PROBABILISTIC SENSOR MANAGEMENT FOR TARGET TRACKING VIA COMPRESSIVE SENSING

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ABSTRACT

In this paper, we consider the problem of sensor management for target tracking in a wireless sensor network (WSN). To determine the set of sensors that have the most information, we develop a probabilistic sensor management scheme based on the concepts developed in compressive sensing. In the proposed scheme, each senor node decides whether it should transmit its observation via multiple access channels to the fusion center with a certain probability. With this probabilistic transmission scheme, the observation vector received at the fusion center becomes a compressed version of the original observations. Our goal is to determine the optimal values of the probability using which each node should transmit so that the determinant of the Fisher information matrix (**FIM**) is maximized at any given time instant with a constraint on the available energy. Numerical examples are provided to show the performance of the proposed scheme.

***Index Terms*—** sensor management, compressive sensing, target tracking, particle filters

1. INTRODUCTION

Sensor management is an important problem in resource constrained wireless sensor networks (WSNs). Different approaches have been proposed to solve this problem in the literature for various inference tasks. To name a few, in [1], the sensor selection problem was formulated as an integer programming problem, which has been relaxed and solved through convex optimization. In [2], a multi-step sensor selection strategy by reformulating the Kalman filter was proposed, which is able to address different performance metrics and constraints on available resources. In [3], a sensor selection scheme based on an entropy-based information measure is proposed. Instead of information based metrics, in [4][5], the recursive one-step-ahead posterior Cramér-Rao lower bound (PCRLB) on the mean squared error (MSE) of estimating the state vector has been explored as the metric to select informative sensors.

Consider a WSN with a set of distributed sensor nodes and a fusion center. Since only few nodes have significant observations, the concatenated measurement vector at the fusion center can be considered to be sparse and compressible. This interpretation naturally brings the concept of compressive sensing (CS) [6][7] into sensor management problem. The first attempt to solve the sensor management problem by CS was proposed in [8], in which the sensor selection decision is considered as a sparse signal, and the sensor selection problem is solved in terms of recovering the sparse signal by l_1 norm minimization.

In this paper, we propose a novel CS based sensor management approach. To get a compressed version of the observations at the fusion center, we employ a multiple access channel (MAC) model with probabilistic transmissions. Then, the received observation vector at the fusion center has an equivalent representation as with the standard CS problem. With this model, the sensing matrix is completely determined by each sensor's probability of transmission, and the design of the sensing matrix is reduced to finding the optimal probability of transmission for each sensor such that a desired performance guarantee in tracking is achieved.

There are several major differences between our work and the work presented [8]: 1) In [8], a subset of sensors is selected and selected sensors send their measurements to the fusion center over parallel channels. In this paper, a subset of sensors is chosen probabilistically and different combinations of weighted measurements are sent to the fusion center over M MACs. 2) In [8], the sensor selection decision is considered as a sparse signal and the sensor selection problem is solved by recovering the sparse signal by l_1 norm minimization. However, in this paper, the concatenated measurement vector is considered to be sparse due to non-informative measurements, and the sensing matrix is designed such that a desired tracking performance is achieved with compressed measurements. Thus, there is no recovery of signal, but the compressed signal is used directly for state inference; 3) In [8], the sensing matrix is deterministic or is made be semi-random by adding some random disturbance, while in this paper, element of the sensing matrix are random variables whose distributions are related to sensors' probabilities of transmission.

2. PROBLEM FORMULATION

2.1. System model

We focus on a target tracking problem, where a moving target is tracked by a WSN with N uniformly deployed sensors in the region of interest (ROI). The dynamical model of an acoustic or electromagnetic target is assumed to be

$$\mathbf{x}_{k+1} = F\mathbf{x}_k + \mathbf{w}_k \tag{1}$$

where $\mathbf{x}_k \in \mathcal{R}^d$ is the state vector of the target at time instant k, $F \in \mathcal{R}^{d\times d}$ is the state transition model and $\mathbf{w}_k$ is the process noise which is assumed to be Gaussian with mean zero and covariance matrix $Q \in \mathcal{R}^{d\times d}$.

At time k, the measurement model at each sensor is

$$s_{i,k} = a_{i,k} + v_{i,k}, \;\; i = 1, 2, \cdots, N \tag{2}$$

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where $a_{i,k} = \sqrt{\frac{P_0}{1+d_{i,k}^n}}$, P_0 is the signal power of the source, n is the signal decay parameter, $d_{i,k}$ denotes the distance between the target and the i^{th} sensor at time k, $i.e.$, $d_{i,k} = \sqrt{(x_i - x_k)^2 + (y_i - y_k)^2}$, where (x_i, y_i) is the location of the i^{th} sensor, and $v_{i,k}$ is the measurement noise, which is assumed to be Gaussian with mean zero and variance r and mutually independent over i for $i = 1, \cdots, N$.

2.2. Compressive sensing

CS is a recently developed signal processing technique for acquiring and reconstructing a sparse signal with a small number of measurements compared to the original signal dimension. Consider a signal $\mathbf{f} \in \mathcal{R}^L$, that can be expressed in an orthonormal basis $\Psi = [\Psi_1 \ \Psi_2 \ \cdots \ \Psi_L]$ as

$$\mathbf{f} = \sum_{l=1}^{L} b_l \Psi_l \ \text{ or } \ \mathbf{f} = \Psi \mathbf{b} \tag{3}$$

where b_l is the coefficient of the signal projected on to Ψ_l and $\mathbf{b} = [b_1, \cdots, b_L]^T$. The signal $\mathbf{f}$ is said to be K-sparse, if only K coefficients in $\mathbf{b}$ are significant and all the others are zeros or negligible.

To get a compressed signal, the sparse signal $\mathbf{f}$ is projected to a lower dimension via a sensing matrix Φ with dimension $M \times L$, where $M \ll L$, $i.e.$,

$$\mathbf{y} = \Phi \mathbf{f} = \Phi \Psi \mathbf{b}. \tag{4}$$

Then, the standard CS problem is to recover $\mathbf{b}$ from only $M \ll L$ measurements $\mathbf{y}$. The reconstruction capability is determined by the properties of the sensing matrix Φ in addition to the sparsity index and the number of compressed measurements [6]. Several such properties including RIP and mutual coherence of the sensing matrix, and recovery algorithms are discussed in [9, 10, 11].

2.3. Sparsity formulation

Let the measurement vector be $\mathbf{s}_k = [s_{1,k}, \cdots, s_{N,k}]^T$ at time k, where $(\cdot)^T$ denotes the matrix or vector transpose. We consider a relatively large distributed network. Based on the observation model (2), it is seen that the signal amplitude received at a given node at a given time becomes smaller and eventually negligible as the distance between that particular node and the true target location increases. Therefore, at time k, $\mathbf{a}_k = [a_{1,k}, \cdots, a_{N,k}]^T$ can be considered to contain only few significant values.

To obtain a compressed version of observations at the fusion center, we consider the following transmission scheme as considered in [12]. Let the j^{th} sensor transmit its measurement after multiplying it by $\phi_{ij,k}$ (to be defined later) via a MAC, so that after M transmissions, the received signal at the fusion center is given by

$$z_{i,k} = \sum_{j=1}^{N} \phi_{ij,k} s_{j,k} + e_{i,k}, \ i = 1, \cdots, M \tag{5}$$

where $e_{i,k}$ is the receiver noise, which is assumed to be white and Gaussian with mean zero and variance ϵ. Note that (5) can be written in a vector form as

$$\mathbf{z}_k = \Phi \mathbf{s}_k + \mathbf{e}_k \tag{6}$$

where $\mathbf{z}_k = [z_{1,k}, \cdots, z_{M,k}]^T$, the (i,j)-th element of Φ is given by ϕ_{ij} for $i = 1, \cdots, M$ and $j = 1, \cdots, N$, and $\mathbf{e}_k$ is the receiver noise, which is assumed to be white Gaussian with mean zero and covariance matrix $\Sigma_{\mathbf{e}} = \epsilon I_{M \times M}$, where $I_{M \times M}$ is an identity matrix of size $M \times M$.

We consider each $\phi_{ij,k}$ to be a random variable so that

$$\phi_{ij,k} = \begin{cases} 1, & \frac{1}{2} p_{j,k} \\ 0, & 1 - p_{j,k} \quad i = 1, \cdots, M \\ -1, & \frac{1}{2} p_{j,k} \quad\quad j = 1, \cdots, N \end{cases} \tag{7}$$

where $p_{j,k}$ is the probability of transmission of j^{th} sensor at time instant k.

Based on how Φ_k is constructed, it is obvious that, though the elements in a given column in Φ_k are independent and identically distributed ($i.i.d.$), elements in different columns are independent but not identically distributed. Therefore, Φ_k does not follow the RIP as the one with the same isometry constant which has $i.i.d.$ random elements. Further, it is noted that, the matrix Φ_k can be very sparse when only a small number of sensors decide to transmit with a high probability. With this sensing matrix, we show numerically that compressed observations in (6) provide us with a comparable tracking performance to that with (2) with relatively small M.

In the context of sensor management, Φ_k plays the role of a sensor management entity that divides the sensors into M sub-sets. Sensors in the same sub-set send their weighted measurements over the same MAC (there are a total of M MACs) if FDMA is used or in the same time slot (there are total M time slots) if TDMA is used. Note that, the weight could be '0', which means that the associated sensor does not send its measurement. Therefore, the problem of managing sensors is equivalent to the design of the sensing matrix Φ_k or the probability vector $\mathbf{p}_k = [p_{1,k}, \ p_{2,k}, \ \cdots, \ p_{N,k}]^T$, such that a certain objective function is optimized.

3. THE SENSOR MANAGEMENT PROBLEM

We find the probability vector $\mathbf{p}_k$ such that, the determinant of the Fisher information matrix (**FIM**) of the system averaged over the sensing matrix Φ is maximized at time k. For the target tracking problem under consideration, a nice recursive computation of the **FIM** is proposed in [13], which is given as follows

$$J_{k+1} = D_k^{22} - D_k^{21}(J_k + D_k^{11})^{-1} D_k^{12} \tag{8}$$

where $D_k^{11} = E\{-\Delta_{\mathbf{x}_k}^{\mathbf{x}_k} \log p(\mathbf{x}_{k+1}|\mathbf{x}_k)\}$

$$D_k^{12} = E\left\{-\Delta_{\mathbf{x}_k}^{\mathbf{x}_{k+1}} \log p(\mathbf{x}_{k+1}|\mathbf{x}_k)\right\} = (D_k^{21})^T$$

$$\begin{aligned} D_k^{22} &= E\left\{-\Delta_{\mathbf{x}_{k+1}}^{\mathbf{x}_{k+1}} [\log p(\mathbf{x}_{k+1}|\mathbf{x}_k) + \log p(\mathbf{z}_{k+1}|\mathbf{x}_{k+1})]\right\} \\ &= D_k^{22,a} + D_k^{22,b}. \end{aligned} \tag{9}$$

For the problem considered in this paper, we have $D_k^{11} = F^T Q^{-1} F$, $D_k^{12} = -F^T Q^{-1}$, $D_k^{22,a} = Q^{-1}$ and

$$D_k^{22,b} = -E\left\{\Delta_{\mathbf{x}_{k+1}}^{\mathbf{x}_{k+1}} \log p(\mathbf{z}_{k+1}|\mathbf{x}_{k+1}, \Phi_{k+1})\right\} \tag{10}$$

where the expectation is with respect to $\mathbf{z}_{k+1}$, $\mathbf{x}_{k+1}$ and Φ_{k+1}. Hence,

$$D_k^{22,b} = -E_{p(\Phi_{k+1})} E_{p(\mathbf{x}_{k+1})} \{J^D\} \tag{11}$$

where

$$J^D = E_{p(\mathbf{z}_{k+1}|\mathbf{x}_{k+1}, \Phi_{k+1})} \left\{\Delta_{\mathbf{x}_{k+1}}^{\mathbf{x}_{k+1}} \log p(\mathbf{z}_{k+1}|\mathbf{x}_{k+1}, \Phi_{k+1})\right\}. \tag{12}$$

We can write (6) as

$$\mathbf{z}_k = \Phi_k \mathbf{a}_k + \Phi_k \mathbf{v}_k + \mathbf{e}_k \tag{13}$$

where $\mathbf{v}_k = [v_{1,k},\ v_{2,k},\ \cdots,\ v_{N,k}]^T$, $i.e.$, it is the concatenation of the measurement noises of N sensors. Since the measurement noises are mutually independent, $\mathbf{v}_k \sim \mathcal{N}(\mathbf{0}, rI_{N\times N})$.

Given $\mathbf{x}_{k+1}$ and Φ_{k+1}, based on Eq. (13), one can get $\mathbf{z}_{k+1} \sim \mathcal{N}(\Phi\mathbf{a}_{k+1}, R_{k+1})$, where $R_{k+1} = r\Phi_{k+1}\Phi_{k+1}^T + \Sigma_e$. Then

$$\begin{aligned}&\log p(\mathbf{z}_{k+1}|\mathbf{x}_{k+1}, \Phi_{k+1})\\ &= -\frac{1}{2}(\mathbf{z}_{k+1} - \Phi_{k+1}\mathbf{a}_{k+1})^T R_{k+1}^{-1}(\mathbf{z}_{k+1} - \Phi_{k+1}\mathbf{a}_{k+1}). \end{aligned} \quad (14)$$

Therefore,

$$J^D = -\nabla_{\mathbf{x}_{k+1}}(\Phi_{k+1}\mathbf{a}_{k+1})R_{k+1}^{-1}\nabla_{\mathbf{x}_{k+1}}^T(\Phi_{k+1}\mathbf{a}_{k+1}), \quad (15)$$

$$\begin{aligned}&D_k^{22,b}\\ &= E_{\mathbf{x}_{k+1}}\left\{\nabla_{\mathbf{x}_{k+1}}\mathbf{a}_{k+1}E_\Phi\left\{\Phi_{k+1}^T R_{k+1}^{-1}\Phi_{k+1}\right\}\nabla_{\mathbf{x}_{k+1}}^T\mathbf{a}_{k+1}\right\}\end{aligned} \quad (16)$$

where

$$\nabla_{\mathbf{x}_{k+1}}\mathbf{a}_{k+1} = \begin{bmatrix} \frac{\partial a_{1,k+1}}{\partial x_{k+1}} & \frac{\partial a_{2,k+1}}{\partial x_{k+1}} & \cdots & \frac{\partial a_{N,k+1}}{\partial x_{k+1}} \\ 0 & 0 & \cdots & 0 \\ \frac{\partial a_{1,k+1}}{\partial y_{k+1}} & \frac{\partial a_{2,k+1}}{\partial y_{k+1}} & \cdots & \frac{\partial a_{N,k+1}}{\partial y_{k+1}} \\ 0 & 0 & \cdots & 0 \end{bmatrix}_{d\times N} \quad (17)$$

and

$$\frac{\partial a_{i,k+1}}{\partial x_{k+1}} = \frac{P_0 n d_{i,k+1}^{n-2}}{2a_{i,k+1}(1+d_{i,k+1}^n)^2}(x_i - x_{k+1}), \quad (18)$$

$$\frac{\partial a_{i,k+1}}{\partial y_{k+1}} = \frac{P_0 n d_{k+1,i}^{n-2}}{2a_{i,k+1}(1+d_{k+1,i}^n)^2}(y_i - y_{k+1}) \quad (19)$$

for $i = 1, 2, \cdots, N$. Note that (x_i, y_i) is the location of the i^{th} sensor and (x_{k+1}, y_{k+1}) represents the location of the target at time $k+1$.

Up to this point, we have not observed the explicit relationship between **FIM** at time $k+1$ and $\mathbf{p}_{k+1}$, due to the complexity of $D_k^{22,b}$. The following result can be used to simplify the mathematical representation.

Let $\Gamma_{k+1} \triangleq E_\Phi\left\{\Phi_{k+1}^T R_{k+1}^{-1}\Phi_{k+1}\right\}$. If N is large, then we have the following proposition.

Proposition 1. *If the number of sensors N in the WSN is large, then, at any given time $k+1$, we may approximate*

$$\Gamma_{k+1} \approx \frac{M}{r\Sigma_{j=1}^N p_{j,k+1} + \epsilon}\mathrm{diag}(\mathbf{p}_{k+1}) \quad (20)$$

where $\mathrm{diag}(\mathbf{p})$ denotes a diagonal matrix, with $\mathbf{p}$ on the main diagonal.

Proof. Let $\Theta \triangleq \Phi\Phi^T$. The time index is omitted in the proof for the sake of simplicity. Diagonal elements of Θ are given by

$$\Theta_{i,i} = \sum_{j=1}^N \phi_{ij}^2 \quad i = 1,\ 2,\ \cdots,\ M \quad (21)$$

and off-diagonal elements are

$$\Theta_{i,j} = \sum_{c=1}^N \phi_{ic}\phi_{jc} \quad i, j = 1,\ 2,\ \cdots,\ M \ \text{ and } i \neq j. \quad (22)$$

It is straightforward to get $E\{\phi_{ij}^2\} = p_j$, var$\{\phi_{ij}^2\} = \sum(\phi_{ij}^2 - p_j)^2 p(\phi_{ij}) = p_j(1-p_j)$, $E\{\phi_{ic}\phi_{jc}\} = 0$, and $var\{\phi_{ic}\phi_{jc}\} = p_c^2$.

Therefore, according to the law of large number (LLN) for independent and non-identical random variables, we get

$$\Theta_{i,i} \approx \sum_{j=1}^N E\{\phi_{ij}^2\} = \sum_{j=1}^N p_j,\ \Theta_{i,j} \approx \sum_{c=1}^N E\{\phi_{ic}\phi_{jc}\} = 0. \quad (23)$$

Hence, $\Theta = \left(\sum_{j=1}^N p_j\right) I_{M\times M}$ and $R = r\Theta + \Sigma_{\mathbf{e}} = (r\sum_{j=1}^N p_j + \epsilon)I_{M\times M}$.
Then,

$$\Gamma \approx \left(r\sum_{j=1}^N p_j + \epsilon\right)^{-1} E_\Phi\left\{\Phi^T\Phi\right\}. \quad (24)$$

Diagonal elements of Γ are given by

$$\Gamma_{i,i} = \left(r\sum_{j=1}^N p_j + \epsilon\right)^{-1} Mp_i \quad (i = 1,\ 2,\ \cdots,\ N)$$

and off-diagonal elements are

$$\begin{aligned}\Gamma_{i,j} &\approx \left(r\sum_{j=1}^N p_j + \epsilon\right)^{-1} E\left\{\sum_{k=1}^M \phi_{ki}\phi_{kj}\right\}\\ &= 0 \quad (i, j = 1,\ 2,\ \cdots,\ N \text{ and } i \neq j).\end{aligned}$$

Therefore,

$$\Gamma \approx \frac{M}{r\sum_{j=1}^N p_j + \epsilon}\mathrm{diag}(\mathbf{p}) \quad (25)$$

completing the proof. ■

The goal is to solve the resource management problem in a WSN. The limited resource that we focused here is the energy in the network. For simplicity, we assume that each transmission from a local sensor to the fusion center consumes unit power. Finding the optimal values for transmitting power at sensor nodes while achieving a desired performance is another interesting aspect which will be studied in the future. We aim to solve the following optimization problem:

$$\max_{\mathbf{p}_k}\ \det(J_k(\mathbf{p}_k)) \quad (26)$$

$$\text{s.t.} \quad M\sum_{j=1}^N p_j \leq E \quad (27)$$

where E is the total energy constraint.

Remark: (1) The fusion center maintains a particle filter to track the target. (2) At time step k, the fusion center first solves the optimization problem in (26) to get the optimal $\mathbf{p}_k$ before measurements at this time are available. Then, it generates the sensing matrix Φ_k using $\mathbf{p}_k$, and, according to which, sends control messages to local sensors. Based on these control messages, local sensors will send their measurements over assigned MACs to the fusion center.

4. SIMULATION RESULTS

In this section, we illustrate the performance of the proposed sensor management algorithm by numerical examples. The MATLAB function 'fmincon' is used to solve the constrained optimization problem (26). We compare the MSE of CS based sensor management method to that of the random selection method under the same energy constraint. Both methods are compared to the all-send case where all sensor measurements are available at the fusion center via a set of parallel channels. The effect of the number of MACs, *i.e.*, M of the sensing matrix Φ on the inference performance is also studied.

We consider a WSN, consisting of $N = 25$ sensors grid deployed in a $20m \times 20m$ surveillance area. The dynamical model of the target is given by (1) with state vector $\mathbf{x}_k = [x_k\ \dot{x}_k\ y_k\ \dot{y}_k]^T$. The state transition model F and the covariance of the process noise Q are given as follows:

$$F = \begin{bmatrix} 1 & \mathcal{D} & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & \mathcal{D} \\ 0 & 0 & 0 & 1 \end{bmatrix}, Q = \rho \begin{bmatrix} \frac{\mathcal{D}^3}{3} & \frac{\mathcal{D}^2}{2} & 0 & 0 \\ \frac{\mathcal{D}^2}{2} & \mathcal{D} & 0 & 0 \\ 0 & 0 & \frac{\mathcal{D}^3}{3} & \frac{\mathcal{D}^2}{2} \\ 0 & 0 & \frac{\mathcal{D}^2}{2} & \mathcal{D} \end{bmatrix}$$

where $\mathcal{D} = 0.5$ seconds is the time interval and $\rho = 0.1$ is the process noise parameter. The parameters of the observation model (2) are set as $P_0 = 10^3$ and $r = 1$. The initial state of the target $\mathbf{x}_0$ is assumed to be Gaussian with mean $\mu_0 = [-13\ 2\ \ -13\ 2]^T$ and covariance matrix $\Sigma_0 = \text{diag}([4\ 1\ 4\ 1])$. We perform target tracking over $T_s = 15$ time steps for each Monte-Carlo trial, and set $N_s = 5000$ particles for the particle filter. The total energy available in the WSN at any given time is assumed to be $E = 6$. The MSE of the estimation at each time is averaged over $MC = 100$ Monte-Carlo trials.

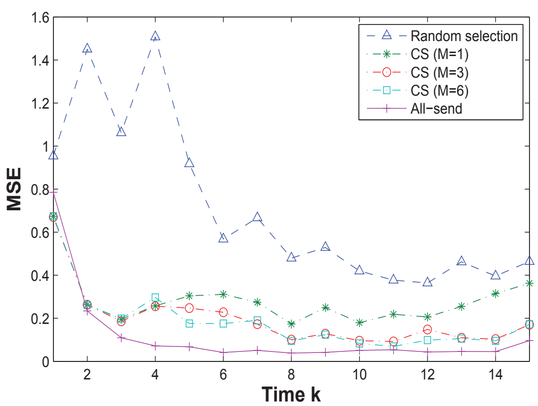

Fig. 1. MSEs comparison for different approaches. $M = 1,\ 3,\ 6$.

In Figure 1, the MSEs of the CS based approach with different M values are compared to that of the random selection method. One can observe that the former one outperforms the latter under the same energy constraint. The MSEs for $M = 1, 3, 6$ show that the proposed approach achieves a better performance as M increases. This reasonable result can be justified based on the following two reasons: 1) If M is interpreted as the number of MACs, then more channels definitely yield better performance; 2) In the context of CS, M is the number of compressed measurements. Then, a larger M should have higher probability to recover the original signal, and therefore, should yield better performance. Note that, according to the theory of CS, it is not necessary to choose a large M, if it already attains a threshold which guarantee the recovery of the original signal with overwhelming probability [7]. On the other hand, compared to the all-send case where a total of 25 units of energy are consumed at each time since $N = 25$ parallel transmissions are necessary, the proposed approach loses only a little performance, especially when $M = 6$, but is energy efficient in the sense that it consumes only $E = 6$ units of energy at any given time on an average. Note that, the compressed measurements are used directly for state estimation in the considered target tracking problem, which is different from the traditional CS problems where the goal is to recover a sparse signal. As M increases, we expect that the tracking performance of the proposed scheme will be close to that of the all-send case where there is no compression.

Since the proposed CS based sensor management scheme employs a probabilistic transmission strategy, intuitively, the optimal solution $\mathbf{p}_k$ to (26) should assign significant probabilities to those sensors which can obtain more informative observations. To show this, we investigate one Monte-Carlo trial of the tracking trajectory and observe the optimal probability vector $\mathbf{p}_k$ at any given time step k. In Figure 2, the optimal $\mathbf{p}$ at time steps $k = 4$ and $k = 10$

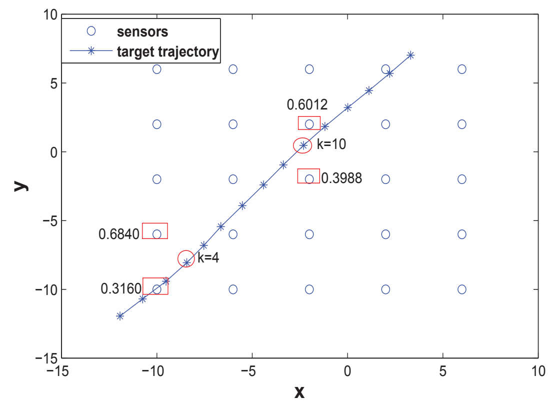

Fig. 2. $\mathbf{p}$ at different time steps. Circle: true state; Square: sensor assigned non-negligible transmission probability.

are marked. We can observe that, at time step $k = 4$, two sensors close to the target are assigned non-negligible probabilities, *i.e.*, one is 0.6840 and another is assigned 0.3160, while others are assigned almost zero probability. This is because, the two sensors are close to the target from two very different locations relative to the target. Similar observations can be made for time step $k = 10$.

5. CONCLUSION

In this paper, we proposed a novel probabilistic sensor management approach for target tracking in sensor networks based on compressed observations. With this model, the sensor management problem becomes a constrained optimization problem, where the goal is to determine the optimal values of probabilities that each sensor should transmit with such that the determinant of the **FIM** at any given time step is maximized. Numerical results show that the proposed approach saves a lot of energy with a little performance loss compared to the optimal scenario in which all sensor observations are transmitted to the fusion center via parallel channels. Under the same energy constraint, the proposed scheme outperforms the random selection approach significantly. An interesting future work is to take the channel statistics into consideration.

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