhuangdao 066004, China
4Department of Computing, The Hong Kong Polytechnic University, Hong Kong

Correspondence should be addressed to Long Cheng; chenglong8501@gmail.com

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1. Introduction

With the advances of wireless communication and sensor techniques, source localization based on sensor network is getting more attention. However, fewer works investigate the multiple source localization for binary sensor network. In this paper, a self-adaptive particle swarm optimization based multiple source localization method is proposed. A detection model based on Neyman-Pearson criterion is introduced. Then the maximum likelihood estimator is employed to establish the objective function which is used to estimate the location of sources. Therefore, the multiple-source localization problem is transformed into optimization problem. In order to improve the ability of global search of particle swarm optimization, the self-adaptive particle swarm optimization is used to solve this problem. Various simulations have been conducted, and the results show that the proposed method owns higher localization accuracy in comparison with other methods.
In this paper, we propose a self-adaptive particle swarm optimization based multiple source localization method (SAPSO-MSL). We employ the maximum likelihood (ML) method to establish the localization objective function. The regular maximum likelihood method is cumbersome, implying tremendous efforts for solving the ML method in multiple targets localization problems. The challenge is to find a solution which is easy to implement and meanwhile capable of approximating the ML method with rather low computational complexity [4]. Therefore, we proposed a self-adaptive particle swarm optimization (SAPSO) method to solve this problem.

The main contribution of this paper is given as follows.

(1) We convert the multiple source localization problem into the optimization problem through the maximum likelihood method.

(2) The self-adaptive particle swarm optimization which owns low computational complexity is used to estimate the location of source.

The remaining parts of this paper are organized as follows. In Section 2, we describe the related works in recent years. The signal model and detection model are introduced in Section 3. In Section 4, the proposed multiple source localization method is explained. Simulation and numerical results are presented in Section 5. Section 6 concludes the paper.

2. Related Works

The source localization approaches can broadly be divided into two categories: single source localization and multiple source localization.

Many researchers have proposed several methods to solve the single source localization problem. In [5], a new incremental optimization algorithm called normalized incremental subgradient algorithm is proposed. This algorithm could solve the energy based distributed sensor network source localization problem where the decay factor of the energy decay model is unknown. Several different algorithms (least squares algorithm, un constrained least squares calibration algorithm, constrained least squares calibration algorithm, and weighted least square algorithm) [6] are proposed for the acoustic energy based localization when the beacon positions are uncertain. The proposed algorithms do not require iteration or initialization. In [7], a fully distributed localization algorithm is investigated. This algorithm is scalable for use in large sensor networks. For this algorithm, the scalability is achieved by forming sensor nodes into groups which collaborate to locate sources. Since the objective function of single source localization method has multiple local optima and saddle points [8], the authors formulate the problem as a convex feasibility problem and propose a distributed version of the projection onto convex sets method. A hybrid particle swarm optimization (PSO) and sequential number-theoretic optimization (SNTO) algorithm [9] are proposed for acoustic source localization in sensor networks. The SNTO provides a rigid method for PSO to initialize its particles while the virtual force-based heuristic method can direct the particles to the optimal solution.

Multiple sources localization for sensor network has been drawing a lot of research interest recently. A maximum likelihood estimation method [10] is used for the multiple source localization. And a multiresolution search algorithm and an expectation-maximization (EM) like iterative algorithm are proposed to expedite the computation of source locations. An efficient expectation maximization algorithm [11] is proposed to improve the estimation accuracy and to avoid being trapped into local optima through the effective sequential dominant-source initialization and incremental search schemes. In [12], a novel expectation-maximization (EM) based multiple source localization scheme is proposed in the presence of nonuniform noise variance. This algorithm is much more computationally efficient and robust than the existing stepwise-concentrated maximum-likelihood and approximately concentrated maximum-likelihood algorithms. An alternating projection approach [13] is proposed to solve the problem of localizing multiple sources using energy measurements from distributed sensors. This approach decomposes the multiple sources localization problem into a number of simpler optimization problems. It exhibits lower computational complexity as compared to the maximum likelihood estimator. In [14], two additional constraints are proposed to improve the localization accuracy after the initial location estimates are obtained from some existing localization algorithm. The additional constraints are an assumption of consistency of relative locations within a group of targets.

The above methods focus on the energy measurement based source localization; that is, the sensor node should transmit the measurement to the fusion center. Therefore, large amounts of data need to transmit in the network. For the large scale sensor network, it would likely overload the internodes communication network and create an excessively large computational burden to the large amount of measurement data. The binary sensor only detects the presence of a target or not; that is, it may transmit if it has detected a source or it may not transmit anything. Therefore, the binary sensor is a low-power and bandwidth-efficient solution for wireless sensor network since they communicate only a single bit of information.

Most of the existing works focus on the single source localization in binary sensor network. The authors propose a maximum likelihood source localization method in [15]. A subtract on negative add on positive (SNAP) algorithm [16] which is a simple, efficient, and fault-tolerant algorithm is proposed. This algorithm can be applied in time-critical applications for estimating the position of source for binary sensor node. It is slightly less accurate but computationally less demanding in comparison with maximum likelihood estimation. In [17], a real-time approximated maximum likelihood estimator is developed to reduce the computational complexity of the maximum likelihood estimator. A spatial topology of binary sensor network based source localization and tracking method [18] is proposed. This method employs an efficient wake-up strategy to activate a particular group of sensors for cooperative localization. To the best of our
knowledge, only a few papers investigate the multiple source localization in binary sensor network. A trust index based subtract on negative add on positive (TISNAP) method [19] is developed for multiple source localization in binary sensor network. However, this method assumes that the distance between two sources is far enough initially; that is, the node is influenced by only one source initially. So the localization process is similar to the single source localization process. In our previous work [20], the fuzzy C-means and likelihood matrix are used to estimate the localization of sources. This is a lightweight solution for multiple source localization in binary sensor network. However, the accuracy of this method is low. So we develop a high accuracy localization method further.

3. System Model

In this section, we firstly introduce the signal propagation model for acoustic source, and then the detection model for binary sensor node is presented.

3.1. Signal Model.

We make the following assumptions in the study. There are $N$ acoustic sensor nodes and $K$ acoustic sources in the field. Each sensor node is equipped with an acoustic energy measuring sensor. Each source emits acoustic signal that attenuates inside the area under observation. The intensity of an acoustic signal is emitted omnidirectionally from a point sound source. The received energy (signal intensity measured at the sensor node) at time $t$ is given by [10]

$$z_i(t) = \begin{cases} s_i(t) + y_i(t), & H_1 \\ y_i(t), & H_0 \end{cases}$$

(1)

where $H_1$ represents the acoustic sources emitted signal in the field, $H_0$ represents that there is no source, $s_i$ is the acoustic intensity measured at the $i$th sensor node due to all $K$ acoustic sources, and $y_i$ is the background noise and is modeled as zero mean white Gaussian noise random variable with variance $\sigma_i^2$.

During the time interval $T = M/f_s$, the intensity of the $K$ acoustic sources will be linearly superimposed. And the average energy measurements over the time window $[t-T/2, t + T/2]$ as $y_i(t)$ lead to

$$y_i(t) = \frac{1}{f_s} \sum_{j=(t-T/2)f_s}^{(t+T/2)f_s} s_i^2(t)$$

$$= \frac{1}{f_s} \sum_{j=(t-T/2)f_s}^{(t+T/2)f_s} s_i^2(t) + \frac{1}{f_s} \sum_{j=(t-T/2)f_s}^{(t+T/2)f_s} y_i^2(t),$$

(2)

where $M$ is the number of sampling points used for estimating the signal strength received by the sensor node during this time interval and $f_s$ is the sampling frequency.

In this paper, we assume that the acoustic intensity and energy emitted from each source do not vary too much during the time interval and thus we neglect the propagation delay in this paper. A concise acoustic energy decay model can be expressed as

$$y_i(t) = \begin{cases} n_i(t), & H_1 \\ n_i(t), & H_0 \end{cases}$$

(3)

$$= \begin{cases} s_i(t) + n_i(t), & H_1 \\ n_i(t), & H_0 \end{cases}$$

(4)

where $g_i$ represents the gain factor of the $i$th sensor node. We assume that $g_i = 1$ in this paper. $S_i(t)$ is the signal energy at 1 meter away from the $k$th source, and $d_{ik}$ is the Euclidean distance between the $i$th sensor and the $k$th source. In addition $n_i$ is the measurement noise modeled as zero mean white Gaussian with variance $\sigma_i^2$, namely, $n_i \sim N(0, \sigma_i^2)$.

3.2. Detection Model for Binary Sensor Node.

The detection model is very important for binary sensor network. It reflects the physical characteristics of the sensor. One of the most commonly used models is the binary detection model. The event occurs within the sensing radius of a sensor being detected with probability 1 while an event outside this circle of influence is not detected with probability 0. So the detection probability of a target by sensor $j$ can be expressed as

$$p_j = \begin{cases} 1, & d_j \leq R \\ 0, & d_j > R \end{cases}$$

(4)

where $R$ is the influence radius of the sensor.

The binary model is commonly adopted because of its analytical simplicity, but it is based on unrealistic assumption of perfect coverage for sensors. It cannot reflect the relationship between the signal attenuation and detection probability. The Elfes model is more realistic than binary model. The detection probability of a target $i$ by sensor $j$ is

$$p_{ij} = \begin{cases} 1, & d_{ij} \leq d_{T1} \\ e^{-\lambda d_{ij} - d_{T2}}, & d_{T1} < d_{ij} < d_{T2} \\ 0, & d_{T2} \leq d_{ij} \end{cases}$$

(5)

where $d_{T1}, d_{T2}, \lambda$, and $\beta$ are adjusted according to the physical properties of the sensor. $d_{ij}$ is the distance between target $i$ and sensor $j$.

In this paper, we introduce the Neyman-Pearson (NP) criterion to establish a more realistic detection model. This model incorporates the signal characteristics and false alarm rate. According to the signal propagation model in Section 3.1, the acoustic signal received at $i$th sensor can be expressed as

$$y_i = \begin{cases} g_i \sum_{k=1}^{K} S_k(t) + n_i, & H_1 \\ n_i, & H_0 \end{cases}$$

(6)
The probability density function of $y_i$ in conditions $H_1$ and $H_0$ can be expressed as

$$P_i (y_i | H_1) = \frac{1}{\sqrt{2\pi\sigma^2_i}} \exp \left\{ \frac{1}{2\sigma^2_i} \left( y_i - g_i \sum_{k=1}^{K} \frac{S_k}{d_{ik}^2} \right)^2 \right\}$$

(7)

$$P_0 (y_i | H_0) = \frac{1}{\sqrt{2\pi\sigma^2_i}} \exp \left\{ \frac{y_i^2}{2\sigma^2_i} \right\},$$

where $m$ is the number of measurements in each sensor node, $g_i = 1$.

According to the Neyman-Pearson criterion [21, 22],

$$L_i(y_i) = \frac{P(y_i | H_1)}{P(y_i | H_0)} = \exp \left\{ \frac{1}{2\sigma^2_i} \left( 2y_i \sum_{k=1}^{K} \frac{S_k}{d_{ik}^2} - \left( \sum_{k=1}^{K} \frac{S_k}{d_{ik}^2} \right)^2 \right) \right\} H_i \geq H_0$$

(8)

where $\omega$ is the decision threshold.

Equation (8) can be rewritten as

$$\frac{1}{2\sigma^2_i} \left( 2y_i \sum_{k=1}^{K} \frac{S_k}{d_{ik}^2} - \left( \sum_{k=1}^{K} \frac{S_k}{d_{ik}^2} \right)^2 \right) \geq \omega,$$

(9)

The above equation can be expressed as

$$\frac{y_i \sum_{k=1}^{K} \frac{S_k}{d_{ik}^2} \geq H_i}{H_0} \sigma^2_i \ln \omega + \frac{1}{2} \left( \sum_{k=1}^{K} \frac{S_k}{d_{ik}^2} \right)^2.$$

(10)

Therefore, we can obtain that

$$H_0: h \sim N \left( 0, \sigma^2_i \left( \sum_{k=1}^{K} \frac{S_k}{d_{ik}^2} \right)^2 \right)$$

$$H_1: h \sim N \left( \left( \sum_{k=1}^{K} \frac{S_k}{d_{ik}^2} \right)^2, \sigma^2_i \left( \sum_{k=1}^{K} \frac{S_k}{d_{ik}^2} \right)^2 \right)$$

(11)

We set $\mu_k = (\sum_{k=1}^{N} \beta_k (d_{ik}/2)^2)^2, \sigma^2_k = (\sum_{k=1}^{N} \beta_k (d_{ik}/2)^2)^2$. So the false alarm rate is as follows:

$$P_F = P(h > k | H_0) = 1 - \Phi \left( \frac{k}{\sigma_1} \right),$$

(12)

where $\Phi(\cdot)$ is the standard Gaussian cumulative distribution function; that is, $\Phi(x) = \int_{-\infty}^{x} \frac{1}{\sqrt{2\pi}} \exp(-y^2/2)dy$.

Therefore, the detection probability of the sensor node is

$$P_D = P(h > k | H_1) = 1 - \Phi \left( \frac{k - \mu_1}{\sigma_1} \right).$$

(13)

Figure 1 shows the detection probability of the sensor node in the presence of two sources. The X coordinate depicts the distance between the first source and the sensor node. The Y coordinate indicates the distance between the second source and the sensor node. We can see that the detection probability will decrease gradually with the distance increase. And it is very low when the sensor node is far from the sources.

Figure 2(a) shows the relationship between the distance and detection probability under different source energy values. We can notice that the detection probability decreases with the distance increase. And the higher the energy values, the higher the detection probability of the sensor node. Figure 2(b) illustrates the detection probability under different false alarm rates. The false alarm rate shows the instability of the hardware.

4. Proposed Multiple Source Localization Method

The source localization can be implemented in both traditional network and binary sensor network. In traditional networks, the measurement is performed between the source and sensor node. This method needs higher hardware requirements and transmits large amounts of data; it will consume relatively more energy. Therefore, this method is not suitable for large-scale applications. With the development of the low cost and low bandwidth binary sensor, the multiple
source localization using binary sensor network received more and more attention recently.

The running process of the binary sensor network is as follows: the base station knows the location of each binary sensor node in prior. Each sensor node is programmed with a common threshold $T$. If the measurement $y_i \geq T$, the sensor node will send an alarm to the base station; that is, it will transmit its ID to the base station; otherwise, it remains silent. The base station estimates the locations of sources according to the alarm/nonalarm information and the location of the sensor nodes. In this section, we firstly introduce a maximum likelihood estimation method to establish an objective function. Secondly, we employ the self-adaptive particle swarm optimization method to estimate the location of source.

4.1. Maximum Likelihood Estimation. The maximum likelihood estimation (MLE) is one of the most common estimation procedures used in practice. The MLE could obtain highestimation accuracy when the measurement error obeys the identical and independently Gaussian distribution. In this paper, we establish an objective function based on the signal propagation model (6) through the MLE.

The state of sensor node can be defined as follows:

$$I_i = \begin{cases} 0, & y_i < T \\ 1, & y_i \geq T \\ \end{cases}, \quad (16)$$

where $I_i = 1$ means the $i$th sensor node alarm and $I_i = 0$ indicates the $i$th sensor node keep silent.

In (6), the unknown parameters are $\theta = \{S_1, \ldots, S_K, x_1, y_1, \ldots, x_K, y_K\}$. $(x_k, y_k)$ is the location of $k$th source and $S_k$ is the signal energy at 1 meter away from the $k$th source.

We can obtain the likelihood function according to the state of sensor node and (6) as follows:

$$P(I | \theta) = \prod_{i=1}^{N} \left[ Q \left( T - \sum_{k=1}^{K} \frac{S_k}{d_{ik}^2} \right) \right]^{1-I_i} \left[ 1 - Q \left( T - \sum_{k=1}^{K} \frac{S_k}{d_{ik}^2} \right) \right]^{1-I_i}, \quad (17)$$

where $Q(x) = \int_{x}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-t^2/2} dt$ and $d_{ik}$ is the Euclidean distance between the $i$th sensor and the $k$th source.

The log-likelihood function can be expressed as

$$\ln P(I | \theta) = \sum_{i=1}^{N} I_i \ln Q(\bullet) + (1 - I_i) \ln [1 - Q(\bullet)], \quad (18)$$

where $Q(\bullet) = Q(T - \sum_{k=1}^{K} (S_k/d_{ik}^2))$.

Therefore, the objective function is formulated as follows:

$$\arg \max \ln P(I | \theta). \quad (19)$$

The multiple source localization problem is transformed into nonlinear optimization problem. The estimated source location can be obtained at base station by maximizing the objective function (19). And the signal energy $S_k$ which is considered as unknown parameter can also be estimated. So the following goal is to maximize the objective function $\ln P(I | \theta)$. The most straightforward method to solve (19) is the exhaustive search method. However, the computational complexity is very high. In order to reduce the complexity, we propose an improved particle swarm optimization to solve this problem.

4.2. Self-Adaptive Particle Swarm Optimization Based Localization Method. The particle swarm optimization (PSO) is well known because it is efficient, straightforward, and easy.
to implement. It is a population based stochastic optimization technique, inspired by social behavior of bird flocking or fish schooling. PSO has been successfully applied to solve a broad range of optimization problems. Unfortunately, conventional PSO suffers from the premature convergence problem, especially in complex problems since the interactive information among particles in PSO is too simple to encourage a global search [23]. The traditional PSO method is easy to trap in local optimum. In this paper, we employ the self-adaptive PSO algorithm to improve the ability of global search.

The PSO is initialized with a group of random particles and then searches for optima by updating generations. In this paper, we assume that a swarm consists of \( P \) particles \( S = \{X_1, \ldots, X_P\} \). The search space is \( 3K \) dimensional vector, so \( i \)th particle can be represented by vector \( X_i = [S_1, \ldots, S_K, x_1, y_1, \ldots, x_K, y_K] \). In \( t \)th iteration, each particle is updated by the two following equations:

\[
v_i^t = \omega v_i^{t-1} + c_1 \xi (p_{best}^{t-1} - X_i^{t-1}) + c_2 \eta (g_{best}^{t-1} - X_i^{t-1}) \tag{20}
\]

\[
X_i^t = X_i^{t-1} + v_i^t, \tag{21}
\]

where \( v_i^t \) stands for the velocity of particle \( i \) at step \( t \). \( X_i^t \) is the position of the \( i \)th particle. \( \omega \) is the inertia weight to balance exploitation and exploration, \( p_{best} \) represents the best location in the search space ever visited by particle \( i \), and \( g_{best} \) is the best location discovered so far. \( c_1 \) and \( c_2 \) are two acceleration constants, where \( c_1 = c_2 = 2 \), \( \xi \) and \( \eta \) are two uniform random numbers in \([0, 1]\).

The inertia weight \( \omega \) is used to balance the global and local search abilities of PSO, and it is very important for PSO. The large inertia weight improves global search ability and small inertia weight facilitates local search. So we employ the self-adaptive weight particle swarm optimization to improve the search ability of the PSO. The self-adaptive weight for \( t \) iteration is given by

\[
\omega = \begin{cases} 
\omega_{\min} + \frac{(\omega_{\max} - \omega_{\min}) (f - f_{\min})}{(f_{\avg} - f_{\min})}, & f \leq f_{\avg} \\
\omega_{\max}, & f > f_{\avg}
\end{cases} \tag{22}
\]

where \( \omega_{\min} \) and \( \omega_{\max} \) indicate the minimization and maximization for inertia weight, respectively, \( f \) is the current fitness value (objective function value for current particle), and \( f_{\avg} \) and \( f_{\min} \) indicate the average and minimize fitness value for all of the particles in each iteration.

The proposed strategy is shown in Pseudocode 1.

### 5. Simulation and Numerical Results

In this section, simulation results are presented and analyzed. And we compare the proposed SAPSO-MSL method with FCM [24] and FCM-LM [20] methods via computer simulations. We consider a 2-dimensional square region of size 100 m by 100 m, where we randomly deploy \( N \) sensor nodes. The default parameter values in the simulation are shown in Table 1. The performance of localization can be measured quantitatively with the following criterion, given by

\[
\text{error} = \frac{1}{N_s K} \sum_{i=1}^{N_s} \sqrt{(x_{ki} - \hat{x}_k)^2 + (y_{ki} - \hat{y}_k)^2}, \tag{23}
\]

where \( N_s = 2000 \), \((x_{ki}, y_{ki})\) is the true location of \( k \)th source, \((\hat{x}_k, \hat{y}_k)\) is the estimated location of \( k \)th source.

Table 1: The default parameter values.

| Parameters               | Symbol | Default values |
|--------------------------|--------|----------------|
| Number of sensor nodes   | \( N \) | 200            |
| Number of sources        | \( K \) | 2              |
| Source energy at 1 meter | \( S_k \) | 3000           |
| away from the \( k \)th source |        |                |
| Variance of measurement noise | \( \sigma^2 \) | 1              |
| The threshold            | \( T \) | 8              |

Figure 3 shows the relationship between the threshold \( T \) and the localization error. The localization errors of all methods decrease with the increase of the value of \( T \); it is because the larger the value \( T \), the smaller the noise interference. It can be observed that the proposed SAPSO-MSL method outperforms other methods when the value of \( T \) is small. Compared with FCM and FCM-LM methods, the...
localization accuracy improves 35.27% and 33.45%, respectively, when $T = 4$.

Figure 4 shows the impact of source energy $S_k$ on the localization error. The lower the $S_k$, the smaller the number of nodes influenced by multiple sources. Therefore, the localization error increases with the increases of $S_k$. The proposed SAPSO-MSL method owns the highest localization accuracy.

In Figure 5, we investigate how the standard variance of measurement noise $\sigma_i$ affects the localization error. We vary $\sigma_i$ from 1 to 6. Due to the increase in $\sigma_i$, the sensor nodes observe measurement with higher fluctuations. So the localization error increases sharply with the increases of $\sigma_i$. The FCM method achieves almost the same performance as the FCM-LM method when $\sigma_i \leq 3$. The proposed SAPSO-MSL method outperforms FCM and FCM-LM methods.

Figure 6 shows the localization error for different number of sensor nodes. It is demonstrated that the SAPSO-MSL method is affected by the number of sensor nodes greatly. When the number of sensor nodes is small, the performance of SAPSO-MSL method is worse than FCM-LM. In most cases, the SAPSO-MSL owns the highest localization accuracy.

In Figure 7, we investigate the effect of false alarm rate on the localization error. It is noticed that the FCM and FCM-LM methods remain almost stable with increase in
false alarm rate. The SAPSO-MSL method is affected by false alarm rate greatly. The proposed method owns the best performance when the false alarm rate is low. However, FCM-LM outperforms the SAPSO-MSL and FCM methods when false alarm rate is larger.

Figure 8 shows the evaluation for the convergence of the SAPSO method. Obviously, the convergence of SAPSO algorithm occurs when the number of iterations is 40.

6. Conclusion

Multiple source localization technique in sensor network has recently received intensive interests for a large variety of applications. In this paper, we proposed a self-adaptive particle swarm optimization based multiple source localization method for binary sensor network. The maximum likelihood estimator is used to establish objective function. And then the self-adaptive particle swarm optimization is employed to estimate the location of sources. We compared the proposed method with FCM and FCM-LM methods, and simulation results show that the proposed method outperforms other methods. However, the localization accuracy of proposed method decreases when false alarm is large. In the future work, we will improve this method, so that it is more robust to false alarm rate.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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