Energy-Aware, Collaborative Tracking with Ad-Hoc Wireless Sensor Networks

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***Abstract*— An energy aware, collaborative tracking algorithm is proposed for ad-hoc wireless sensor networks consisting of randomly distributed low-end sensors and a high-end data gathering node which is assumed to be located at the center of each cluster. The collaborative tracking algorithm is implemented distributively by passing sensing and computation operations from one cluster to another based on an energy-based cost function that attempts to maximize the whole network lifetime. The performance of the proposed collaborative algorithm is evaluated in terms of both tracking error and energy consumption of the whole network. Simulation based performance results for both single and multiple simultaneously active sensors have also been presented.**

I. Introduction

An ad-hoc wireless sensor network consists of a set of randomly distributed sensors that communicate with each other over a radio link. In this paper, we focus on such an ad-hoc wireless sensor network deployed for collaborative target tracking. The sensors in this network are assumed to have finite sensing radii and hence the network can conveniently be divided into multiple *clusters*. An *active cluster* in such a network is defined as one in which a moving target of interest is currently present. For simplicity, the moving target is assumed to be on the same plane on which the sensors are located and only an *active sensor* is expected to detect and track the target. All other sensors will be in an idle mode so as to save the energy.

Most often sensor nodes in an ad-hoc wireless sensor network are battery driven. Energy consumption is possibly the most important performance metrics for wireless ad-hoc sensor networks since it determines the operational lifetime of the network. An important design choice for achieving energy efficiency in multisensor networks is the collaborative signal and information processing (CSIP); i.e, how to dynamically determine who should sense the target, what should be sensed, who should be the next leader and who should perform the collaborative tracking [1]. Thus, power management is one of the most challenging problems in such networks [2]–[4]. These energy constraints impact both hardware operations and signal transmissions associated with node operation [5]. Thus design of energy-aware collaborative signal processing algorithms is important in order to maximize the lifetime of such sensor networks [6].

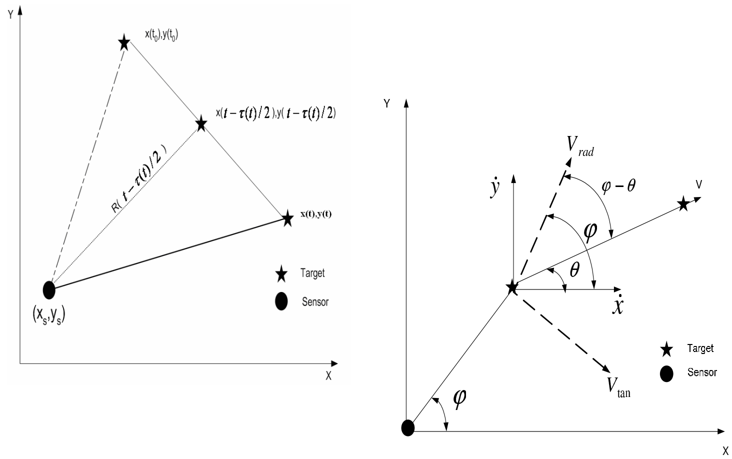
In this paper, a collaborative tracking algorithm is developed for such a wireless ad-hoc sensor network consisting of randomly distributed low-end sensors. Every cluster of sensors is assumed to have a high-end sensor that acts as a data gathering node and communicate with all the sensors in its cluster to collect observations from them. Only this data gathering node is able to communicate with a base station and other data gathering nodes in the network. The proposed distributed collaborative algorithm is based on the total energy consumption of the sensor network, in which the active sensors at each time instant are chosen by a data gathering node in order to minimize the total energy spent by the network. The data gathering node decides the next set of active sensors based on a cost function calculated by taking into account energy requirements for both communication and sensing.

The remainder of this paper is organized as follows: In Section II the system model is presented. In Section III the basic distributed tracking algorithm based on the Kalman filter is presented. Next, in Section IV the energy-aware, collaborative algorithm for active sensor determination is described. In Section V sensing and communication energy computation is performed. Simulation results for target tracking with single and multiple active sensors and energy consumption comparison of the network are presented in Section VI. Finally concluding remarks are given in Section VII.

II. System Model

We model the ad-hoc wireless sensor network as a combination of randomly distributed low-end sensors who sense a moving target and pass information to a high-end sensor which acts as a data gathering node. The entire network is divided into N_c clusters each having N_s data collection low-end sensors. Hence the total number of sensors in the network is $N = (N_c \times N_s) + N_c$, where the last term represents the high-end sensors located at the center of each cluster.

Protocol design to implement energy-aware collaborative tracking algorithm is done in such a way that when a target enters a particular cluster, it becomes the active cluster for that moment and the data gathering node in that cluster becomes the *leader sensor*. We assume that data gathering nodes are not energy constrained and thus data gathering nodes in all the clusters will be in active mode. In each cluster periodically a small set of low-end sensors will be chosen randomly to be in a sleep-awake mode. In this mode these sensors will turn on for a short interval of time and check the presence of a target. If a sensor detects a target, then it sends the



(a) (b)

Fig. 1. (a) The Orientation of an Active Sensor and the Target for Computing Delay and Doppler. (b) Velocity Components of the Target.

observations to the data gathering node and the data gathering node starts the collaborative tracking algorithm. If there is no target, the sensors will go back to sleep mode. The scheduling is performed in such a way that, each sensor's on-time is significantly less than the sleep-time. During the short on-time, each sensor will await for any notification from the data gathering node regarding a current active sensor in the network. If it does not receive any such notice, then it will go back to scheduled sleep. Note that, this small number of randomly chosen active sensors in each cluster ensures the detection of a new target that enters the area covered by the sensor network. Moreover, it is assumed that there is a wake-up channel that can be used by the data gathering node to awaken the next active sensor (or multiple active sensors) to sense the target during the collaborative tracking process. The data gathering node will allow the current active sensor (or sensors) to go to sleep only after confirming the received data from the next active sensor. Such wake-up channel and sensor modules consisting of very low-power tone-based wake-up modules have been previously considered in, for example [7]. In the absence of a wake-up channel, the data gathering node will have to wait until the required next active sensor becomes awake. Effectively, active sensors are chosen in such a way that they are nearer to the target so that the sensing cost is minimized and they are also nearer to the data gathering node in order to minimize the communication cost. When the target leaves the current active cluster and enters the next cluster the leadership is passed from the current data gathering node to the data gathering node in the next active cluster. Special case of multiple active sensor scenario, when one active low-end sensor is in the neighboring cluster and other active low-end sensor are in current active cluster, the leadership will not be changed to the next cluster until most of the active low-end sensors are in the next cluster.

Similar, collaborative target tracking schemes for wireless sensor networks have been considered previously, for example, in [1], [8]–[10]. In [8], the target is assumed to move in a straight line, whereas in this paper we model the target movement using a linear dynamical system. Moreover, extended Kalman filter is used as the tracking algorithm in [9], while here we use the Kalman filter for a linear system (after linearizing the system model). The target location estimate in [8] was based on a simple centroid computation. Also, [10] considered the same model but with only a single cluster and a single active sensor at each time. In this paper, however, multiple clusters with multiple active sensors are considered and a method for computing energies for sensing and communication are also presented.

A. Target Movement Model

We assume that the target movement can be modeled by a discrete-time, linear, dynamical system perturbed by additive noise. Let $\mathbf{x}(t-\frac{\tau(t)}{2})$ be the state of the target at time t which consists of the position and velocity (i.e, $\mathbf{x}(t-\frac{\tau(t)}{2}) = [x(t-\frac{\tau(t)}{2}), y(t-\frac{\tau(t)}{2}), \dot{x}(t-\frac{\tau(t)}{2}), \dot{y}(t-\frac{\tau(t)}{2})]^T$) where superscript T denotes the transpose and $\tau(t)$ is the round trip delay of the transmitted signal between the sensor and the target. We can then model the target movement as,

$$\mathbf{x}\left(t-\frac{\tau(t)}{2}+T\right) = \mathbf{Ax}\left(t-\frac{\tau(t)}{2}\right) + \mathbf{u}\left(t-\frac{\tau(t)}{2}\right), \quad (1)$$

where $\mathbf{u}\left(t-\frac{\tau(t)}{2}\right)$ is the state noise which is assumed to be zero-mean with covariance matrix $\mathbf{Q}$, T is the sampling time and the system matrix $\mathbf{A}$ is given by,

$$\mathbf{A} = \begin{bmatrix} 1 & 0 & T & 0 \\ 0 & 1 & 0 & T \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}. \quad (2)$$

Note that, while for simplicity we only consider the target location and velocity as the state of the system, it is easy to incorporate target acceleration in order to obtain a better system model. Suppose that a signal $E(t)$ is transmitted by a particular sensor at time t. The received signal reflected from the target is given by,

$$s_r(t) \quad = \quad \Re(A_r E(t-\tau(t))e^{j\omega_c(t-\tau(t))}), \qquad (3)$$

where $A_r = \sqrt{2P_r}$ and (P_r includes the transmit power and the two-way propagation and reflection processes [11]) ω_c is the carrier frequency. Note that $\Re(\cdot)$ denotes the real part of a complex number.

The delay $\tau(t)$ is given by,

$$\tau(t) = \tau_0 - \frac{2v_{rad}}{c}t, \qquad (4)$$

where τ_0 is a reference delay and v_{rad} is the radial velocity of the target. Substituting (4) in (3) we get

$$s_r(t) = \Re\left(A_r E\left(t-\tau_0+\frac{2v_{rad}}{c}t\right)e^{j\omega_c(t-\tau_0+\frac{2v_{rad}}{c}t)}\right). \quad (5)$$

From (5), we note that the doppler frequency shift f_D of the received signal is,

$$f_D = \frac{2f_c}{c}v_{rad}. \qquad (6)$$

Referring to Fig. 1(a), the time delay $\tau(t)$ can be written as,

$$\tau(t) = \frac{2}{c}\sqrt{\left(x\left(t-\frac{\tau(t)}{2}\right)-x_s\right)^2+\left(y\left(t-\frac{\tau(t)}{2}\right)-y_s\right)^2},$$

where (x_s, y_s) represents the location of the active sensor.

Linearizing the above equation around (x_{t-1}, y_{t-1}), where (x_{t-1}, y_{t-1}) is the previous location of the target, we have

$$\tau(t) = \frac{2}{c}\left[\left(\frac{x_{t-1}-x_s}{R_{t-1}}\right)x\left(t-\frac{\tau(t)}{2}\right)+\left(\frac{y_{t-1}-y_s}{R_{t-1}}\right)y\left(t-\frac{\tau(t)}{2}\right)\right].$$

Suppose that the target is moving with a total velocity v as shown in Fig. 1(b). Then, the radial component of the velocity is given by,

$$v_{rad} = \dot{x}\left(t-\frac{\tau(t)}{2}\right)\cos(\varphi)+\dot{y}\left(t-\frac{\tau(t)}{2}\right)\sin(\varphi), \qquad (7)$$

where angle φ represents the orientation of the line connecting the target and the sensor.

Substituting (7) in (6) we have that,

$$f_D(t) = \frac{2f_c}{c}\left[\dot{x}\left(t-\frac{\tau(t)}{2}\right)\cos(\varphi)+\dot{y}\left(t-\frac{\tau(t)}{2}\right)\sin(\varphi)\right].$$

B. Observation Model with a Single Active Sensor

Observation vector for a single active sensor is given by,

$$\begin{aligned}\mathbf{y}\left(t-\frac{\tau(t)}{2}\right) &= \begin{bmatrix}\tau(t)\\ f_D(t)\end{bmatrix}\\ &= \mathbf{C}\mathbf{x}\left(t-\frac{\tau(t)}{2}\right)+\mathbf{v}\left(t-\frac{\tau(t)}{2}\right),\end{aligned}$$

where $\mathbf{v}\left(t-\frac{\tau(t)}{2}\right)$ is a vector of zero-mean, Gaussian random disturbance with a covariance matrix $\mathbf{R}$ and $\mathbf{C}$ is the observation matrix defined as,

$$\mathbf{C} = \begin{bmatrix}\frac{2}{c}\left[\frac{x(t_{-1})-x_s}{R(t_{-1})}\right] & \frac{2}{c}\left[\frac{y(t_{-1})-y_s}{R(t_{-1})}\right] & 0 & 0\\ 0 & 0 & \frac{2f_c}{c}\cos(\varphi) & \frac{2f_c}{c}\sin(\varphi)\end{bmatrix}.$$

C. Observation Model with Multiple Active Sensors

The observation vector with M active sensors can be written as,

$$\begin{aligned}\mathbf{y}\left(t-\frac{\tau(t)}{2}\right) &= \begin{bmatrix}\tau(t)_1\\ f_D(t)_1\\ \vdots\\ \tau(t)_m\\ f_D(t)_m\end{bmatrix}\\ &= \tilde{\mathbf{C}}\mathbf{x}\left(t-\frac{\tau(t)}{2}\right)+\tilde{\mathbf{v}}\left(t-\frac{\tau(t)}{2}\right),\end{aligned}$$

where $\tau(t)_m$ and $f_D(t)_m$ are the time delay and Doppler measurements by the m-th active sensor and $\tilde{\mathbf{C}}$ is the augmented observation matrix defined as,

$$\tilde{\mathbf{C}} = \begin{bmatrix}\frac{2}{c}\left[\frac{x(t_{-1})-x_{s_1}}{R(t_{-1})}\right] & \frac{2}{c}\left[\frac{y(t_{-1})-y_{s_1}}{R(t_{-1})}\right] & 0 & 0\\ 0 & 0 & \frac{2f_c}{c}\cos(\varphi) & \frac{2f_c}{c}\sin(\varphi)\\ \vdots & \vdots & \vdots & \vdots\\ \vdots & \vdots & \vdots & \vdots\\ \frac{2}{c}\left[\frac{x(t_{-1})-x_{s_m}}{R(t_{-1})}\right] & \frac{2}{c}\left[\frac{y(t_{-1})-y_{s_m}}{R(t_{-1})}\right] & 0 & 0\\ 0 & 0 & \frac{2f_c}{c}\cos(\varphi) & \frac{2f_c}{c}\sin(\varphi)\end{bmatrix}.$$

The new observation noise vector $\tilde{\mathbf{v}}\left(t-\frac{\tau(t)}{2}\right)$ is assumed to be zero-mean, Gaussian with covariance matrix $\tilde{\mathbf{R}}$.

III. Tracking Algorithm for Sensor Networks

In this section, we develop a distributed tracking algorithm based on the Kalman filter [12], [13] which recursively updates the estimate of the state vector by processing successive measurements. It should be noted that this Kalman filter is implemented distributively in that as active cluster changes the Kalman filter computation changes from one data gathering node to another. Also, the observation that forms the vector $\underline{\mathbf{y}}(\cdot)$ comes from different sensing nodes depending on which sensors are active. When the leadership is passed from one cluster to another cluster, the Kalman filter at the next leader sensor is initialized with the predicted state obtained from the previous leader sensor.

The predicted state and its corresponding error covariance matrix, denoted by $\hat{\mathbf{x}}(t+1|t)$ and $\mathbf{P}(t+1|t)$, respectively are given by,

$$\begin{aligned}\hat{\mathbf{x}}(t+1|t) &= \mathbf{A}\hat{\mathbf{x}}(t|t), &(8)\\ \mathbf{P}(t+1|t) &= \mathbf{A}\mathbf{P}(t|t)\mathbf{A}^T+\mathbf{Q}. &(9)\end{aligned}$$

where $\hat{\mathbf{x}}(t|t)$ is the filtered state estimate at time t. The filtered estimate $\hat{\mathbf{x}}(t+1|t+1)$ is given by

$$\begin{aligned}\hat{\mathbf{x}}(t+1|t+1) = {} & \hat{\mathbf{x}}(t+1|t) + \qquad (10)\\ & \mathbf{K}(t+1)\left(\mathbf{y}(t+1)-\tilde{\mathbf{C}}(t+1)\hat{\mathbf{x}}(t+1|t)\right).\end{aligned}$$

where the Kalman gain $K(t)$ is defined as

$$\begin{aligned}\mathbf{K}(t+1) = {} & \mathbf{P}(t+1|t)\tilde{\mathbf{C}}^{\mathbf{T}}(t+1) \qquad (11)\\ & (\tilde{\mathbf{C}}(t+1)\mathbf{P}(t+1|t)\tilde{\mathbf{C}}^{\mathbf{T}}(t+1)+\tilde{\mathbf{R}})^{-1}.\end{aligned}$$

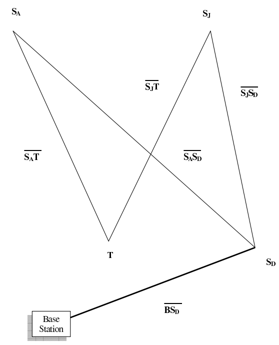


Fig. 2. Geometric Arrangement of Sensors with Respect to Target, Data Gathering Node and the Base Station

The corresponding filtered error covariance matrix is,

$$\mathbf{P}(t+1|t+1) = \mathbf{P}(t+1|t) - \mathbf{K}(t+1)\tilde{\mathbf{C}}(t+1)\mathbf{P}(t+1|t). \quad (12)$$

IV. Energy-based Multisensor Collaboration

In this section we develop the proposed energy-based collaborative tracking algorithm for a wireless ad-hoc sensor network model described in Section II above. We assume that the sensing cost depends on the distance between the sensor and the target, i.e, larger the distance to the target, more energy is required for a reliable sensor measurement. Let P_s be the sensor transmit power. The sensor received power can be written as,

$$P_L = \frac{P_s\ r}{|\overline{S_AT}|^{2\beta}}, \quad (13)$$

where $|\overline{S_AT}|$ is the distance between the active sensor S_A and the target T as shown in Fig. 2, r is the reflection coefficient and β is an attenuation exponent. From (13), the required transmit power for sensing is given by

$$P_s = \frac{P_L|\overline{S_AT}|^{2\beta}}{r}. \quad (14)$$

The communication cost is assumed to depend on the distance between the sensor and the data gathering node, i.e, larger the distance between them, more energy will be needed for reliable communication. Let P_c be the transmit power by an active sensor S_A communicating with the data gathering node S_D. The received power at data gathering node S_D is given by,

$$P_D = \frac{P_c}{|\overline{S_AS_D}|^{\alpha}}, \quad (15)$$

where $|\overline{S_AS_D}|$ is the distance between S_A and S_D and α is an attenuation factor. From (15), the required transmit power for communication is,

$$P_c = P_D|\overline{S_AS_D}|^{\alpha}. \quad (16)$$

The data gathering node chooses the set of active sensors at each time instant t so that the total energy spent by the whole network is minimized.

Let $\mathcal{S}$ be the set of indices of all the sensors in the active cluster and $\mathcal{A}$ be the set of indices of the current active sensors. Then the energy-based active sensor selection algorithm can be written compactly as:

```
Initialization: 𝒜 = φ
for i ∈ 𝒮
     C_T(i) = (P_L/r)|S_iT|^{2β} + P_d|S_DS_i|^α
end,
C̃_T = sort (C_T),
for  m = 1 : M
     𝒜 = 𝒜 ∪ C̃_T(m)
end,
```

where $\cup$ denotes the union of sets and ϕ is the empty set.

The total energy cost incurred by the whole network, $C_{T,M}$, at each time instant is then given by,

$$C_{T,M} = \sum_{m\in\mathcal{A}} \left(\frac{P_L}{r}|\overline{S_mT}|^{2\beta} + P_D|\overline{S_mS_D}|^{\alpha} \right). \quad (17)$$

V. Energy Computation for Sensing Cost and Communication Cost

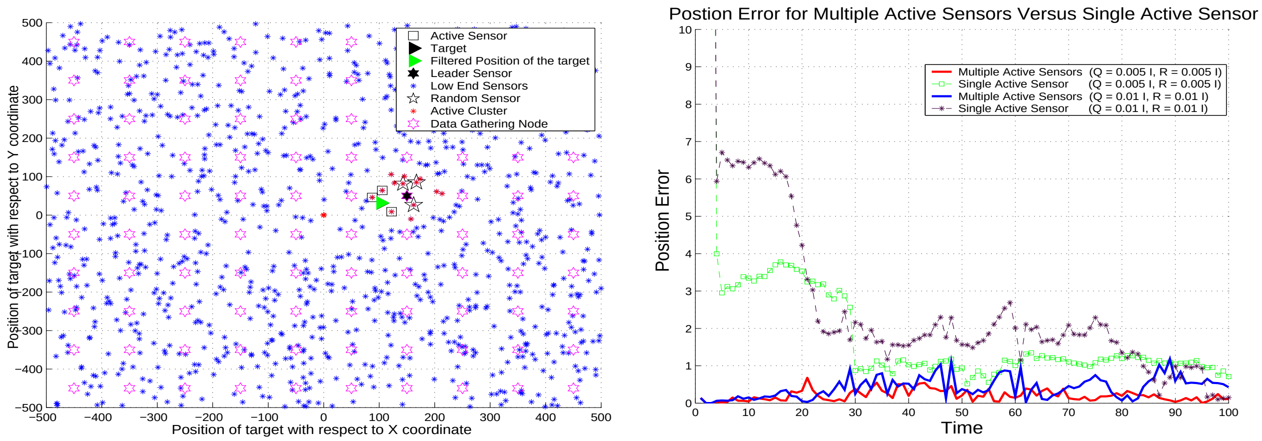
Here, we develop a model for computing the sensing energy expenditure based on a commercial Doppler radar speed sensor, which can see a large target up to approximately 300 meters with an effective radiated power of $P_s = 0.98\ W \approx 1\ W$ [14]. The sensor measures the speed of the target by transmitting a signal at a fixed frequency and observing the shift in frequency of the received reflected signal (Doppler shift).

Based on the above model an approximation to the constant P_L is given by,

$$P_L = \frac{r}{(300)^{2\beta}}. \quad (18)$$

Substituting (18) in (14) we have,

$$P_s = \left(\frac{|\overline{S_AT}|}{300} \right)^{2\beta}.$$



(a) (b)

Fig. 3. (a) A Snapshot of Location of Sensors and the Target with Multiple Active Sensors. (b) Target Position Error with Multiple Active Sensors Versus Single Active Sensor.

If we assume that an active sensor is on during the whole sampling time, the sensing energy is:

$$E_{sensing} = \left(\frac{|\overline{S_A T}|}{300}\right)^{2\beta} \times T. \qquad (19)$$

In (16), only distance is considered, since all other parameters are common for both energy-based and conventional algorithms to choose the active sensors. Hence we use the following model to compute the communication energy which considers all the parameters that is needed. The radio dissipates E_{elec} J/bit to run the transmit or receive circuitry and E_{amp} $J/bit/m^2$ for the transmit amplifier to achieve an acceptable E_b/N_0 at the receiver [15]. Thus, the energy needed to transmit a k-bit message for a distance d is given by,

$$\begin{aligned} E_{Tx}(k,d) &= E_{Tx-elec}(k) + E_{Tx-amp}(k,d) \\ &= E_{elec} \times k + E_{amp} \times k \times d^2. \qquad (20) \end{aligned}$$

Similarly, the energy spent by the radio circuitry to receive a k-bit message is,

$$\begin{aligned} E_{Rx}(k) &= E_{Rx-elec}(k) \\ &= E_{elec} \times k. \qquad (21) \end{aligned}$$

As in [15], we choose the parameters $E_{elec} = 50\ nJ/bit$ and $E_{amp} = 100\ pJ/bit/m^2$. Hence from (20) and (21), the total communication energy required for a k-bit message over a distance d is,

$$\begin{aligned} E_{comm} &= E_{Tx}(k,d) + E_{Rx}(k) \\ &= 2 \times E_{elec} \times k + E_{amp} \times k \times d^2. \end{aligned}$$

The total energy spent by the network at each instant is the sum of the sensing and the communication energies:

$$\begin{aligned} E_{Total} &= E_{sensing} + E_{comm} \\ &= \left(\frac{|\overline{S_A T}|}{300}\right)^{2\beta} \times T + \\ &\qquad 2 \times E_{elec} \times k + E_{amp} \times k \times d^2. \end{aligned}$$

Note that, here we are not considering the communication cost involved in passing the leadership to a new data gathering node since it is common for both proposed algorithm and the conventional method of choosing the active sensors randomly.

If E_{Total}^{rand} is the total energy spent by a network using the conventional method (i.e choosing the active sensors in a cluster randomly) then the percentage of energy savings achieved by the proposed energy-based multisensor collaboration algorithm is,

$$\eta_E = \left(\frac{E_{Total}^{rand} - E_{Total}}{E_{Total}^{rand}}\right) \times 100.$$

VI. Simulation Results

We simulate an ad-hoc wireless sensor network of an area $1000 \times 1000\ m^2$ which is divided into $N_c = 100$ clusters of equal area. The entire sensor network consist of $N = 1100$ total number of sensors with 1000 randomly distributed low-end sensors and 100 data gathering nodes located at the center of each cluster. It is assumed that at each time instant only the M-active sensors in the network measure the time delay and the Doppler shift corresponding to the target. Figure 3(a) shows a snapshot of the locations of the sensors and the target. The sampling interval T is set to 1 and $M = 3$ in the following results.

Figure 3(b) corresponds to the target position estimate error at the leader sensor. Note that here the initial target velocity was chosen as $(\dot{x}, \dot{y}) = (0.2, 0.2)$, $\mathbf{Q} = {\sigma_s}^2 I$ and $\mathbf{R} = {\sigma_o}^2 I$ where position error is plotted for $({\sigma_s}^2, {\sigma_o}^2) = (0.01, 0.01)$ and $({\sigma_s}^2, {\sigma_o}^2) = (0.005, 0.005)$. From Fig. 3(b), we can observe that the proposed energy efficient collaborative tracking algorithm with multiple active sensors can achieve smaller

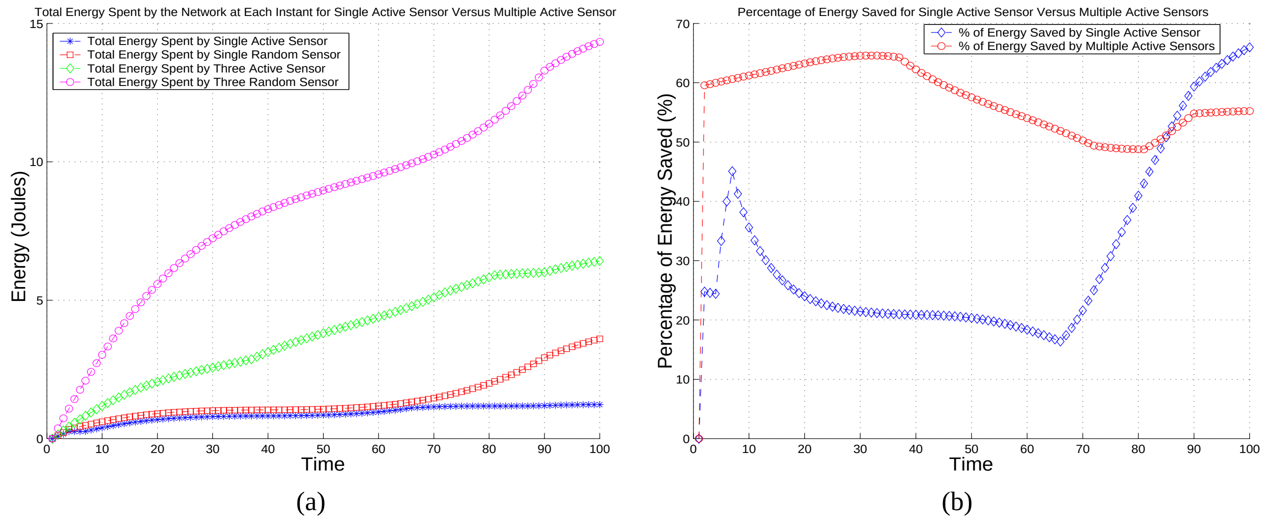


Fig. 4. (a) Total Energy Spent by the Network at Each Instant with Single Active Sensor Versus Multiple Active Sensors. (b) Percentage of Energy Savings for Single Active Sensor Versus Multiple Active Sensors.

error values compared to a similar algorithm with only a single active sensor considered in [10].

Next Fig. 4(a) shows the accumulated total energy spent by the network. From Fig. 4(a), we can see the significant energy-savings offered by the proposed collaborative algorithm compared to a conventional scheme that chooses active sensors randomly. Figure 4(b) shows the percentage of energy savings achieved by using the energy aware collaborative tracking algorithm as compared to a conventional scheme. From Fig. 4(b) we can see that about $48\% - 65\%$ of energy is saved by using the multiple active sensors and $17\% - 66\%$ of energy is saved by using a single active sensor.

VII. Conclusion

In this paper, we presented an energy-aware collaborative tracking algorithm and a method to compute the achieved energy efficiencies for a wireless ad-hoc sensor network. The proposed energy-based distributed tracking algorithm attempts to reduce the total energy consumption of the whole network (as against that of a particular sensor) in order to maximize the life time of the total network. Energy requirements for communications and sensing are taken into account in computing the cost associated in deciding the next set of active sensors. From our simulation results we observe that multiple active sensors with the proposed collaborative algorithm provides small estimation errors compared to previously proposed algorithms based on a single-active sensor and improved energy savings compared to algorithms that use randomly chosen active sensors.

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