CPCRLB based local node selection for passive acoustic target tracking in a distributed sensor network

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Abstract: For passive acoustic target tracking in a distributed sensor network, this paper proposed a local node selection algorithm based on conditional posterior Cramér-Rao lower bounds (CPCRLB). The approximate analytical expression of CPCRLB is derived by utilizing particle filters for bearing-only measurements, and it is used to define the utility contribution as the node selection criterion. In the proposed algorithm, each node can only use the local information to determine whether to be activated without the knowledge of all nodes in the network. Simulation results prove the effectiveness of our method and show good performance in tracking accuracy, energy consumption and computational complexity.

Key words: node selection; posterior Cramér-Rao lower bounds; bearings-only target tracking; particle filter; distributed sensor network

0 Introduction

Wireless sensor networks (WSNs) are information-driven systems that rely on collaboration of randomly deployed sensor nodes. Target Tracking is one of the most important applications in WSNs, which is a target state estimation problem fusing the measurements of sensor nodes. However, the resources of WSNs are extremely constrained. It is unreasonable to allow all nodes to participate in tracking at every time step because of the superfluous energy expenditure. Therefore, an efficient node selection is necessary to make a trade-off between tracking accuracy and energy consumption.

The node selection is an optimization problem to find the best subset of active nodes. F. Zhao et al.[1] propose an information-driven sensor querying (IDSQ) approach to sensor selection. H. Wang et al.[2] present an entropy-based sensor selection heuristic method. G. M. Hoffmann et al.[3] use mutual information as the objective function of sensor management. However, as the information theory methods, their computational complexity becomes very high with the increase in the number of sensor nodes[4]. In recent years, the posterior Cramér-Rao lower bound (PCRLB) attracts much concern of scholars[5]. The PCRLB provides a mean squared error (MSE) lower bound of the target state estimation, but it does not use the actual observation data. L. Zuo et al.[6-7] propose conditional posterior Cramér–Rao lower bounds (CPCRLB). It provides a more accurate and effective online performance limit than PCRLB when the past measurements up to the current time are all known. In order to simplify the calculation, Y. Zhang et al.[8] give a new approximate iteration formula for directly calculating CPCRLB. There has been a lot of researches about node selection for reference[9-13].

In this paper, we consider a distributed system for passive acoustic target tracking and propose a local node selection algorithm based on CPCRLB. The microphone array nodes are used in this system, which can give bearing-only measurements by direction of arrival (DOA) estimations. There is no data processing center for nodes to send their measurements. The advantage of the distributed system is that the failure of one sensor node does not impact the entire system. In the proposed algorithm each node only uses their local node information and does not need the knowledge of all nodes. Therefore, it does not need to recalibrate when nodes burn out or new nodes are added to the

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network. Moreover, it can reduce most of the communication cost and realize autonomous node selection.

In order to more clearly describe the algorithm, we use the following notations throughout this paper, as shown in Table 1.

Table 1 The notations throughout this paper

Notation	Significance
N	The number of nodes in the WSN
S	The number of particles in particle filters
$\boldsymbol{N}_a$	The set of active nodes
N_a	The number of active nodes in $\boldsymbol{N}_a$
$\boldsymbol{N}_s$	The set of all nodes
N_s	The number of nodes in $\boldsymbol{N}_s$
$\boldsymbol{N}_d$	The set of nodes from N_a that retain active at the next snapshot
N_d	The number of nodes in $\boldsymbol{N}_d$
$\tilde{\boldsymbol{N}}_a$	The final set of active nodes at the next snapshot
$\boldsymbol{N}_c$	The set of the candidate nodes
N_c	The number of candidate nodes in $\boldsymbol{N}_c$

1 CPCRLB

1.1 System Model

The two-dimensional target state is denoted as $\boldsymbol{X}_k=[x_k, y_k, \dot{x}_k, \dot{y}_k]^{\mathrm{T}}$, where $[x_k, y_k]^{\mathrm{T}}$ and $[\dot{x}_k, \dot{y}_k]^{\mathrm{T}}$ represent the target position components and velocity components at the k snapshot respectively. The system state equation can be written as

$$\boldsymbol{X}_{k+1}=\boldsymbol{F}_k\boldsymbol{X}_k+\boldsymbol{W}_k \tag{1}$$

where $\boldsymbol{F}_k$ is the state transition matrix and $\boldsymbol{W}_k$ is the process noise. Assume that the target motion model is the constant velocity (CV) model and $\boldsymbol{W}_k$ is the Gaussian white noise with covariance matrix $\boldsymbol{Q}$, then

$$\boldsymbol{F}=\begin{bmatrix}1&0&t&0\\0&1&0&t\\0&0&1&0\\0&0&0&1\end{bmatrix},\boldsymbol{Q}=q\begin{bmatrix}t^3/3&0&t^2/2&0\\0&t^3/3&0&t^2/2\\t^2/2&0&t&0\\0&t^2/2&0&t\end{bmatrix}$$

where t is the time between snapshots, q is a parameter of the process noise.

A bearings-only measurement of the microphone array node j at the $k+1$ snapshot is given by

$$z_{k+1}^j=h_{k+1}^j+v_{k+1}^j=\arctan\left(\frac{x_{k+1}-x^j}{y_{k+1}-y^j}\right)+v_{k+1}^j \tag{2}$$

where h_{k+1}^j represents the ideal measurement, $[x^j, y^j]$ is the location of node j and the measurement noise v_{k+1}^j is the zero-mean Gaussian white noise with the standard deviation σ_v, i.e., $v_{k+1}^j\sim N(0,\sigma_v^2)$.

The measurement set of all N nodes at the $k+1$ snapshot is denoted as

$$\boldsymbol{Z}_{k+1}=[z_{k+1}^1,\cdots,z_{k+1}^N]^{\mathrm{T}} \tag{3}$$

1.2 Derivation of CPCRLB

The CPCRLB provides a conditional mean squared error limit of the state vector for the upcoming snapshot $k+1$ given by the measurements up to the snapshot k, which is lower bounded by the inverse of the conditional Fisher information matrix as

$$\mathrm{E}\{[\hat{\boldsymbol{X}}_{k+1}-\boldsymbol{X}_{k+1}]^{\mathrm{T}}[\hat{\boldsymbol{X}}_{k+1}-\boldsymbol{X}_{k+1}]|\boldsymbol{Z}_{1:k}\}\geq\boldsymbol{L}^{-1}(\boldsymbol{X}_{k+1}|\boldsymbol{Z}_{1:k}) \tag{4}$$

According to the corollary[8], the conditional Fisher information $\boldsymbol{L}(\boldsymbol{X}_{k+1}|\boldsymbol{Z}_{1:k})$ for the linear state model with additive Gaussian noise is given by

$$\boldsymbol{L}(\boldsymbol{X}_{k+1}|\boldsymbol{Z}_{1:k})\approx(\boldsymbol{Q}+\boldsymbol{F}_k\boldsymbol{L}^{-1}(\boldsymbol{X}_k|\boldsymbol{Z}_{1:k-1})\boldsymbol{F}_k^T)^{-1}+\boldsymbol{B}_k^{22,b} \tag{5}$$

$$\boldsymbol{B}_k^{22,b}=\mathrm{E}_{p_{k+1}^c}\{-\Delta_{\boldsymbol{X}_{k+1}}^{\boldsymbol{X}_{k+1}}\ln p(\boldsymbol{Z}_{k+1}|\boldsymbol{X}_{k+1})\} \tag{6}$$

$$\begin{aligned}p_{k+1}^c&=p(\boldsymbol{X}_{0:k+1},\boldsymbol{Z}_{k+1}|\boldsymbol{Z}_{1:k})\\&=p(\boldsymbol{Z}_{k+1}|\boldsymbol{X}_{k+1})p(\boldsymbol{X}_{k+1}|\boldsymbol{X}_k)p(\boldsymbol{X}_{0:k}|\boldsymbol{Z}_{1:k})\end{aligned} \tag{7}$$

where $\mathrm{E}_{p_{k+1}^c}$ is the expectation of the probability density function (PDF) p_{k+1}^c. The calculation can begin the initial iteration with $\boldsymbol{L}(\boldsymbol{X}_0|\boldsymbol{Z}_{-1})=\mathrm{E}\{-\Delta_{\boldsymbol{X}_0}^{\boldsymbol{X}_0}\cdot\ln p(\boldsymbol{X}_0)\}$.

For the bearings-only target tracking system, the mathematical expression of $\boldsymbol{B}_k^{22,b}$ does not exist. Here particle filters are used to approximate the target state estimation. Assume that there are S weighted particles $\{\boldsymbol{X}_k^{(l)},\omega_k^{(l)}\}_{l=1}^S$ at the k snapshot, and all weights are equal to $1/S$ after the resampling step. Then, the posterior PDF $p(\boldsymbol{X}_{0:k}|\boldsymbol{Z}_{1:k})$ at the k snapshot can be given by

$$p(\boldsymbol{X}_{0:k}|\boldsymbol{Z}_{1:k})\approx\frac{1}{S}\sum_{l=1}^S\delta(\boldsymbol{X}_{0:k}-\boldsymbol{X}_{0:k}^{(l)}) \tag{8}$$

Hence,

$$p_{k+1}^c\approx\frac{1}{S}\sum_{l=1}^S\delta(\boldsymbol{X}_{0:k}-\boldsymbol{X}_{0:k}^{(l)})p(\boldsymbol{Z}_{k+1}|\boldsymbol{X}_{k+1}^{(l)}) \tag{9}$$

According to the measurement model (see (2) and (3)), we can get the logarithmic likelihood function as

$$\ln p(\boldsymbol{Z}_{k+1}|\boldsymbol{X}_{k+1})=\sum_{j=1}^N\left[-\frac{(z_{k+1}^j-h_{k+1}^j)^2}{2\sigma_v^2}-\ln\sqrt{2\pi}\sigma_v\right] \tag{10}$$

From (6)～(10), we can derive the approximate analytical expression of the symmetric matrix $\boldsymbol{B}_k^{22,b}$ as follows:

$$\boldsymbol{B}_k^{22,b}(1,1)=\frac{1}{S\sigma_v^2}\sum_{l=1}^S\sum_{j=1}^N\frac{(y_{k+1}-y^j)^2}{[(x_{k+1}-x^j)^2+(y_{k+1}-y^j)^2]^2}\Bigg|_{\boldsymbol{X}_{k+1}=\boldsymbol{X}_{k+1}^{(l)}} \tag{11}$$

$$\boldsymbol{B}_k^{22,b}(1,2)=\frac{1}{S\sigma_v^2}\sum_{l=1}^S\sum_{j=1}^N\frac{(y_{k+1}-y^j)(x_{k+1}-x^j)}{[(x_{k+1}-x^j)^2+(y_{k+1}-y^j)^2]^2}\Bigg|_{\boldsymbol{X}_{k+1}=\boldsymbol{X}_{k+1}^{(l)}} \tag{12}$$

$$\boldsymbol{B}_k^{22,b}(2,2)=\frac{1}{S\sigma_v^2}\sum_{l=1}^{S}\sum_{j=1}^{N}\frac{(x_{k+1}-x^j)^2}{[(x_{k+1}-x^j)^2+(y_{k+1}-y^j)^2]^2}\Bigg|_{\boldsymbol{X}_{k+1}=\boldsymbol{X}_{k+1}^{(l)}} \quad (13)$$

$$\boldsymbol{B}_k^{22,b}(1,3)=\boldsymbol{B}_k^{22,b}(1,4)=0, \boldsymbol{B}_k^{22,b}(2,3)=\boldsymbol{B}_k^{22,b}(2,4)=0 \quad (14)$$

$$\boldsymbol{B}_k^{22,b}(3,3)=0, \boldsymbol{B}_k^{22,b}(3,4)=0, \boldsymbol{B}_k^{22,b}(4,4)=0 \quad (15)$$

Then the condition Fisher information $\boldsymbol{L}(\boldsymbol{X}_{k+1}|\boldsymbol{Z}_{1:k})$ can be calculated by (5).

2 Local Node Selection for Distributed Target Tracking

2.1 Criterion for Node Selection

The goal of node selection for target tracking is to achieve better tracking accuracy with less resource consumption. Because the CPCRLB gives a lower bound of the target state estimation error, the position components of CPCRLB can be used as the object function for node selection. In this paper, we consider finding the active nodes set $\boldsymbol{N}_a$ of N_a nodes in a network $\boldsymbol{N}_s$ of N_s nodes. The conditional mean squared position error can be expressed as

$$\rho(\boldsymbol{N}_a)=[\boldsymbol{L}^{-1}(\boldsymbol{X}_{k+1}|\boldsymbol{Z}_{1:k})]_{1,1}+[\boldsymbol{L}^{-1}(\boldsymbol{X}_{k+1}|\boldsymbol{Z}_{1:k})]_{2,2} \quad (16)$$

where $[\boldsymbol{A}]_{i,j}$ is the $(i,j)_{th}$ element of the matrix $\boldsymbol{A}$.

We define the information utility of $\boldsymbol{N}_a$ as the reciprocal of the mean squared position error,

$$u(\boldsymbol{N}_a)=\frac{1}{\rho(\boldsymbol{N}_a)} \quad (17)$$

then node selection becomes the problem of finding $\boldsymbol{N}_a$ to maximize the utility $u(\boldsymbol{N}_a)$.

At a given snapshot, each node needs to decide whether or not to become active or inactive. In the local node selection algorithm, the active nodes have no knowledge of other nodes. The inactive nodes can determine their added utility to the active nodes set $\boldsymbol{N}_a$. We define the utility contribution for each node j in the active nodes set $\boldsymbol{N}_a$ as

$$uc(j|\boldsymbol{N}_a)=u(\boldsymbol{N}_a)-u(\boldsymbol{N}_a\backslash j) \quad (18)$$

The utility contribution of the inactive node i which is potential to be activated is defined as the incremental utility by replacing one of the active nodes in $\boldsymbol{N}_a$,

$$uc(i|\boldsymbol{N}_a)=\max_{j\in\boldsymbol{N}_a}[u((\boldsymbol{N}_a\backslash j)\cup i)-u(\boldsymbol{N}_a\backslash j)] \quad (19)$$

When the added utility of the inactive node i is greater than that of the active node j, the inactive node i maybe can become active to improve the overall utility by replacing the active node j.

2.2 Local Node Selection Algorithm

This section describes our proposed node selection algorithm based on CPCRLB for passive acoustic target tracking in a distributed sensor network. It is a local method because the node can only use its local information, the active nodes do not know if any inactive nodes are available.

Initialization At the beginning of target tracking, this algorithm incorporates an exhaustive search strategy to first find the best active set $\boldsymbol{N}_a$ of N_a nodes by maximizing the utility as (17). Then the best N_a nodes communicate with each other to use their bearing measurements for the target state estimation.

Local node selection At this stage, we need to achieve the local node selection for the next upcoming snapshot. First, each node j in $\boldsymbol{N}_a$ uses the greedy method as stated above to search the best N_d nodes from $\boldsymbol{N}_a$. The set of the N_d nodes is labeled as $\boldsymbol{N}_d$, and these nodes remain active to participate in tracking at the next snapshot. However, it is possible that an inactive node is better than the nodes in $\boldsymbol{N}_d$ for activation.

In order to allow appropriate inactive nodes to join the active nodes set, the steps are taken as follows. First, all nodes in $\boldsymbol{N}_d$ calculate their own utility contribution $uc(j|\boldsymbol{N}_d)$ via (18). Then, these nodes set a threshold τ for an inactive node i to join $\boldsymbol{N}_d$ as the κ_{th} largest utility where the integer $\kappa\in[1,N_d]$. Next, the active nodes in $\boldsymbol{N}_d$ broadcast the threshold τ, their locations and the predicted target position. Here, the inactive nodes which can receive data from all nodes in $\boldsymbol{N}_d$ are called as candidate nodes, that is, candidate nodes are in the communication range of all nodes in $\boldsymbol{N}_d$. The set and the number of the candidate nodes are denoted as $\boldsymbol{N}_c$ and N_c respectively. It can be known that only the candidate nodes are possible to be active at the next snapshot. Therefore, we use a communication range r_c to limit the number of candidate nodes for saving energy consumption.

Then the candidate nodes can calculate their utility contribution $uc(i|\boldsymbol{N}_d)$ by (19). If $uc(i|\boldsymbol{N}_d)$ is greater than the threshold τ, then the inactive node i joins $\boldsymbol{N}_d$ to become active. The final set of active nodes is labeled as $\tilde{\boldsymbol{N}}_a$, which will be the active status at the next snapshot.

From the above, the local node selection is parameterized by N_d and κ. The parameter N_d represents the minimum number of nodes that will remain active, and the parameter κ decides the threshold of the utility contribution that an inactive node becomes active. Fig. 1 shows the flow chart of the local node selection algorithm.

2.3 Communication Model

The local node selection algorithm can be implemented at each node in a distributed sensor network. The proposed algorithm can balance the need for tracking accuracy with less energy cost. In order to evaluate the energy consumption of the algorithm, this paper introduces the communication model [13]. Under the simplified assumptions, the energy to transmit m bits of data over a distance of d meters is

$$E_t = m\varepsilon_{\text{elec}} + m\varepsilon_{\text{amp}} d^4 \tag{20}$$

The energy of receiving this data is

$$E_r = m\varepsilon_{\text{elec}} \tag{21}$$

where $\varepsilon_{\text{elec}}$ and ε_{amp} are the energies to run the electronics and the power amplifier per bit respectively. Here we set the parameters as follows: $\varepsilon_{\text{elec}}=0.5\times10^{-7}$ J·bit^{-1}, m=500 bits and $\varepsilon_{\text{amp}}=1.3\times10^{-14}$ J·bit^{-1}·m^{-4}.

3 Simulation

In order to demonstrate the performance of the proposed algorithm (labeled as LNS-CPCRLB), we apply it to the distributed sensor network for acoustic target tracking and compare it with the CPCRLB method and the RANDOM method in terms of tracking accuracy and energy consumption. Here, the CPCRLB method for distributed target tracking is a completely greedy search approach to optimal nodes. The RANDOM method uses the random selection of activate nodes.

Consider that 50 microphone array nodes randomly deployed over a field of 250×250 m^2. The

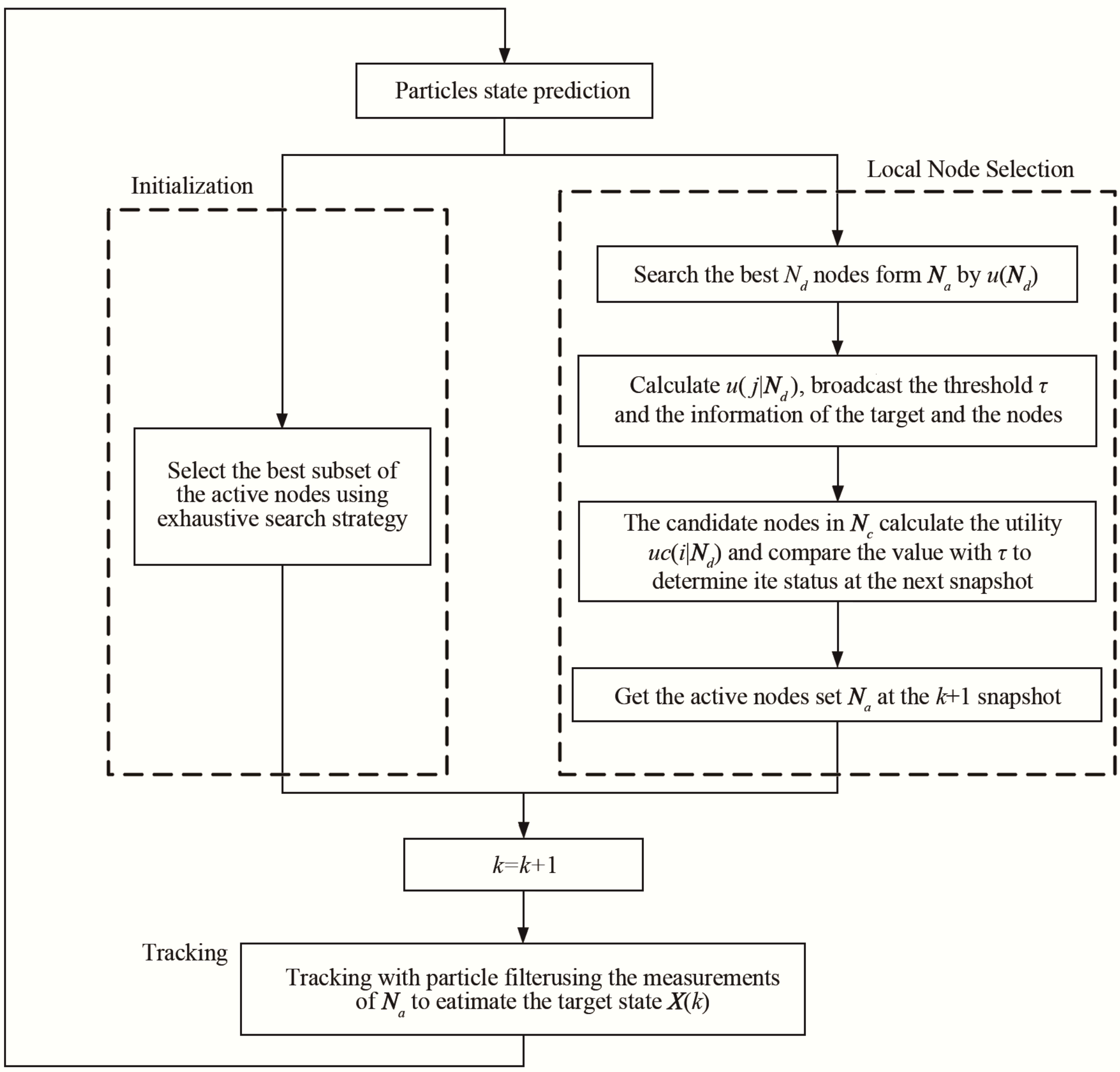

Fig.1 The flow chart of the local node selection algorithm

initial target state is [-100,-100,5,5] and the target movement follows the CV model with t=1 and q=0.5. The tracking duration is 50 s. The Fig.2 shows the target trajectory and the nodes deployment. The standard deviation of the measurement noise is $\sigma_v = 5\times\pi/180$ rad. One hundred Monte Carlo simulations are generated for performance evaluation. The number of particles in the particle filter is $S = 300$, and the communication range is $r_c = 80\,\mathrm{m}$. According to the practical requirement and the characteristics of bearings-only tracking, we use the setting of the parameters as $N_a = 3$, $N_d = 2$ and $\kappa = 1$. The Fig.3 illustrates the root mean square error (RMSE) of node selection algorithms over 100 Monte Carlo simulations. It is shown that all three algorithms are able to complete the target tracking task.

From Fig.4, we can see that our proposed algorithm has good performance on the tracking accuracy almost as the CPCRLB method. The CPCRLB algorithm has the best tracking accuracy, because it chooses the best nodes subset from all nodes using exhaustive search strategy. During tracking, the energy consumption of the three algorithms can be calculated by the communication model as previously described. Table 2 shows the statistical average results over 50 snapshots for 100 Monte Carlo simulations and the computations for node selection per snapshot. It can be seen that our proposed algorithm significantly reduces the energy consumption while maintaining the accurate target state estimation. The CPCRLB and RAN-DOM method have more energy consumption because of the communication between active nodes and all other inactive nodes. Moreover, the total computations for node selection are given in the last column of Table 2.

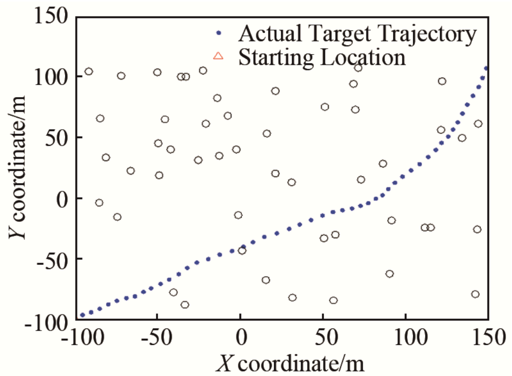

Fig.2　The target trajectory and the nodes deployment

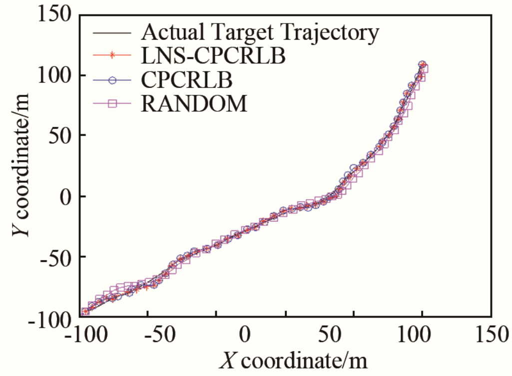

Fig.3　The tracking results of three different node selection method

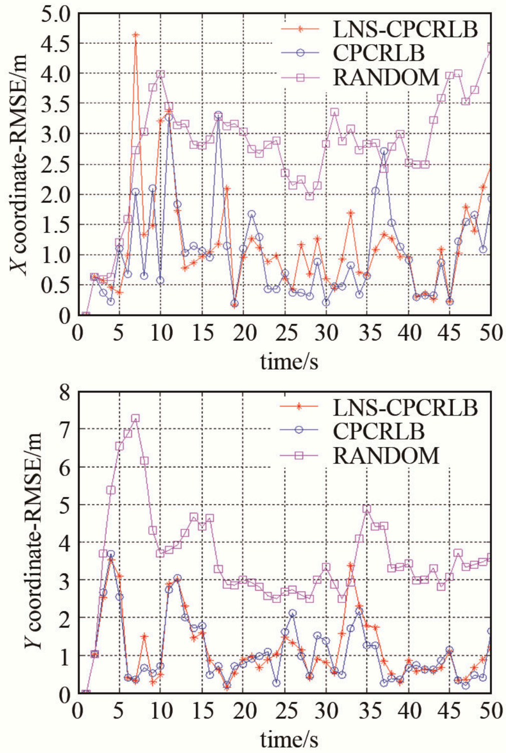

Fig.4　The RMSE for tracking on the X axis and Y axis

Table 2　The statistical average results over 50 snapshots

Algorithm	Average active nodes number	Energy Consumption	Average RMSE (X axis)	Average RMSE (Y axis)	Total computations for node selection
LNS-CPCRLB	4.536 9	0.054 9	1.141 1	1.165 2	$\frac{N_a!}{N_d!(N_a-N_d)!}+N_c$
CPCRLB	3	2.608 4	1.015 3	1.094 1	$\frac{N_s!}{N_a!(N_s-N_a)!}$
RANDOM	3	2.689 3	2.756 0	3.583 8	Depend on randomized method

In other words, the times of computing the utility are described by the number of nodes as shown in Table 2. The computations of LNS-CPCRLB consist of two parts: searching the largest utility $u(\boldsymbol{N}_d)$ from $\boldsymbol{N}_a$ and computing the utility of each candidate node from $\boldsymbol{N}_c$. For the CPCRLB algorithm, the computations are the times of calculating $u(\boldsymbol{N}_a)$ from $\boldsymbol{N}_s$. LNS-CPCRLB can reduce computations generally because N_a is much less than N_c. The RANDOM algorithm is not related to the computation of the utility. Overall, the simulation results show good performance of the proposed algorithm on the trade-off between the tracking RMSE and energy usage.

4 Conclusions

This paper proposed a local node selection algorithm based on CPCRLB for passive acoustic target tracking in a distributed sensor network. In order to use the CPCRLB as the node selection criterion, we derive the computational formula of CPCRLB based on bearing-only measurement model, and define the utility contribution of active nodes and inactive nodes. The candidates of inactive nodes can only use their local information to decide the activation by the added utility contribution to the active set. Simulation results prove that the proposed algorithm has good tracking accuracy with less energy expenditure.

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分布式传感器网络中基于条件后验克拉美-罗下界的被动声目标跟踪局部节点选择算法

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摘要：针对分布式传感器网络下的被动声目标跟踪问题，提出了一种基于条件后验克拉美罗下界(Conditional Posterior Cramér-Rao Lower Bounds, CPCRLB)的局部传感器节点选择算法，基于被动声探测背景下的纯方位量测数据，采用粒子滤波器推导得到了 CPCRLB 的近似解析表达式，进而在该 CPCRLB 的基础上定义了节点效用贡献作为节点选择准则，结合分布式传感器网络的特点提出了一种局部节点选择方法，节点无需知道全网传感器节点的信息，而是仅利用局部节点信息来决定下一时刻节点的活动状态，从而在实现自治节点选择的同时大大减少网络通信量。通过仿真结果表明，该算法在跟踪精度、能量消耗和计算复杂度方面都表现出较好的性能。

关键词：节点选择；后验克拉美罗下界；纯方位目标跟踪；粒子滤波；分布式传感器网络
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