

# Information Content-Based Sensor Selection and Transmission Power Adjustment for Collaborative Target Tracking

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**Abstract**—For target tracking applications, wireless sensor nodes provide accurate information since they can be deployed and operated near the phenomenon. These sensing devices have the opportunity of collaboration among themselves to improve the target localization and tracking accuracies. An energy-efficient collaborative target tracking paradigm is developed for wireless sensor networks (WSNs). A mutual-information-based sensor selection (MISS) algorithm is adopted for participation in the fusion process. MISS allows the sensor nodes with the highest mutual information about the target state to transmit data so that the energy consumption is reduced while the desired target position estimation accuracy is met. In addition, a novel approach to energy savings in WSNs is devised in the information-controlled transmission power (ICTP) adjustment, where nodes with more information use higher transmission powers than those that are less informative to share their target state information with the neighboring nodes. Simulations demonstrate the performance gains offered by MISS and ICTP in terms of power consumption and target localization accuracy.

**Index Terms**—Distributed tracking, wireless sensor networks, multisensor systems, mutual information, power control.

## 1 INTRODUCTION

TARGET tracking, or processing of the measurements obtained from a target in order to maintain estimates of its current and future states, has major importance in Command, Control, Communications, Computer, Intelligence, Surveillance, and Reconnaissance (C4ISR) applications [1], [2]. Due to environmental perturbations, data collected near the phenomenon are more reliable than those obtained far from it. Emerging wireless sensor technologies facilitate the tracking of targets just within the phenomenon. In Fig. 1, small-sized, battery-operated, wireless communicating sensor devices are deployed very close to the hostile environment, and they are used for distributed sampling of signals from the target of interest in a C4ISR application. An unmanned aerial vehicle (UAV) patrolling above the area of surveillance relays the target position that is obtained from the sensor network toward the command and control center, where the Threat Evaluation, Weapon Assignment, and Sensor Allocation function takes place [3], [4]. If the reported target is evaluated as a threat, then the most appropriate weapon is assigned to that target. At that moment, a firing channel between the wireless sensor network (WSN), UAV, command and control center, and the weapon is formed. The target position, where the

weapon is to be directed, is fed continuously to the weapon via the firing channel. Command and control center monitors the communication delay in the firing channel in order to maintain the appropriate extrapolation about the target position. In the area of operation, units such as the soldier in Fig. 1 may need rapid and roughly accurate target position information. The soldier near the sensor field has limited communication capability when compared to the rocket launcher truck. Hence, the best the soldier can do is to ask a sensor node nearby him about the target position. The sensor node, with its current knowledge of the target state, immediately responds to the soldier's query. In this scenario, the rocket launcher truck obtains the target state information from the communication link composed of a sink node, UAV, and the command and control center. The target state information obtained by the rocket launcher truck is more accurate than that collected by the soldier. However, the soldier has the target state information more rapidly than the rocket launcher truck. With a distributed data fusion (DDF) architecture, benefiting from the far-reaching communication range of the sensor node compared to its detection range, we aim to have an acceptable target position information to be available at every sensor node. The reason is that the soldier may query any one of the sensor nodes that is close to him for an immediate and acceptably accurate target position information. The wireless communication characteristics of the emerging wireless sensor nodes provide an excellent distributed coordination mechanism to improve the global target localization accuracies in the WSN.

Collaborative target tracking brings along questions such as how to dynamically determine who should sense what needs to be sensed and whom the information must be passed on to. Sensor collaboration improves detection

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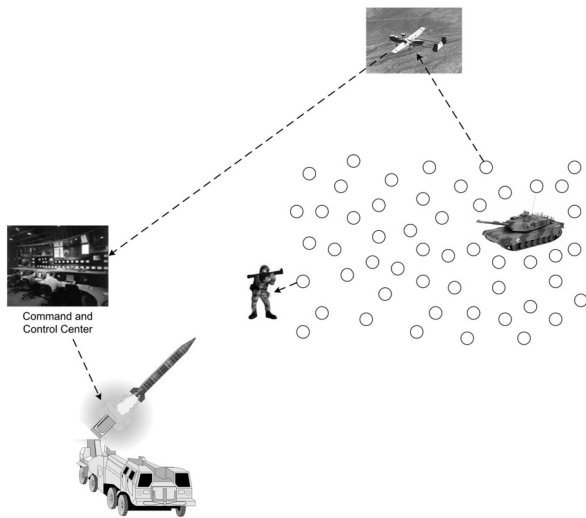


Fig. 1. C4ISR scenario with wireless sensor devices.

quality, tracking quality, scalability, survivability, and resource usage [5]. As an example, collaborative beamforming is used in [6] to localize acoustical sources. Sensor nodes in WSNs are battery-operated, which puts an energy constraint on their operation lifetimes. Reducing the energy exhausted by the nodes improves the duration of the time over which the sensor network's surveillance duty is carried out. In order to conserve the valuable battery power of the wireless devices, a common trend is to put some of the sensor nodes into a dormant state, which is controlled by a sleep schedule [7], [8]. Moreover, only a subset of the sensor nodes are active at any instant of time to also avoid redundant data flow in the network. Sensor activation strategies can be listed as *naive activation* in which all the sensor nodes are active, *randomized activation* in which a random subset of the sensor nodes are active, *selective activation* in which a subset of the sensor nodes are chosen according to some performance measure, and *duty-cycled activation* in which the sensor nodes are active for some duty cycle and in dormant state thereafter. There is an inevitable trade-off between the energy expenditure and the tracking quality in sensor networks [9].

In information-driven sensor querying (IDSQ) [5], [10], the so-called clusterheads decide on the sensor nodes that are to participate actively in the tracking task. In [11], a dual-space paradigm is presented in which the subset of nodes toward whom the target is approaching are selected to be active. Clusters are formed dynamically around the high-capability sensor nodes in [12]. In the location-centric approach to collaborative sensing and tracking, addressing and communication are performed among geographic regions within the network rather than individual nodes [13], [14]. This makes localized selective-activation strategies simpler to implement. Prediction-based target tracking techniques such as the Pheromones, Bayesian, and Extended Kalman Filter are presented in [15], [16], and a real implementation can be found in [17]. Multiple target tracking is examined in [18], [19], [20], [21].

Censoring sensors [22], [23], [24], [25], [26] is one approach to control the network traffic load. Sensor nodes

that are deemed as noninformative do not send their decisions or observations if their local likelihood ratio falls in a certain single interval. A special case of this phenomenon occurs when the lower bound of the no-send interval is zero. In this particular case, the problem reduces to sending the local decision/observation if the local likelihood ratio is above some threshold. A deficiency with this approach occurs for tracking applications if all the sensor node local likelihood ratios fall in the no-send region, and no belief about the target state is shared among the nodes.

In this paper, we concentrate on the WSN part of the C4ISR application depicted in Fig. 1. Sensor nodes try to collaboratively maintain accurate target position and speed estimates to report to the UAV in an energy-efficient manner. We consider the problem of tracking a single target using immobile sensor nodes that collaborate with each other through a broadcast communication mechanism. With collaboration among the sensor nodes, we aim to improve the target localization accuracy achieved by each sensor node. Moreover, we try to retrieve the target location from the network with low delay by querying any one of the nodes in the network. Collaborative target tracking makes it possible for each sensor node in the network to have an acceptable localization accuracy. As an extreme case, if there were no communication constraints, in other words, if every sensor node could communicate with every other node in the network, then the posterior target position information after the collaboration would be the same value for all nodes. The above-mentioned capability of the collaborative target tracking framework eliminates the need for a sink node inside the sensor network to collect the target position estimates of the neighboring sensor nodes. Any node that can be communicated within a single hop is a neighbor.

Previous research [27], [28], [29] has focused on how to provide full or partial sensing coverage in the context of energy conservation. Nodes stay in a dormant state as long as their neighbors can provide sensing coverage for them. These solutions regard the sensing coverage of a certain geographic area as binary, i.e., coverage is either provided, or not [7]. They consider the sensor selection problem only in terms of coverage and energy-saving aspects, without paying attention to detection quality. In tracking applications, when selecting the subset of sensor nodes to contribute to the global decision, we have to consider how informative the sensor nodes are about the state of the target.

In [10], [30], the sensor node which will result in the smallest expected posterior uncertainty of the target state is chosen as the next node to contribute to the decision. Specifically, minimizing the expected posterior uncertainty is equivalent to maximizing the mutual information between the sensor node output and the target state [30]. An entropy-based sensor selection heuristic is proposed for target localization in [31] where a sensor node is chosen at each step and the observation of that node is incorporated into the target location distribution using sequential Bayesian filtering.

In this paper, the information state is a function of the real target state and the information matrix is a function of the target state uncertainty, i.e., target state covariance.

The contribution of the sensor node to the information state is called its information state denomination. Similarly, the contribution of a sensor node to the information matrix is called its information matrix denomination.

Sensor nodes share with the other nodes in the WSN their information state and the information matrix denomination values, which are obtained from the collected target location data. With this mechanism, a collaboration among the sensor nodes is maintained in order to improve the target location estimate. Another possibility is to share the location of the target with the WSN after local information filtering. The latter paradigm in the sensor collaboration requires more complicated fusion operations as described in [32], [33], whereas the former provides a simple additive fusion framework within the distributed architecture.

Multiple sensor nodes usually perceive similar observations about the target state, which results in an inherent redundancy of sensory data. We develop an energy-efficient collaborative target tracking paradigm for WSNs. To that end, the network lifetime is prolonged and the desired tracking accuracy is maintained by selecting a subset of sensor nodes that are the most informative in the mutual information sense. In addition to the selective sensor activation strategy based on the maximum mutual information, with a novel approach to energy savings in WSNs, we devise a transmission power adjustment scheme whose essence lies behind the idea that the sensor nodes with more information should use higher transmission powers in order to share their information about the target state with their neighbors than those that are less informative.

In Section 2, we describe the DDF architecture. Then, in Section 3, mutual information-based sensor selection (MISS) algorithm for participation in the fusion process is defined. Information-controlled transmission power (ICTP) scheme is introduced in Section 4. Simulation results demonstrating the performance improvement offered by the MISS algorithm and the ICTP scheme are presented in Section 5. In Section 6, we conclude our work, and give some directions toward future research.

## 2 DATA PROCESSING ARCHITECTURE

In this section, we first define the process model for the target motion. The next state of the target is calculated with the knowledge of its current state and the target state transition matrix. The observation model is defined next to simulate the sensor behavior when the target's existence is known. It determines the observable state of the target by the sensor given the target's real state. The foundations of the DDF architecture are presented in Section 2.3.

The following assumptions are in effect regarding the system model:

- A1. Due to the high energy consumption and the cost of the mobile sensor nodes [34], we assume that immobile sensor nodes are deployed in the surveillance area. Hostile and hard to access environments may make it necessary to deploy sensors randomly from an airplane [35].
- A2. In order to concentrate on the target localization and the energy consumption performances of the

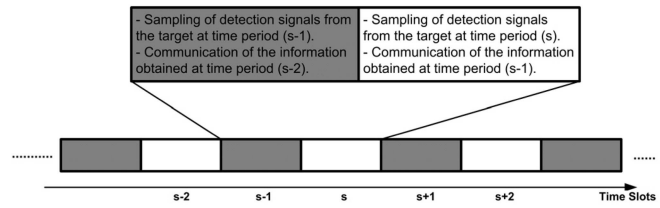


Fig. 2. Time synchronization of sampling and communication periods of the sensor nodes.

proposed algorithms, we assume that a single target is present in the environment.

- A3. Sensor nodes communicate with each other using a broadcast communication mechanism. They receive the broadcasted target location information from every neighboring node, and update their target state information with a simple additive fusion framework. The communicating sensor nodes for collaboration do not address their information denomination values to any specific sensor node. Instead, sensor nodes just broadcast their denomination values related with the information state and the information matrix they have. As a consequence, each sensor node receiving the denomination values from the neighbors just updates its target state information. Broadcasting eliminates the need for a routing algorithm among the sensor nodes. It also helps achieve the aim of having as many sensor nodes as possible to update their beliefs about the target state.
- A4. Sink nodes are not mandatory. Collaborative tracking makes it possible for any sensor node in the sensor field to respond to the target location queries from the command and control center. Moreover, the target position may be queried by the units that cannot reach or that do not have sufficient time to reach the sink node or to the command and control center. The soldier in Fig. 1 is an example of such a unit. Hence, any node in the sensor field must have an acceptable target position information available immediately to the querying unit. Producing the target position information at the sink node by collecting the information denominations of the detecting sensor nodes introduces a certain delay due to the data propagation toward the sink node and processing at the sink. In addition, the sink node is a single point of failure in the network and consensus is required for its selection. Instead, we distribute the data processing throughout the network.
- A5. Sensor node coordinates are known. Sensor position estimation is a problem of its own (see e.g., [36], [37] for sensor localization), and is beyond the scope of this paper.
- A6. Sampling is synchronized among the sensor nodes. Moreover, sampling periods are long enough to carry out the necessary communication needed for collaboration in the previous sampling period. While the detection signals are sampled at period  $s$ , the information obtained from the target at  $s-1$  is broadcasted, as shown in Fig. 2.

The collaborative target tracking paradigm implemented by each sensor node is explained in Section 3. In the sequel, we describe the associated components of the system including the fusion procedure, the sensor selection strategy, and the transmission power adjustment scheme, which collectively deliver good performance while simultaneously keeping the energy expenditure low. We consider a field that is put under surveillance with a total of  $N_T$  sensors. The reference will be some arbitrary sensor node  $S_m$ .

## 2.1 Process Model

The process model describes the target motion. The process model finds the state of the target at time instant  $k + 1$  given the state of the target at time instant  $k$ . The model contains a noise term to account for possible randomness in the target motion. The target state is a four-dimensional vector that consists of the two-dimensional position of the target,  $(\xi, \eta)$ , and the velocity of the target at each of these dimensions,  $(\dot{\xi}, \dot{\eta})$ . The target state vector is defined by

$$\mathbf{x} = [\xi \quad \eta \quad \dot{\xi} \quad \dot{\eta}]^T, \quad (1)$$

and it evolves in time according to

$$\mathbf{x}(k+1) = \mathbf{F}\mathbf{x}(k) + \mathbf{v}(k),$$

where  $\mathbf{x}(k)$  is the real target state vector at time  $k$  as given in (1),  $\mathbf{F}$  is the transition matrix, and  $\mathbf{v}$  is the independent, Gaussian-distributed process noise with zero mean and covariance matrix  $\mathbf{Q}$ .

## 2.2 Observation Model

Noise is added to the real target state in order to model the sensor observation uncertainties. Sensor nodes can only observe the first two dimensions of the target state. The velocity of the target is not observable. Furthermore, nodes collect range and bearing data, but they do not have the coordinates of the target directly. Because the target state is observed in polar coordinates, linear filtering formulations do not help. There are two implementation alternatives to remedy this problem: 1) by using the inverse transformation, obtain directly a converted measurement of the target position; 2) leave the measurement in its original form. The former yields a purely linear problem, allowing for linear filtering. The latter leads to a mixed coordinate filter [38]. In [39], the mean and covariance of the errors of Cartesian measurements, which are obtained by converting polar measurements, are derived. This conversion provides better estimation accuracy than the Extended Kalman Filter, in which the nonlinear target state measurements are utilized without conversion [39].

The range  $r_{m,d}$  and bearing  $\theta_{m,d}$  measured by  $S_m$  are defined with respect to the true range  $r_m$  and bearing  $\theta_m$  as

$$\begin{aligned} r_{m,d} &= r_m + \tilde{r}_m, \\ \theta_{m,d} &= \theta_m + \tilde{\theta}_m, \end{aligned} \quad (2)$$

where the errors in range  $\tilde{r}_m$  and bearing  $\tilde{\theta}_m$  are assumed to be independent and Gaussian-distributed with moments

$$E[\tilde{r}_m] = 0, \quad E[\tilde{\theta}_m] = 0, \quad E[\tilde{r}_m^2] = \sigma_{r_m}^2, \quad E[\tilde{\theta}_m^2] = \sigma_{\theta_m}^2,$$

where the time dependence is implicit. The mean target state observed after the unbiased polar-to-Cartesian conversion is given by [39]

$$\varphi_m = \begin{bmatrix} \xi_{m,d}^c \\ \eta_{m,d}^c \end{bmatrix} = \begin{bmatrix} r_{m,d} \cos \theta_{m,d} \\ r_{m,d} \sin \theta_{m,d} \end{bmatrix} - \boldsymbol{\mu}_m, \quad (3)$$

where  $\boldsymbol{\mu}_m$  is the average true bias

$$\boldsymbol{\mu}_m = \begin{bmatrix} r_{m,d} \cos \theta_{m,d} (e^{-\sigma_{\theta_m}^2} - e^{-\sigma_{\theta_m}^2/2}) \\ r_{m,d} \sin \theta_{m,d} (e^{-\sigma_{\theta_m}^2} - e^{-\sigma_{\theta_m}^2/2}) \end{bmatrix}.$$

The covariance matrix  $\mathbf{R}_m$  of the observation errors in  $\varphi_m$  is [38], [39]

$$\mathbf{R}_m = \begin{bmatrix} R_{m11} & R_{m12} \\ R_{m21} & R_{m22} \end{bmatrix}, \quad (4)$$

where

$$\begin{aligned} R_{m11} &= r_{m,d}^2 e^{-2\sigma_{\theta_m}^2} [\cos^2 \theta_{m,d} (\cosh 2\sigma_{\theta_m}^2 - \cosh \sigma_{\theta_m}^2) \\ &\quad + \sin^2 \theta_{m,d} (\sinh 2\sigma_{\theta_m}^2 - \sinh \sigma_{\theta_m}^2)] \\ &\quad + \sigma_{r_m}^2 e^{-2\sigma_{\theta_m}^2} [\cos^2 \theta_{m,d} (2 \cosh 2\sigma_{\theta_m}^2 - \cosh \sigma_{\theta_m}^2) \\ &\quad + \sin^2 \theta_{m,d} (2 \sinh 2\sigma_{\theta_m}^2 - \sinh \sigma_{\theta_m}^2)], \end{aligned}$$

$$\begin{aligned} R_{m22} &= r_{m,d}^2 e^{-2\sigma_{\theta_m}^2} [\sin^2 \theta_{m,d} (\cosh 2\sigma_{\theta_m}^2 - \cosh \sigma_{\theta_m}^2) \\ &\quad + \cos^2 \theta_{m,d} (\sinh 2\sigma_{\theta_m}^2 - \sinh \sigma_{\theta_m}^2)] \\ &\quad + \sigma_{r_m}^2 e^{-2\sigma_{\theta_m}^2} [\sin^2 \theta_{m,d} (2 \cosh 2\sigma_{\theta_m}^2 - \cosh \sigma_{\theta_m}^2) \\ &\quad + \cos^2 \theta_{m,d} (2 \sinh 2\sigma_{\theta_m}^2 - \sinh \sigma_{\theta_m}^2)], \end{aligned}$$

$$\begin{aligned} R_{m12} &= R_{m21} \\ &= \sin \theta_{m,d} \cos \theta_{m,d} e^{-4\sigma_{\theta_m}^2} [\sigma_{r_m}^2 + (r_{m,d}^2 + \sigma_{r_m}^2)(1 - e^{\sigma_{\theta_m}^2})]. \end{aligned}$$

## 2.3 Distributed Data Fusion Architecture

In the information filter formulation, the information state  $\hat{\mathbf{y}}_m$  and the information matrix  $\mathbf{Y}_m$  associated with the state estimate  $\hat{\mathbf{x}}_m$  and the posterior estimation error covariance  $\mathbf{P}_m$  of sensor node  $S_m$ ,  $m = 1, 2, \dots, N_T$ , at time instant  $k$  are given by

$$\begin{aligned} \hat{\mathbf{y}}_m(k) &= \mathbf{P}_m^{-1}(k) \hat{\mathbf{x}}_m(k), \\ \mathbf{Y}_m(k) &= \mathbf{P}_m^{-1}(k). \end{aligned}$$

In [40], it is shown that by means of sufficient statistics, the observation  $\varphi_m$  contributes  $\mathbf{i}_m(k)$  to the information state  $\hat{\mathbf{y}}_m$ , and  $\mathbf{I}_m(k)$  to the information matrix  $\mathbf{Y}_m$ , where the denomination values are computed as

$$\begin{aligned} \mathbf{i}_m(k) &= \mathbf{H}_m^T \mathbf{R}_m^{-1}(k) \varphi_m(k), \\ \mathbf{I}_m(k) &= \mathbf{H}_m^T \mathbf{R}_m^{-1}(k) \mathbf{H}_m \end{aligned} \quad (5)$$

with  $\mathbf{H}_m$  being the observation matrix of  $S_m$  that relates the target state estimate  $\hat{\mathbf{x}}_m$  to the sensor measurement  $\varphi_m(k)$ . The node updates its own belief upon receiving its own sensory observation according to

$$\begin{aligned} \hat{\mathbf{y}}_m(k|k) &= \hat{\mathbf{y}}_m(k|k-1) + \mathbf{i}_m(k), \\ \mathbf{Y}_m(k|k) &= \mathbf{Y}_m(k|k-1) + \mathbf{I}_m(k), \end{aligned} \quad (6)$$

where  $\hat{\mathbf{y}}_m(k|k-1)$  represents the information state estimate at time  $k$  given the observations up to and including time  $k-1$ .

Instead of sending the measurements related to the target state to the collaborating sensor nodes, sharing the information form of the observations results in a simple additive fusion framework that can be run on each of the tiny sensing devices. Other advantages of the information form of filtering over the canonical form are [38]:

1. Saving the limited energy resources of sensor nodes by reducing the computational load of the processors.
2. In the canonical form of filtering, updates in the state covariance matrix may cause loss of symmetry and positive definiteness as a result of rounding errors. Information filtering improves the numerical accuracy by preserving the symmetry and positive definiteness property of the state covariance matrix.
3. Information filtering provides a means for the start-up of the estimation without an initial estimate.

Note that the fusion of posterior information requires the extraction of the information denomination values. This procedure, which should be done for every received posterior information, leads to a drastic growth in the amount of processing, especially with increasing number of sensor nodes in the network. Define  $\mathcal{S}_m(k)$  to be the set of nodes that are neighbors with  $S_m$  at time  $k$ . Letting  $\mathbf{i}_n(k)$  and  $\mathbf{I}_n(k)$  denote the  $n$ th neighboring node's contribution to  $\hat{\mathbf{y}}_m$  and  $\mathbf{Y}_m$ , respectively, the DDF equations are

$$\hat{\mathbf{y}}_m(k|k) = \hat{\mathbf{y}}_m(k|k-1) + \sum_{n: S_n \in \mathcal{S}_m(k)} \mathbf{i}_n(k), \quad (7)$$

$$\mathbf{Y}_m(k|k) = \mathbf{Y}_m(k|k-1) + \sum_{n: S_n \in \mathcal{S}_m(k)} \mathbf{I}_n(k).$$

Just before the data at time  $k$  are collected, if we are given the observations up to  $k-1$ , the predicted information state and the information matrix at time  $k$  can be calculated as

$$\begin{aligned} \hat{\mathbf{y}}_m(k|k-1) &= \mathbf{Y}_m(k|k-1) \mathbf{F}_m \mathbf{Y}_m^{-1}(k-1|k-1) \hat{\mathbf{y}}_m(k-1|k-1), \\ \mathbf{Y}_m(k|k-1) &= [\mathbf{F}_m \mathbf{Y}_m^{-1}(k-1|k-1) \mathbf{F}_m^T + \mathbf{Q}_m]^{-1}, \end{aligned} \quad (8)$$

where  $\mathbf{Q}_m$  is the noise covariance matrix for node  $S_m$ ,  $m = 1, 2, \dots, N_T$ .

The state estimate of the target, given the observations up to and including the time  $k$ , can be found from

$$\hat{\mathbf{x}}_m(k|k) = \mathbf{Y}_m^{-1}(k|k) \hat{\mathbf{y}}_m(k|k). \quad (9)$$

The information state and information matrix denominations in (6) are functions of  $\varphi_m$  as in (5). However, in the DDF paradigm described by (7), these are obtained from the neighboring sensor nodes by means of wireless communication. A sensor's own observation and the information received from the neighboring nodes have similar means for updating the belief about the target state. The ease of the belief update in the target position estimation is another

reason for utilizing the information filtering while distributing the target tracking process throughout the network.

### 3 MAXIMUM MUTUAL-INFORMATION-BASED SENSOR SELECTION ALGORITHM

Mutual information measures how much uncertainty is removed by one random variable about another one. By computing the mutual information between the target state and the measurement, one can gain insight as to how much the current observation tells about the current target state.

The mutual information gained with the last observation of the  $m$ th sensor can be formulated as

$$J_m(k, \varphi_m(k)) = J_m(k) = \frac{1}{2} \log \left[ \frac{|\mathbf{Y}_m(k|k)|}{|\mathbf{Y}_m(k|k-1)|} \right], \quad (10)$$

where  $\mathbf{Y}_m(k|k)$  is the information matrix at time instant  $k$  after the target state is observed,  $m = 1, 2, \dots, N_T$  [40].

In the data fusion paradigm described by (7), the number of neighboring nodes, which is counted by the cardinality  $|\mathcal{S}_m(k)| \leq N_T$ , is usually too large, causing excessive data communication in the network and a strain on the energy resources. To alleviate this problem, we introduce the MISS algorithm, where node  $S_m$  shares its own information about the target state with all its neighbors at time  $k$  only if the mutual information gain  $J_m(k)$  is high enough to participate in the current cycle. Otherwise,  $S_m$  withholds transmission. To that end, all neighboring nodes of  $S_m$  are ranked in decreasing mutual information order. Let  $\mathcal{J}_m(k) = \{J_{m,1}(k), J_{m,2}(k), \dots, J_{m,|\mathcal{S}_m(k)|}(k)\}$  be the ordered set of mutual information values as predicted by  $S_m$  at time instant  $k$ . Thus,  $J_{m,n}(k)$  is  $S_m$ 's estimate of  $J_n(k)$ , and  $J_{m,1} \geq J_{m,2} \geq \dots \geq J_{m,|\mathcal{S}_m(k)|}$ . Define  $\mathcal{J}'_m(k) = \{J_{m,1}(k), J_{m,2}(k), \dots, J_{m,N_{\max}}(k)\} \subset \mathcal{J}_m(k)$ , where  $N_{\max} < |\mathcal{S}_m(k)|$ , as the ordered subset that keeps the first  $N_{\max}$  elements of  $\mathcal{J}_m(k)$ . Let  $\mathcal{S}'_m(k) \subset \mathcal{S}_m(k)$  denote the set of nodes that are sufficiently informative<sup>1</sup> to contribute to data fusion at  $S_m$  in the  $k$ th cycle.

For  $N_{\max} < |\mathcal{S}_m(k)|$ , the MISS algorithm can be formulated as follows:

1. If  $S_m$  detects the target, and  $J_m(k) > \min \mathcal{J}'_m(k)$ , then  $S_m$  broadcasts its information state and the information matrix denominations,  $\mathbf{i}_m(k)$ ,  $\mathbf{I}_m(k)$ , to the network, and

$$\begin{aligned} \mathcal{S}'_m(k) &= \{S_n \in \mathcal{S}_m(k), n = 1, 2, \dots, |\mathcal{S}_m(k)| : \\ &J_{m,n} \in \mathcal{J}'_m(k)\} - S_{N_{\max}}. \end{aligned}$$

2. If  $S_m$  detects the target, and  $J_m(k) \leq \min \mathcal{J}'_m(k)$ , or if  $S_m$  does not detect, then  $S_m$  withholds, and

$$\begin{aligned} \mathcal{S}'_m(k) &= \{S_n \in \mathcal{S}_m(k), n = 1, 2, \dots, |\mathcal{S}_m(k)| : \\ &J_{m,n} \in \mathcal{J}'_m(k)\}. \end{aligned}$$

The algorithm tries to limit the maximum number of sensors that communicate in the neighborhood (in the sense

1. The informativeness of a sensor node will be associated with a quantitative measure in (12).

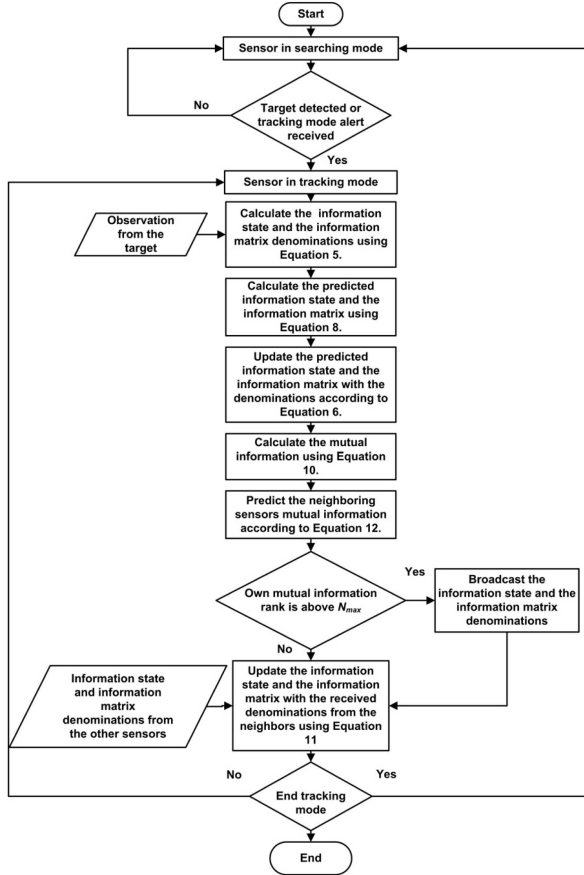


Fig. 3. Target tracking algorithm employed by each sensor node.

defined by Assumption A3) of each node to  $N_{\max}$ . Revisiting (7), the current belief is updated with the received information from the nodes in  $\mathcal{S}'_m(k)$  according to

$$\hat{\mathbf{y}}_m(k|k) = \hat{\mathbf{y}}_m(k|k-1) + \sum_{n: S_n \in \mathcal{S}'_m(k)} \mathbf{i}_n(k), \quad (11)$$

$$\mathbf{Y}_m(k|k) = \mathbf{Y}_m(k|k-1) + \sum_{n: S_n \in \mathcal{S}'_m(k)} \mathbf{I}_n(k).$$

In the event that  $N_{\max} \geq |\mathcal{S}_m(k)|$ , all nodes in  $\mathcal{S}_m(k)$  simply transmit their data. The MISS algorithm, implemented by each sensor node, is presented in an algorithmic fashion in Fig. 3.

For some sensor node  $S_m$  to implement the MISS algorithm in the  $k$ th cycle,  $S_m$  has to locally create  $\mathcal{J}_m(k)$ . That is, every node needs to estimate the mutual information values of all its neighbors. Assuming that  $\mathbf{Y}_n(k|k-1) \approx \mathbf{Y}_m(k|k-1), \forall S_n \in \mathcal{S}_m(k)$ , due to the past collaboration among the neighboring nodes, and  $\mathbf{H}_n = \mathbf{H}_m, \forall S_n \in \mathcal{S}_m(k)$ , because neighboring sensor nodes observe the same properties of the target, we define

$$J_{m,n}(k) = \frac{1}{2} \log \left[ \frac{|\mathbf{Y}_{m,n}(k|k)|}{|\mathbf{Y}_m(k|k-1)|} \right], \quad (12)$$

where

$$\mathbf{Y}_{m,n}(k|k) = \mathbf{Y}_m(k|k-1) + \mathbf{I}_{m,n}(k)$$

with

$$\mathbf{I}_{m,n}(k) = \mathbf{H}_m^T \mathbf{R}_{m,n}^{-1}(k) \mathbf{H}_m \quad (13)$$

being the information matrix denomination estimate of  $S_n$  by  $S_m$ . The *informativeness* of a node is measured by (12), which assesses the reduction in the target state uncertainty with the incoming new data. The higher the value obtained from (12), the more informative the sensor about the target state is.  $\mathbf{R}_{m,n}$  is the estimate of  $S_m$  about the covariance matrix of the observation errors by  $S_n$ . Consequently,  $\mathbf{Y}_{m,n}$  is the information matrix estimate of  $S_n$  by  $S_m$ . Therefore, by (4), to have the estimate  $\mathbf{R}_{m,n}$  in (13) (and hence, the estimate  $\mathbf{Y}_{m,n}(k|k)$  in (12)), it is required that each sensor node holds a list whose elements are the standard deviations of the target range observations  $\sigma_{r_n}$ , and the standard deviations of the target bearing observations  $\sigma_{\theta_n}$ , for all  $S_n \in \mathcal{S}_m(k)$ . Moreover,  $S_m$  needs to find  $r_{n,d}, \theta_{n,d}$ , which can be determined from  $r_{m,d}, \theta_{m,d}$ , and  $S_n$ 's position information, which is assumed to be known. Note that before the observation at time instant  $k$  arrives, node  $S_m$  already has the prediction  $\mathbf{Y}_m(k|k-1)$  about the target state information at  $k$ .

The list  $\mathcal{J}_m(k)$  is formed using the estimated mutual information values of its neighbors. During the simulation studies, which are reported in Section 5, we also examine the number of times the actual mutual information list differs from the estimated list.

Collaboration among the sensor nodes in the network results in  $\mathbf{Y}_n(k|k-1) \approx \mathbf{Y}_m(k|k-1), \forall S_n \in \mathcal{S}_m(k)$ , which follows from (11). If every node in the network was able to communicate with the others (i.e., fully connected network topology), the equality  $\mathbf{Y}_n(k|k-1) = \mathbf{Y}_m(k|k-1)$  would hold. The reason for having  $\mathbf{Y}_n(k|k-1) \approx \mathbf{Y}_m(k|k-1)$  lies behind the fact that the communication range is much larger than the detection range of the sensor node,  $S_m$ . With its own observation from the target,  $S_m$  can find  $\mathbf{Y}_m(k|k)$ . The decision as to whether  $S_m$  should collaborate with  $S_n$  or not depends on the utility of the information that comes from  $S_n$ , and it should be made before  $S_n$  transmits. To remedy this, we assume that  $S_m$  and  $S_n$  detect the target at the same location. With the aid of this assumption,  $S_m$  can predict  $\mathbf{Y}_{m,n}(k|k)$  and use it instead of  $\mathbf{Y}_n(k|k)$ . Moreover,  $S_m$  neglects the discrepancy between  $\mathbf{Y}_{m,n}(k|k)$  and  $\mathbf{Y}_n(k|k)$  that is caused by the observation noises of  $S_m$  and  $S_n$ . A better approach in terms of precision would be  $S_m$  to predict the target position and the uncertainty estimation of  $S_n$  using the mean of  $L$  predictions. However, this would incur a delay and an increase in the processing power requirements.

#### 4 INFORMATION-CONTROLLED TRANSMISSION POWER ADJUSTMENT

In this section, we introduce the ICTP adjustment scheme as the energy-saving strategy, in addition to the MISS algorithm. The block diagram representation of the sensor node whose task is distributed target tracking with MISS and ICTP is shown in Fig. 4. Sensory observation is transferred to the information extractor module to retrieve the information state and the information matrix denomination values from the received observation using (5),

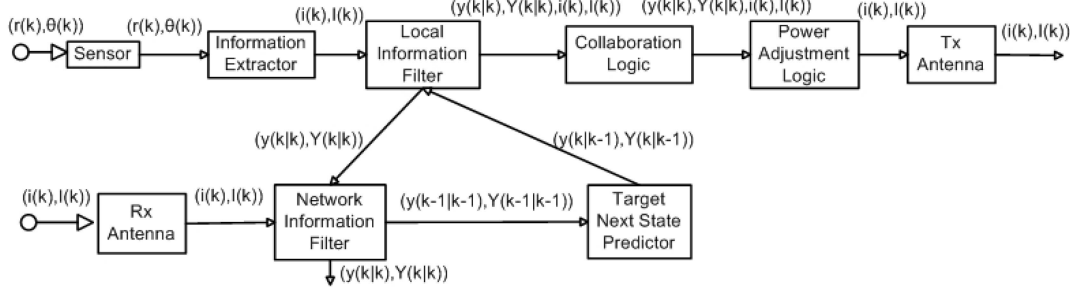


Fig. 4. Block diagram of the sensor node employing the MISS and ICTP algorithms.

which are then passed to the local information filter module where local target tracking takes place according to the operations in (6). The target state belief obtained from the local information filter is handed over to the collaboration logic and the network information filter modules. Using the mutual information measure in (12), the collaboration logic decides if the sensor node is going to share the current target observation with the network or not. The collaboration logic works as described in Section 3. The network information filter is the place where the information state and the information matrix denominations received from the neighboring sensor nodes are incorporated to the current target state estimate of the sensor node according to (11). The resulting collaborated target state estimate is passed to the target next state predictor module which functions as described by (8).

The ICTP scheme is embodied in the power adjustment logic module in which a node consults the mutual information list index of the sensor node and the preset power adjustment pattern, and subsequently, decides on the transmission power for communicating its information state and information matrix denominations to the network. Sample power adjustment patterns are shown in Fig. 5. In general, each pattern consists of an ordered set of transmission power levels,  $\mathcal{P} = \{P_1, P_2, \dots, P_{N_{\max}}\}$  where  $P_1 \geq P_2 \geq \dots \geq P_{N_{\max}}$ . If the node  $S_m$  is such that  $J_m(k) > \min \mathcal{J}_m^l(k)$  and if  $J_m(k)$  is ranked  $l$ th in the ordered set  $\mathcal{J}_m^l(k)$  that lists  $\mathcal{J}_m^l(k)$  and  $J_m(k)$  together, then  $S_m$  broadcasts with power  $P_l$  at  $k$ . If  $S_m$  is ranked first in  $\mathcal{J}_m^l(k)$ , then it has the privilege of broadcasting with the maximum power,  $P_1$ . Transmitting with a lower power shortens a detecting node's communication range, which results in a reduced degree of collaboration for the DDF

architecture. With the ICTP scheme, we aim to decrease the energy expenditure of each sensor node by regulating its communication transmission power according to its information content. The higher the mutual information a sensor node has about the target state, the more the communication transmission power it uses. Low-power transmission of a sensor node having low information assists the nondetecting sensors to update their belief about the target state.

The performance of ICTP varies depending on the way the network is queried about the target location information. In sensor network applications, the data collected by the network are carried to a processing (data collection) center on a periodic basis or upon a query [41]. The DDF paradigm makes it possible to query any one of the nodes in the WSN to get an immediate response owing to the communication ranges that are far-reaching in comparison to the sensing ranges. Alternatively, the processing center can be informed by the most informative sensor node (MISN), which is the one with the maximum mutual information  $J_1$ . There is a delay-accuracy trade-off in the above-mentioned two query response mechanisms. Routing the query packets to MISN increases the query response time of the WSN. Responding to a query immediately without consulting the MISN, on the other hand, reduces the query response time with the cost of reduced target localization accuracy.

The experiments in Section 5 show that if a sensor network queries any one of its sensor nodes, then reducing the transmission power deteriorates the overall tracking quality due to the reduced degree of collaboration. However, if the MISN is queried, then adjusting the communication transmission powers of the sensing nodes according to their information content lowers the energy consumption while maintaining the tracking accuracy.

The MISS algorithm requires that every sensor node be aware of the expected mutual information content of their neighboring nodes. This facilitates each sensor node to locate the MISN in its vicinity. The main cost incurred in querying the MISN is in routing the query packets to that node, and routing the target state information packets back to the querying node. The pseudocode of the algorithm of a sensor node running the ICTP scheme in the DDF architecture is given in Algorithm 1. Sensor nodes obtain the target state observations in Statement 1 of Algorithm 1. Information state and the information matrix denominations are calculated in Statements 2 and 3. The next

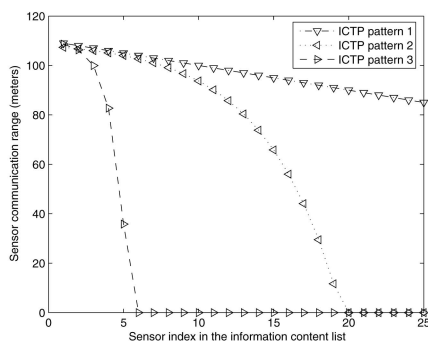


Fig. 5. Power adjustment patterns.

information state and the information matrix are predicted in Statements 4 and 5. In Statements 6 and 7, the local information filter runs for the predicted information state and the information matrix together with the information denominations are obtained from the local sensory observations about the target state. The sensor's own mutual information value is calculated in Statement 8 with the last observation. In Statements 9, 10, and 11, the neighboring sensor nodes' mutual information values are estimated using the current local target state estimate and the previous collaborated target state estimate. The neighboring sensor nodes and the sensor node itself are sorted according to the decreasing mutual information scores in Statement 12. In Statement 13, the index of the sensor node itself in the sorted mutual information score list is found. In Statements 14, 15, 16, and 17, using the mutual information score index, the sensor node decides to actively participate or not to participate in the collaboration cycle. If the index value is smaller than the maximum number of sensor nodes allowed to communicate, then the sensor node calculates the transmission power to broadcast the information state and the information matrix denominations to the WSN using the mutual information score index value and the transmission power reduction pattern used. In Statements 18, and 19, the sensor node updates the information state and the information matrix related with the target location using the received information state and the information matrix denomination values from the neighboring sensor nodes. The estimated target position is calculated in Statement 20 of Algorithm 1 using the collaborated information state and the information matrix values.

**Algorithm 1.** Pseudocode of the MISS/ICTP algorithm running on a sensor node described in Fig. 4.

**Given:** Observations  $r_m(k), \theta_m(k)$  from the target at time instant  $k$ , information state  $\mathbf{i}_i(k)$ , and information matrix  $\mathbf{I}_i(k)$  at time  $k$  from the neighboring sensor nodes  $i$ , system variables  $\mathbf{F}, \mathbf{Q}, \mathbf{H}, \mathbf{R}$ .

**Find:** Target position estimate  $\hat{\mathbf{x}}(k|k)$  at time  $k$ .

**Obtain the observation from the target.**

1:  $\varphi_m(k) \leftarrow f(r_m, \theta_m)$

**Calculate the information denominations.**

2:  $\mathbf{i}(k) \leftarrow \mathbf{H}^T \mathbf{R}^{-1}(k) \varphi_m(k)$

3:  $\mathbf{I}(k) \leftarrow \mathbf{H}^T \mathbf{R}^{-1}(k) \mathbf{H}$

**Predict the target's next information state.**

4:  $\hat{\mathbf{y}}(k|k-1) \leftarrow \mathbf{Y}(k|k-1) \mathbf{F} \mathbf{Y}^{-1}(k-1|k-1) \hat{\mathbf{y}}(k-1|k-1)$

5:  $\mathbf{Y}(k|k-1) \leftarrow [\mathbf{F} \mathbf{Y}^{-1}(k-1|k-1) \mathbf{F}^T + \mathbf{Q}]^{-1}$

**Local information filter.**

6:  $\hat{\mathbf{y}}(k|k) \leftarrow \hat{\mathbf{y}}(k|k-1) + \mathbf{i}(k)$

7:  $\mathbf{Y}(k|k) \leftarrow \mathbf{Y}(k|k-1) + \mathbf{I}(k)$

**Find own mutual information value.**

8:  $J(k, \varphi_m(k)) \leftarrow \frac{1}{2} \log \left[ \frac{|\mathbf{Y}(k|k)|}{|\mathbf{Y}(k|k-1)|} \right]$

**Estimate other sensor nodes' mutual information values.**

9: **for all** *sensor* such that *sensor* is a neighbor **do**

10:  $J_{array}(k, \varphi_m(k))[sensor] \leftarrow \frac{1}{2} \log \left[ \frac{|\hat{\mathbf{Y}}_{sensor}(k|k)|}{|\hat{\mathbf{Y}}_{sensor}(k|k-1)|} \right]$

11: **end for**

**Produce the mutual information content list.**

12: **sort**  $J_{array}(k, \varphi_m(k))[sensor]$

**Find own sensor node's index value in the mutual information content list.**

13:  $index \leftarrow$  index of  $J(k, \varphi_m(k))$  in  $J_{array}(k, \varphi_m(k))$

**Decide to collaborate or not to collaborate. If decision is to collaborate then calculate the transmission power and broadcast the denomination values.**

14: **if**  $index \leq$  maximum number of sensor nodes allowed to communicate **then**

15: Transmission Power  $\leftarrow f(index)$

16: Broadcast  $\mathbf{i}(k)$  and  $\mathbf{I}(k)$

17: **end if**

**Network information filter.**

18:  $\hat{\mathbf{y}}(k|k) = \hat{\mathbf{y}}(k|k-1) + \sum_n \mathbf{i}_n(k)$

19:  $\mathbf{Y}(k|k) = \mathbf{Y}(k|k-1) + \sum_n \mathbf{I}_n(k)$

**Find the target state estimate.**

20:  $\hat{\mathbf{x}}(k|k) = \mathbf{Y}^{-1}(k|k) \hat{\mathbf{y}}(k|k)$

## 5 SIMULATIONS AND FURTHER DISCUSSION

We run Monte Carlo simulations to examine the performance of the proposed MISS algorithm and the ICTP scheme for the DDF architecture described in Section 2.3 in terms of power consumption and target localization accuracy. We examine two scenarios: the first is the sparser one, which consists of 300 sensor nodes randomly deployed in a 200 m  $\times$  200 m area. The second is a denser scenario in which 800 sensor nodes are placed in the same area. All data points in the graphs represent the means of 20 runs. A target moves in the area according to the process model described in Section 2.1. We use the parameters of the TWR-ISM-002-I micropower impulse radar (MIR) with pseudorandom signaling. Typical detection range of a TWR-ISM-002-I is 18 meters [42]. As in [39], we assume constant range and bearing standard deviation of  $\sigma_{r_m} = 0.1$  m and  $\sigma_{\theta_m} = 1$  degree, respectively, for all sensory observations.

The sensor node tracks the target locally using the information form of the Kalman filter [43] as described in Section 2.3. If the sensor does not detect a target, it updates its belief about the target state according to the track history.

In collaborative information fusion, if a sensor node is eligible to share its belief about the target state with other sensor nodes, it broadcasts its information state and the information matrix denominations. Sensor nodes update their belief about the target state with these received denominations as described in Section 2.3.

The simulations are run for a flat, rural setting where the radio signal propagation is characterized by the shadow fading model with parameters given in Table 1 [44]. As the target state transition matrix and the target state transition covariance, we respectively use

$$\mathbf{F} = \begin{bmatrix} 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}, \quad \mathbf{Q} = \xi \cdot \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

TABLE 1  
Shadow Fading Communication Model Parameters

|                                  |         |
|----------------------------------|---------|
| Carrier frequency                | 1.8 GHz |
| Path loss exponent               | 2       |
| TX & RX antenna height           | 0.1 m   |
| Shadow-fading standard deviation | 4       |
| Sensor node transmission power   | -30 dB  |

for all sensors, where  $\xi$  is the target maneuvering index. A lower  $\xi$  value means that the target maneuvers slowly, and vice versa. In the simulations,  $\xi$  is set to unity. A sensor node can only observe the position related with the target. The velocity information is not directly observable. We therefore use

$$\mathbf{H} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix}$$

as the observation matrix of each sensor node.

Even for the sparse scenario, the mean number of sensor nodes detecting the target is 14 so that at most 14 sensor nodes can actively participate in the collaboration. Hence, it is assumed that the sampling period of the signals from the target is sufficiently long to allow for the collaboration of 14 nodes.

On average, 12 percent of the sensor nodes are located in positions different from the true mutual information list. Moreover, an inaccurately formed list contains on the average just two sensor nodes that are ranked in wrong positions in the mutual information list. This deviation from the correct list is acceptable from a practical standpoint as evidenced by the performance graphs. The reason behind the successful mutual information score list formation lies in the fact that communication ranges are more far-reaching compared to the detection ranges of the sensor devices. This results in consistent posterior target information state and information matrix estimates with collaboration, which, in turn, help generate consistent mutual information scores throughout the sensor network. Inconsistencies in the target information state and information matrix estimates are caused by sensor nodes which cannot hear each other primarily due to radio propagation characteristics, including path loss.

Tests show that average target localization errors are of the order of 0.5 meters based on 20 simulations, each one run for 100 seconds and with a distinct random seed. The sensor with the worst target position estimation has a localization error of 3.7 meters. Target localization errors are measured from the weight center of the target, which results in point target tracking errors.

The WSN has two modes of operations, namely, the searching and the tracking modes. Any sensor that detects a target or receives a tracking mode alert from a neighboring sensor node goes into tracking mode and warns the neighboring nodes to do the same. In the tracking mode, the communication transmitter circuit is activated according to the selective activation strategy with the maximum mutual information metric whereas the receiver circuit and the sensor circuit are active all the time. However, in the searching mode, we utilize a duty-cycled activation in which the sensor node receiver and sensing circuit are active

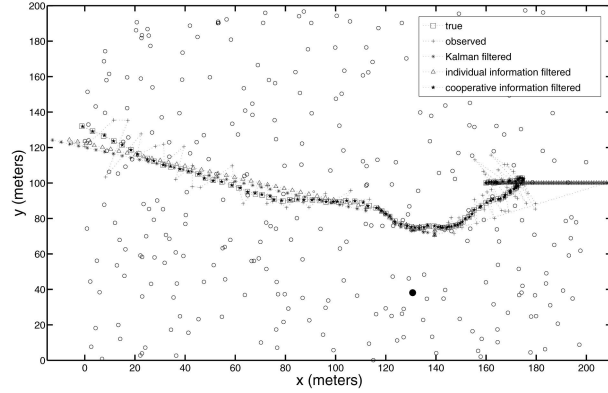


Fig. 6. Target trajectory as seen by the sensor node represented with a solid dot (•) in the 300-sensor scenario.

for some duty cycle and inactive thereafter. In the simulations, we compare the mean error about the target localization for the collaborative tracking framework described in Section 2.3. We achieve the maximum tracking accuracy when all sensor nodes detecting the target participate in the DDF task. As the number of sensor nodes allowed to participate in the fusion task is reduced, the tracking quality deteriorates. This yields higher localization errors about the distributed target position estimates. However, when fewer sensor nodes take part in the collaboration, fewer communication packets travel in the network. A reduction in the number of sent packets affects the energy expenditure of the wireless sensor devices directly. Selecting the sensor nodes to actively participate in the fusion task in an intelligent manner improves tracking quality while allowing the same number of sensor nodes to communicate. Fig. 6 depicts the 300-sensor scenario, target location observation errors, Kalman and information-filtered target localization errors, and cooperative information-filtered target localization errors from the viewpoint of the sensor node that is marked as a solid dot at the grid point (132,40). As the target moves away from the sensor node, observation errors increase. Kalman or information filtering reduces the observation errors. However, at some target maneuver points, if the sensor cannot detect the target, the node tracks the target position by resorting to the target history only. In other words, the Kalman gain is set to zero if the sensor cannot detect the target. This results in the erroneous linear tracking of the target until a positive detection is achieved. Poor detection performance results if target maneuvers are missed by the sensor. With the aid of collaboration among the sensor nodes, these target maneuver misses are avoided. We track the target for 100 seconds in the simulations.

In collaborative target tracking, selecting the participating active sensor nodes randomly means that a node detecting the target broadcasts its information immediately if the maximum number of sensor nodes to participate,  $N_{\max}$ , has not yet been reached. This can be decided by counting the number of target position announcements received from the neighboring sensor nodes. The competing approach considered in the simulations selects the closest sensor nodes to the target location in terms of the Mahalanobis distance,

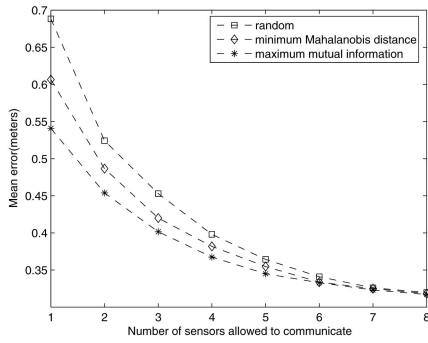


Fig. 7. Mean error comparison for the sparse scenario.

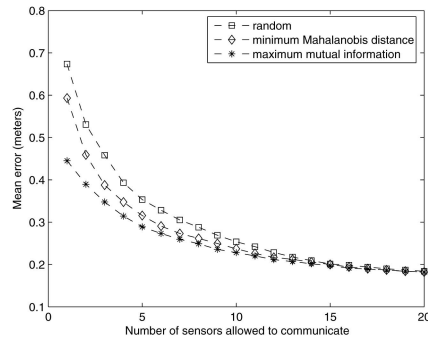


Fig. 8. Mean error comparison for the dense scenario.

which differs from the euclidian distance in a way that it takes into account the correlation in the uncertainty over the target position. Mahalanobis distance between the two random vectors, the observed target position  $\varphi_m(k)$  and the sensor position  $\mathbf{L}_S(k)$ , is defined as

$$D_M(\varphi_m(k), \mathbf{L}_S(k)) = \sqrt{(\varphi_m(k) - \mathbf{L}_S(k))^T \mathbf{P}_m(k)^{-1} (\varphi_m(k) - \mathbf{L}_S(k))},$$

where  $\mathbf{P}_m(k)$  is the covariance matrix of the sensor observations at time  $k$ . If  $\mathbf{P}_m(k)$  equals the identity matrix, then the euclidian and Mahalanobis distance measures are the same [45]. Figs. 7 and 8 show, for the sparse and dense scenarios, respectively, that as the maximum number of sensor nodes allowed to communicate increases, the mean error occurring throughout a 100-second scenario decreases for all three sensor selection algorithms. Target localization errors are calculated each second. For the cases studied with the sparse scenario, selecting sensor nodes which improve the global belief about the target position according to the mutual information measure results in average tracking quality improvements of 4.7 percent and 10.8 percent over the minimum Mahalanobis distance-based sensor selection and random selection, respectively. For the dense scenario of 800 sensors, these improvements with MISS, respectively, become 8.9 percent and 19.4 percent for the two selection strategies.

Fig. 9 depicts the total exhausted energy in the network for all three sensor selection algorithms for the sparse scenario. The consumed energy grows as the maximum number of sensor nodes that are allowed to communicate increases. This is a natural result of the increasing number of communication packets in the network. However, the sensor

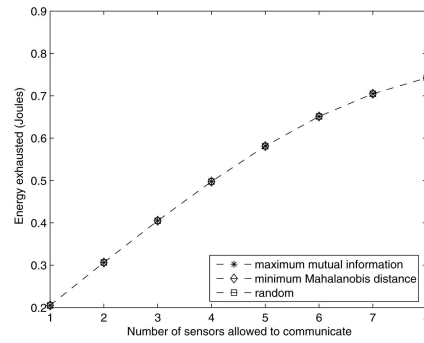


Fig. 9. Comparison of the consumed energy for the sparse scenario.

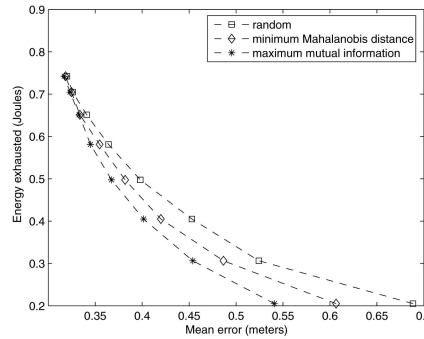


Fig. 10. Comparison of the consumed energy for the desired target localization accuracies for the sparse scenario.

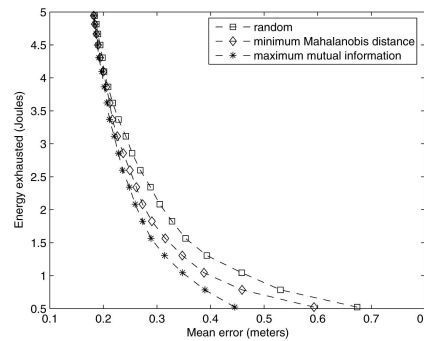


Fig. 11. Comparison of the consumed energy for the desired target localization accuracies for the dense scenario.

selection algorithm does not have any effect on the exhausted energy of the network. The same arguments are also valid for the dense scenario, However, due to the broadcast-based communication mechanism among the sensor nodes, incrementing the number of deployed sensor nodes results in a rise in the total consumed communication energy. The increase in the mean exhausted energy with the increment in the number of deployed sensor nodes is caused by the receivers of the sensor nodes. Broadcast messages are received by more sensor nodes in the dense scenario than in the sparse one.

For a given target tracking accuracy level, we examine the amount of conserved energy by selecting the sensor nodes to participate in the collaboration in an intelligent manner. If we select 0.4 meters as the target tracking accuracy level operating point, the energy savings attained can go up to 30 percent for the sparse scenario and 75 percent for the dense scenario. Figs. 10 and 11 depict the

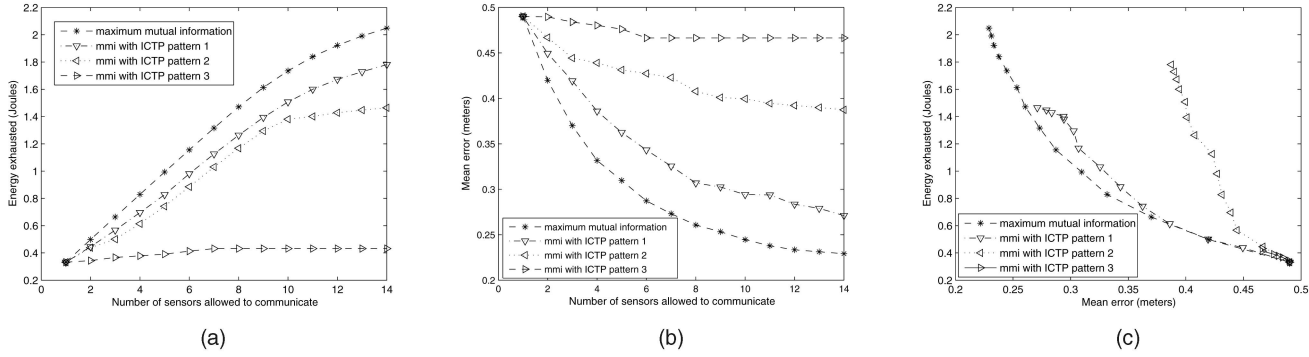


Fig. 12. Mean consumed communication energy and mean target localization error performances for different power adjustment patterns when any sensor node in the network can be queried. (a) Mean consumed communication energy. (b) Mean target localization error for different power adjustment patterns. (c) Effect of power adjustment on the consumed energy for the desired target localization accuracies.

energy savings for the given target tracking accuracies for the sparse and dense scenarios, respectively.

We test the performance of the proposed ICTP scheme according to three power adjustment patterns depicted in Fig. 5. Pattern 3 exhibits the steepest power reduction, while Pattern 1 has the softest slope. In Fig. 12a, we observe that the energy savings increase proportionally to the steepness in power reduction. On the other hand, Fig. 12b points out that the mean error increases as well with the steepness of the power adjustment pattern. Lines representing the maximum mutual information present the case in which no power adjustment is made. If we adjust the transmission powers of the sensor nodes according to Pattern 3, on average, we achieve 2.14 times less energy usage with respect to the case in which no transmission power adjustment is made (Fig. 12a). However, power adjustment, on average, doubles the target localization errors as observed from Fig. 12b. We conclude from Fig. 12c that the gain in terms of the exhausted communication energy does not compensate the increase in the target localization error. Hence, reducing the communication transmission power is not desirable. In Figs. 12a, 12b, and 12c, we measure the expected target localization error when the WSN responds to queries from any sensor node in the network. Another possibility is to query the MISN in the network, which is the one with the highest mutual

information about the target state. This querying scheme has the cost of locating the MISN and routing the target location information query and response packets to and from it. The cost of locating the most informative sensor node is negligible as described at the end of Section 4.

When the MISN is queried, as the power reduction pattern becomes steeper, the exhausted energy drops as shown in Fig. 13a, and the target localization error decreases as shown in Fig. 13b. The reason for this is that the less informative sensor nodes begin to harm the target localization performance of the more informative nodes with their marginal information. In Fig. 13c, we see that the power reduction Pattern 3 consumes the least amount of energy with ICTP. We observe the ceiling effect in the exhausted energy when the number of sensor nodes allowed to communicate reaches 14 (Fig. 13a). The reason of this ceiling effect lies behind the number of detecting sensor nodes. For the cases studied in the simulated scenario, the mean number of detecting sensor nodes is about 14. Even if we allow more than 14 nodes to communicate, the rest will not have detection information to share with the others. For the cases studied, the mean distance of the most informative sensor node to the target is 2.17 meters. This results in very accurate target localization if the MISN is queried. If the most informative sensor node

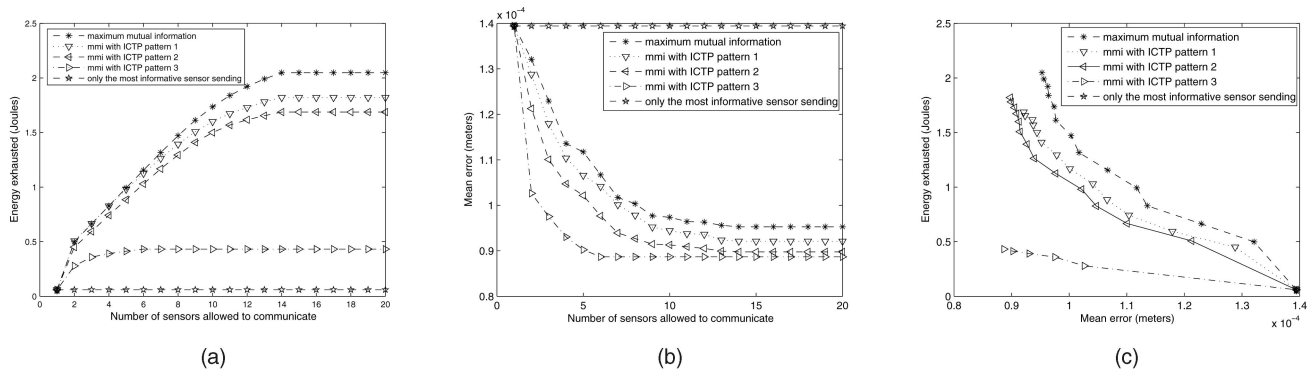


Fig. 13. Mean consumed communication energy and mean target localization error performances for different power adjustment patterns when the most informative sensor node in the network is queried. (a) Mean consumed communication energy. (b) Mean target localization error for different power adjustment patterns. (c) Effect of power adjustment on the consumed energy for the desired target localization accuracies.

is queried, operating at the minimum energy operation point is a rational decision. The minimum energy operation point is achieved only if the MISN shares its information with the neighboring nodes as shown in Fig. 13a. Transmission power adjustment according to Pattern 3 results in 2.11 times the energy savings on the average compared to having no power adjustment (Fig. 13a). On average, 23.7 percent improvement is achieved in the target localization as deduced from Fig. 13b. This happens due to the filtering of the information coming from the less informative sensor nodes that corrupt the information of the more informative sensor nodes. A 2.34-fold energy conservation is possible for a desired target tracking accuracy over the no power adjustment scheme as deduced from Fig. 13c.

We also examine the case where only the MISN broadcasts its data. Thus, other detecting sensor nodes do not transmit, and they consume energy just to process the incoming information signal from the most informative sensor node. The line with stars in Fig. 13a depicts the low energy exhausted by the sensor nodes if only the MISN broadcasts. However, the error of MISN is high as demonstrated with a line with stars in Fig. 13b, because the MISN changes in time as the target moves. Low level of collaboration results in the new most informative sensor node having low prior information about the target. The prior information obtained by means of collaboration causes the information filtering performance of the most informative sensor node to improve.

## 6 CONCLUSIONS

A mutual information-based measure is adopted to select the most informative subset of the sensor nodes to actively participate in the distributed data fusion framework, where the duty of the WSN is to accurately localize and track the targets. The DDF architecture takes advantage of the long communication range of the wireless sensor devices, relative to their sensing range, and facilitates a sensor node to update its belief about the current state of the target. With the detection reports from its neighbors, a belief update takes place even if the sensor is not detecting the target. The information obtained from the neighboring nodes about an approaching target before it is sensed reduces the target localization error by improving the target state filtering performance.

A new communication transmission power adjustment scheme is proposed to further improve the energy savings while preserving the tracking quality constraints. Sensor nodes adjust their transmission powers in proportion to their knowledge: those that know more about the target state should use more power to share their information. Tests indicate that the performance of the proposed power adjustment scheme depends on the network querying technique. If the application is delay-sensitive and needs an immediate response from the network, any sensor node in the WSN can respond right away to the query with an acceptable target localization error. If the application can tolerate some

delay and has strict target localization error constraints, querying just the MISN improves the target localization performance. The proposed Information-Controlled Transmission Power adjustment scheme improves the energy savings while preserving the desired target tracking accuracy when the most informative node is queried. However, querying any sensor node, while reducing the transmission powers of the less informative sensor nodes, ends up with drastically worse target tracking accuracies.

For the cases studied, simulation results show that 75 percent energy savings can be achieved for a given tracking quality by selecting the sensor nodes to cooperate according to the mutual information measure. Moreover, if the sensor network queries are to be routed to the MISN within one-hop distance of the query entry node, 2.34 times more energy savings compared to the no power adjustment scheme can be achievable by adjusting the communication transmission powers of the sensor nodes.

It is generally assumed that all sensor nodes send reliable data to the network. In the future work, the detection of faulty and outlier sensor nodes in the network, and possible precautions that can be taken against them, will be investigated. In addition, the presence of multiple targets brings along challenges with measurement-to-measurement association, measurement-to-track association, track-to-track association, and track-to-sensor association. In the multiple target case, sensor nodes would report only about the target which they were associated to. Hence, the communication transmission power can be adjusted according to the information about the target from which the sensor node is responsible for reporting.

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