INFORMATION CONTENT-BASED SENSOR SELECTION FOR COLLABORATIVE TARGET TRACKING

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ABSTRACT

An energy-efficient collaborative target tracking paradigm is developed for wireless sensor networks (WSNs). The network lifetime is prolonged by selecting a subset of sensors that are informative and provide non-redundant data so that a desired accuracy level is maintained. A distributed data fusion architecture provides the collaborative tracking framework. A mutual information-based sensor selection algorithm (MISS) is adopted for participation in the fusion process. MISS allows the most informative subset of the sensors to transmit data so that in the energy consumption is reduced while the desired accuracies of the target position estimation are preserved. Simulation results that demonstrate the performance improvement offered by the MISS algorithm are also furnished.

1. INTRODUCTION

Wireless sensor devices have two main functionalities. The first one is the distributed detection of the presence of a target and the estimation of the parameters of interest. The second task involves wireless networking to organize and carry information. Target tracking, in other words the processing of the measurements obtained from a target in order to maintain an estimate of its current state, has major importance in Command, Control, Communications, Computer, Intelligence, Surveillance and Reconnaissance (C4ISR) applications. Emerging wireless sensor technologies facilitate the tracking of targets just from within the phenomenon. Due to environmental perturbations, observations obtained close to the phenomenon are more reliable than observations obtained far from it. Wireless communication characteristics of the emerging wireless sensor nodes provide an excellent distributed coordination mechanism to improve the global target localization accuracies. However, there is an inherent energy constraint for wireless sensor devices. In order to conserve the valuable battery energy of wireless sensor devices, some of the sensors should go into a dormant state controlled by the sleep schedule [1]. Only a subset of the sensors are active at any instant of time. Otherwise, a bulk of redundant data would be wandering in the network.

Collaborative target tracking has inherent 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 quality, tracking quality, scalability, survivability, and resource usage [2].

There is a tradeoff between the energy expenditure and the tracking quality in sensor networks. Sensor activation strategies are the *naive activation* in which all the sensors are active, *randomized activation* in which a random subset of the sensors are active, *selective activation* in which a subset of the sensors are chosen according to some performance metric, and *duty-cycled activation* in which the sensors are active for some duty cycle and in dormant state thereafter.

Censoring sensors [3] is one approach to control the network traffic load. Sensors that are deemed as noninformative do not send their decisions or observations if their local likelihood ratio falls in a certain single interval. A deficiency with this approach occurs for collaborative tracking applications if all the sensor local likelihood ratios fall in the no-send region, and no belief about the target state is shared among the sensors.

Previous research [4] focuses 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 to a certain geographic area as binary, i.e., either it provides coverage, or it does not [1]. These approaches consider the sensor selection problem only in terms of coverage and energy saving aspects, without paying attention to the detection quality. In tracking applications, when selecting the subset of sensors to contribute to the global decision, we have to consider how informative the sensors are about the state of the target.

In information driven sensor querying [2], the so-called cluster heads decide on the sensors to participate actively in the tracking task. In [5], the sensor 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 output and the target state [5]. An entropy-based sensor selection heuristic is proposed for target localization in [6]. The heuristic in [6] selects one sensor in each step and the observation of the selected sensor is incorporated into the target location distribution using sequential Bayesian filtering.

We develop an energy-efficient collaborative target tracking paradigm for wireless sensor networks (WSNs). To that end, the network lifetime is prolonged by selecting a subset of sensors that are informative and that provide non-redundant data so that the desired tracking accuracy is maintained. In Section 2, we describe the distributed data fusion architecture. Then, in Section 3, the mutual information-based sensor selection algorithm (MISS) for participation in the fusion process is defined. Simulation results demonstrating the performance improvement offered by MISS are presented in Section 4. Finally, in Section 5, we conclude our work, and give some directions towards future research.

2. DATA PROCESSING ARCHITECTURE

In this section, we first define the process and observation models for target tracking. Then the foundations of the distributed data fusion architecture are presented.

2.1 Process and Observation Models

The target process is a four dimensional vector that consists of the two dimensional position of the target, (ξ, η), and the velocity of the target, $(\dot{\xi}, \dot{\eta})$, at each of these dimensions. The target process state vector is defined by

$$\mathbf{x} = [\xi \; \eta \; \dot{\xi} \; \dot{\eta}]^T, \tag{1}$$

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 process transition matrix, and $\mathbf{v}$ is the process transition noise.

Sensors can only observe the first two dimensions of the process. The velocity of the target is not observable by the sensors. Furthermore, sensors collect range and bearing data, but they cannot observe the coordinates of the target directly. Because sensors observe the target state 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* [7]. In [8], 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 (EKF), in which the nonlinear target state measurements are utilized without conversion [8]. The measured range and bearing are defined with respect to the true range r and bearing θ as

$$\begin{aligned} r_m &= r + \tilde{r}, \\ \theta_m &= \theta + \tilde{\theta}, \end{aligned}$$

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

$$E[\tilde{r}] = 0, \quad E[\tilde{\theta}] = 0, \quad E[\tilde{r}^2] = \sigma_r^2, \quad E[\tilde{\theta}^2] = \sigma_\theta^2.$$

The target mean state observed after the unbiased polar-to-Cartesian conversion is given by

$$\boldsymbol{\varphi} = \begin{bmatrix} \xi_m^c \\ \eta_m^c \end{bmatrix} = \begin{bmatrix} r_m \cos\theta_m \\ r_m \sin\theta_m \end{bmatrix} - \boldsymbol{\mu}$$

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

$$\boldsymbol{\mu} = \begin{bmatrix} r_m \cos\theta_m (e^{-\sigma_\theta^2} - e^{-\sigma_\theta^2/2}) \\ r_m \sin\theta_m (e^{-\sigma_\theta^2} - e^{-\sigma_\theta^2/2}) \end{bmatrix}.$$

The covariances of the observation errors in $\boldsymbol{\varphi}$ are given as [8]

$$\begin{aligned} R_{11} = r_m^2 e^{-2\sigma_\theta^2} [&\cos^2\theta_m(\cosh 2\sigma_\theta^2 - \cosh\sigma_\theta^2) \\ &+ \sin^2\theta_m(\sinh 2\sigma_\theta^2 - \sinh\sigma_\theta^2)] \\ + \sigma_r^2 e^{-2\sigma_\theta^2} [&\cos^2\theta_m(2\cosh 2\sigma_\theta^2 - \cosh\sigma_\theta^2) \\ &+ \sin^2\theta_m(2\sinh 2\sigma_\theta^2 - \sinh\sigma_\theta^2)], \\ R_{22} = r_m^2 e^{-2\sigma_\theta^2} [&\sin^2\theta_m(\cosh 2\sigma_\theta^2 - \cosh\sigma_\theta^2) \\ &+ \cos^2\theta_m(\sinh 2\sigma_\theta^2 - \sinh\sigma_\theta^2)] \\ + \sigma_r^2 e^{-2\sigma_\theta^2} [&\sin^2\theta_m(2\cosh 2\sigma_\theta^2 - \cosh\sigma_\theta^2) \\ &+ \cos^2\theta_m(2\sinh 2\sigma_\theta^2 - \sinh\sigma_\theta^2)], \\ R_{12} = R_{21} = \sin\theta_m \cos\theta_m\, &e^{-4\sigma_\theta^2} [\sigma_r^2 + (r_m^2 + \sigma_r^2)(1 - e^{\sigma_\theta^2})]. \end{aligned}$$

2.2 Distributed Data Fusion Architecture

Information state $\mathbf{y}$ and the information matrix $\mathbf{Y}$ associated with an observation estimate $\hat{\mathbf{x}}$, and the covariance of the observation estimate $\mathbf{P}$ at time instant k are given by [9]

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

In [9], it is shown that by means of sufficient statistics, an observation $\boldsymbol{\varphi}$ contributes $\mathbf{i}(k)$ to the information state $\mathbf{y}$ and $\mathbf{I}(k)$ to the information matrix $\mathbf{Y}$ where

$$\begin{aligned} \mathbf{i}(k) &= \mathbf{H}^T \mathbf{R}^{-1}(k)\boldsymbol{\varphi}(k), \\ \mathbf{I}(k) &= \mathbf{H}^T \mathbf{R}^{-1}(k)\mathbf{H}, \end{aligned} \tag{2}$$

$\mathbf{H}$ is the observation matrix of the sensor and

$$\mathbf{R} = \begin{bmatrix} R_{11} & R_{12} \\ R_{21} & R_{22} \end{bmatrix}.$$

Instead of sharing the measurements related to the target state among the collaborating sensors, 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. The distributed data fusion equations are

$$\hat{\mathbf{y}}(k \mid k) = \hat{\mathbf{y}}(k \mid k-1) + \sum_{i=1}^{N} \mathbf{i}_i(k), \tag{3}$$

$$\mathbf{Y}(k \mid k) = \mathbf{Y}(k \mid k-1) + \sum_{i=1}^{N} \mathbf{I}_i(k) \tag{4}$$

where N is the total number of sensors participating in the fusion process and $\hat{\mathbf{y}}(k \mid k-1)$ represents the information state estimate at time k given the observations up to and including time $k-1$.

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

$$\begin{aligned} \hat{\mathbf{y}}(k \mid k-1) &= \mathbf{Y}(k \mid k-1)\mathbf{F}\mathbf{Y}^{-1}(k-1 \mid k-1)\hat{\mathbf{y}}(k-1 \mid k-1), \\ \mathbf{Y}(k \mid k-1) &= [\mathbf{F}\mathbf{Y}^{-1}(k-1 \mid k-1)\mathbf{F}^T + \mathbf{Q}]^{-1} \end{aligned} \tag{5}$$

where $\mathbf{Q}$ is the state transition covariance.

State estimate of the target at any time k can be found from

$$\hat{\mathbf{x}}(k \mid k) = \mathbf{Y}^{-1}(k \mid k)\hat{\mathbf{y}}(k \mid k). \tag{6}$$

3. MAXIMUM MUTUAL INFORMATION-BASED SENSOR SELECTION ALGORITHM

Mutual information measures how much information one random variable tells about another one. In target localization and tracking applications, the random variables of interest are the target state and the observation obtained about the target state. By measuring 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 algorithm employed by a sensor for tracking targets in a collaborative manner within the distributed data fusion framework is depicted in Fig. 1. The information state and the information matrix denominations associated with the current observation are defined by (2). The predicted information state and the information matrix are computed by (5). The sensor's current belief is updated by its own sensory observation according to

$$\hat{\mathbf{y}}(k \mid k) = \hat{\mathbf{y}}(k \mid k-1) + \mathbf{i}(k), \tag{7}$$

$$\mathbf{Y}(k \mid k) = \mathbf{Y}(k \mid k-1) + \mathbf{I}(k). \tag{8}$$

Active participation in the current cycle is decided based on the mutual information gained with the last observation. This event can be formulated as

$$J(k, \boldsymbol{\varphi}(k)) = \frac{1}{2} \log \left[\frac{|\mathbf{Y}(k \mid k)|}{|\mathbf{Y}(k \mid k-1)|} \right], \tag{9}$$

where $\mathbf{Y}(k \mid k)$ is the information matrix at the time instant k after the target state is observed. If the mutual information gain J

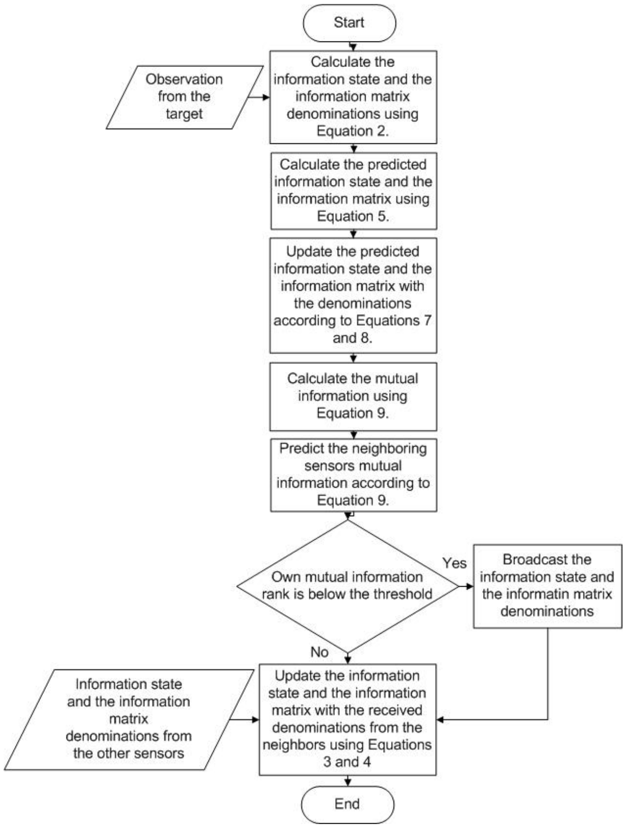


Figure 1: Target tracking algorithm employed by each sensor.

of the sensor is sufficiently high to participate in the current cycle, the sensor shares its own information about the target state with the neighboring nodes. Otherwise, the sensor does not transmit during the current cycle. In (9), $\mathbf{Y}(k \mid k-1)$ denotes the predicted information matrix at the time instant k, given the observations up to the time instant $k-1$. Thus, the sensor has an estimate about the target state information that it will have at time instant k, before the observation of the target state at time instant k.

The mutual information in (9) measures the improvement in the target state estimate achieved with the observation. To decide if the mutual information is adequately high to participate in the current cycle, a sensor needs to know the mutual information values of its neighboring sensors. This information is hard to predict ahead of time. To tackle this problem, we design each sensor to hold a list of its neighboring sensors. The elements of this list are the sensor characteristics such as the standard deviation of the target range observations, standard deviation of the target bearing observations, and the communication transmission power. Knowing the communication signal's transmission power of the neighboring sensor, the relative position of the neighboring sensor can be estimated from the received signal strength [10]. The position estimation is accomplished in a sliding window average of the last Ω communications received from the neighboring sensor. With the sensors' own observation about the target state, the $\mathbf{Y}(k \mid k)$ value of the neighboring sensor can be estimated using the sensor characteristics and the position information.

Given the estimate of the cooperated information matrix $\mathbf{Y}(k \mid k-1)$, the mutual information J for the neighboring sensors is estimated via (9). All the neighboring sensors and the sensor itself are sorted according to the decreasing mutual information order. If the sensor detects the target, and the rank of its mutual information is lower than the maximum allowed number of sensors to communicate, then the sensor broadcasts its information state and the information matrix denominations to the network. The current belief is updated with the received information from the sensors in the vicinity according to (3) and (4). A current state estimate for the target can be found from (6).

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 transmission power	-30 dB

4. SIMULATION RESULTS

We run Monte Carlo simulations to examine the performance of MISS, which is based on the maximization of mutual information for the distributed data fusion architecture. We examine two scenarios: first is the sparser one, which consists of 300 sensors which are randomly deployed in a 200 m $\times$ 200 m area. The second is a denser scenario in which 800 sensors are deployed in the same area. All data points in the graphs represent the means of twenty runs. A target moves in the area according to the process model described in Section 2.1. We adopt the TWR-ISM-002-I radar [11] with pseudo-random signaling, whose typical range is 18 meters. As in [8] we assume constant range and bearing standard deviations $\sigma_r = 0.1$ m and $\sigma_\theta = 1^o$, respectively.

The sensor tracks the target locally using the information form of the Kalman filter as described in Section 2.2. If the sensor does not detect a target, it updates its belief about the target state just by setting the Kalman filter gain to zero, which means that the sensor tracks the target according to the track history.

In collaborative information fusion, if a sensor is eligible to share its belief about the target state with other sensors, it broadcasts its information state and the information matrix. Sensors update their belief about the target state with these received data as described in Section 2.2.

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 [12]. The sensor network has two modes of operations, namely the searching mode and the tracking mode. After detecting a target in the vicinity, a sensor goes into the tracking mode and warns the neighboring sensors to do likewise. Moreover, any sensor detecting a target or receiving a tracking mode alert from a neighboring sensor goes into tracking mode and warns the other neighboring sensors to go into the tracking mode, as well. 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 receiver and sensing circuit are active 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 2.2. We achieve the maximum tracking accuracy when all sensors detecting the target participate in the distributed data fusion task. As the number of sensors allowed to participate in the fusion task is reduced, the tracking quality deteriorates. This yields higher localization errors about the distributed target position estimations. However, a reduced number of sensors allowed to communicate yields a lower number of communication packets traveling in the network. Reduction in the number of sent packets affects the energy expenditure of the wireless sensor devices directly. Selecting the sensors to actively participate in the fusion task in an intelligent manner improves tracking quality while allowing the same number of sensors to communicate. Fig. 2 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 that is marked as a solid dot at the grid point (140,48).

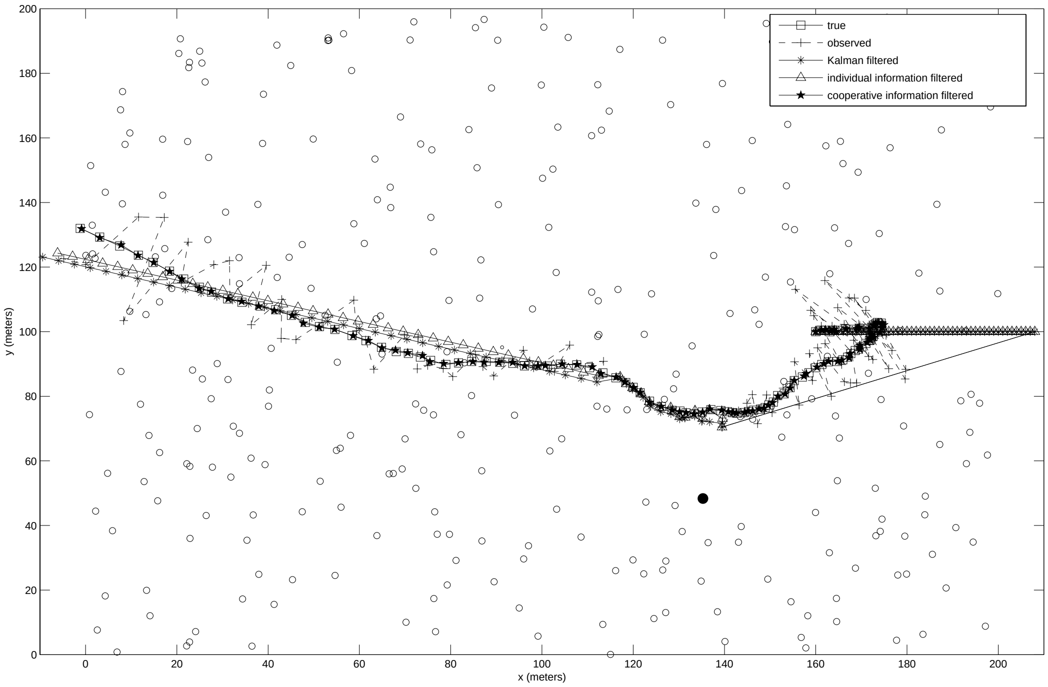


Figure 2: Viewpoint of the sensor represented with a solid dot (•) in 300-sensor scenario.

As the target moves away from the sensor, the observation errors for the sensor increase. Kalman or information-filtering reduces the observation errors. However, at some target maneuver points, if the sensor cannot detect the target, the sensor tracks the target position resorting to only the target history. In other words, the Kalman gain is set to zero if the sensor cannot detect the target. This results with the linear erroneous tracking of the target until a detection from the target is achieved. Poor detection performance of the sensor results in the missed target maneuvers by the sensor. With the aid of collaboration amongst the sensors, these target maneuver misses are avoided.

While estimating the positions of the neighboring sensors, the parameter that defines the window size of the received signals is set to $\Omega = 8$ in order to reduce the uncertainties introduced with the shadow fading. We track the target for one hundred seconds in the simulations.

Selecting the participating active sensors in collaborative tracking randomly means that a sensor detecting the target broadcasts its information immediately if the maximum number of sensors to participate has not yet been reached. This can be decided by counting the number of target position announcements received from the neighboring sensors. The minimum Mahalanobis distance-based sensor selection algorithm selects the closest sensors to the target location in terms of the Mahalanobis distance, which is used to determine the proximity. The Mahalanobis distance differs from the Euclidian distance in a way that it takes into account the correlations of the data. If the covariance matrix is the identity matrix, then the Mahalanobis distance is the same as the Euclidian distance. Figures 3.a and 4.a show, for the sparse and dense scenarios respectively, that as the maximum number of sensors allowed to communicate increase, the mean error occurring throughout a hundred 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 sensors which improve the global belief about the target position according to the mutual information measure results in an average of 10.8% improvement in tracking quality with respect to random sensor selection. A tracking quality improvement of 4.7% is achieved over the minimum Mahalanobis distance-based sensor selection for the sparse scenario. For the dense scenario of 800 sensors, these improvements with MISS become 19.4% and 8.9% compared to the random and the Mahalanobis distance-based algorithms, respectively.

During the 100-second run, Figures 3.b and 4.b depict the total exhausted energy in the network for all three sensor selection algorithms for the sparse and the dense scenario, respectively. Consumed energy grows as the maximum number of sensors that are allowed to communicate increases. This is a natural result of the increasing number of communication packets in the network. However, the sensor selection algorithm does not have any effect on the exhausted energy of the network. Due to the broadcast-based communication mechanism among the sensors, incrementing the number of deployed sensors results in a rise in the total consumed communication energy.

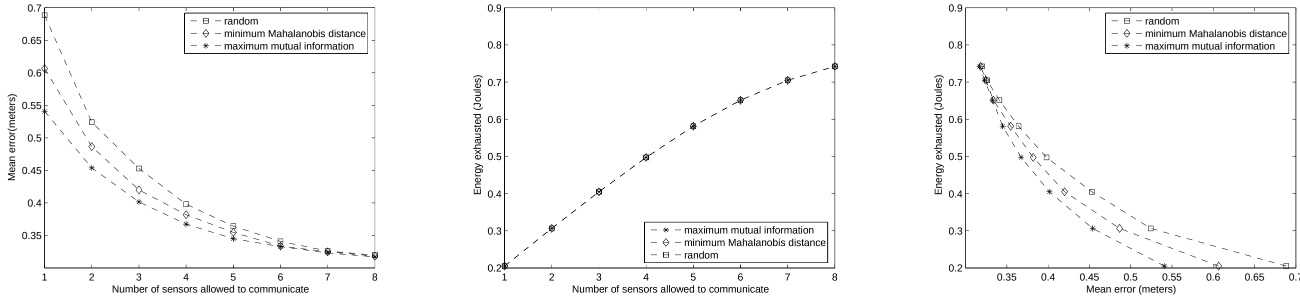
Finally, for a given target tracking accuracy level, we examine the amount of conserved energy by selecting the sensors to participate in the collaboration in an intelligent manner . If we select 0.4 meters as the target tracking accuracy level operating point, the energy savings attained can go up to 30% for the sparse scenario and 75% for the dense scenario. Figures 3.c and 4.c depict the energy savings for the given target tracking accuracies for the sparse and the dense scenarios, respectively.

5. CONCLUSION

A mutual information based information measure is adopted to select the most informative subset of the sensors to actively participate in the distributed data fusion framework, where the duty of the sensor nodes is to accurately localize and track the targets.

For the cases studied, simulation results show that 75% energy savings for a given tracking quality can be achieved by selecting the sensors to cooperate according to the mutual information measure.

In our tests, it is assumed that all sensor nodes send reliable data to the network. In our future work, detection of the faulty and the outlier sensors in the network, and precautions need to be taken against them will be investigated. We consider the effect of the sensor selection algorithms in the context of distributed data fusion for tracking a single target. Existence of multiple targets

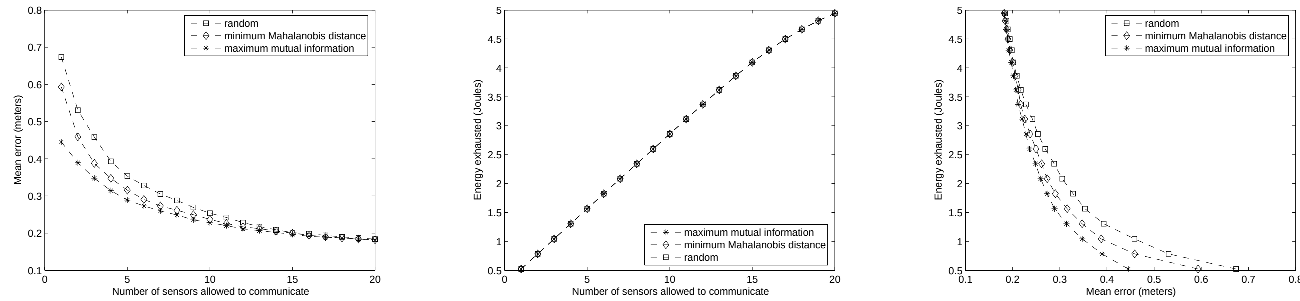


a) Mean error comparison.

b) Comparison of the total consumed energy.

c) Comparison of the consumed energy for the desired target localization accuracies.

Figure 3: Sparse scenario.



a) Mean error comparison.

b) Comparison of the total consumed energy.

c) Comparison of the consumed energy for the desired target localization accuracies.

Figure 4: Dense scenario.

brings along challenges with measurement-to-measurement association, measurement-to-track association track-to-track association and track-to-sensor association.

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