Sensing Range Modification of Spatial Split Algorithm for High Speed Target Tracking in WSN

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Abstract—In this paper, we propose a new approach for selection of subsets of active sensors with some constraints on energy consumption and estimation error for tracking of a target. The proposed approach exploits the decentralized estimation by using the extended information filter for target tracking. Furthermore, a cost function is defined using spatial correlation for sensor selection. Consequently, the Spatial Split algorithm is proposed based on spatial correlation coefficients for sensor selection. At last, for high speed targets, we propose a modification on spatial split algorithm by changing the sensing range with respect to the target speed. Simulation results show that the tracking accuracy is analogous to those of optimal estimation methods. It is also found that energy consumption decreases due to activating only necessary sensors.

Keywords- WSN, target tracking, sensor selection, spatial correlation.

I. INTRODUCTION

Wireless sensor networks (WSN) are event-based systems that rely on the collective effort of densely deployed several micro-sensors which continuously observe physical phenomena. A sensor network is composed of a large number of sensors which are densely deployed either inside a phenomenon or very close to it. The position of sensors need not be engineered or pre-determined. Therefore, random deployment in inaccessible terrains or disaster relief operations is feasible [1]. As such, sensor network protocols and algorithms must possess self-organizing capabilities. Cooperative effort of sensors which are fitted with an on-board processor is one of the unique features of sensor networks. Sensors use their processing abilities to carry out simple computations locally and transmit only the required and partially processed data instead of sending the raw data to the nodes responsible for data fusion [2].

Tracking of mobile targets using WSN is an attractive application for which several distributed tracking algorithms have been considered [3]. However, due to the communication, processing, and energy constraints, sensor networks have not been conclusively studied and are still interesting research topics. Due to the energy limitation of WSN, if sensors function continuously, its energy will be depleted quickly which can lead to its death. The corresponding sensors will then operate under significant energy constraints which preclude them from using large transmission ranges. This fact with the low cost of individual sensors implies that sensors should be densely deployed. It is thus expected that a high degree of spatial correlation exists in the sensor network data. The realization of an effective sensor network with a significant lifespan will rely on energy awareness at both the sensor and system levels. Such a system will require a sensor manager that can determine which sensors should be active which features the sensors should communicate with, and which algorithms the sensors should evoke for feature extraction and information fusion. Recently, some efforts have been done towards the development of sensor selection in WSN. For instance, active sensors can be selected based on closeness to the target [4], its information contribution [5], or spatial correlation in iterative node selection (INS) [6], modified-INS (M-INS) [7], and spatial-split algorithms [8].

In this paper, we use a fully-decentralized estimation [9] for target tracking and spatial-split algorithm for active sensor selection. In spatial-split algorithm, the sensing area where active sensors are selected from this is a circle with a center at the target position and radius of 50m. In practice, we use the predicted target state as the center of sensing area. Therefore, this area is an estimation of actual sensing area. Furthermore, we investigate the effect of the target speed on the spatial-split algorithm and active sensor selection. Finally, a modification on sensing range is proposed.

The paper is organized as follows. In Section 2, we summarize the Spatial-split algorithm for sensor selection. An investigation of sensing range for high speed targets is presented in Section 3. Simulation results are shown in Section 4. Finally, we conclude the paper in Section 5.

II. SENSOR SELECTION

In a typical WSN application, a spatially dense sensor deployment is needed for a satisfactory coverage [10]. Thus, several sensors record the information of a single event in a sensor field while these records are spatially correlated. Therefore, the spatial correlation results in redundancy in each event information. In [11], the authors discuss about possible approaches exploiting spatial correlation and using a smaller...
number of sensors in the event area rather than the whole number of the nodes to achieve an energy-efficient medium access and reliable event transport in the WSN. To investigate the distortion achieved by a subset of nodes, it is deemed that only M out of N nodes is active, where N is the total number of sensors in the event area. As such, the event distortion for M active sensors is defined as

\[ D_E(M) = E \left[ (S - \hat{S}(M))^2 \right], \]

where \( S \) is the event source and \( \hat{S}(M) \) is its estimation using M sensors. This distortion function is a function of two correlation coefficients, \( \rho_{n_i} \) and \( \rho_{S,i} \) between the nodes \( n_i \) and \( n_j \) respectively, and the event S in the sensor field and the sensor \( n_i \). The covariance function is assumed to be non-negative and decreases monotonically with the distance \( d = \|s_i - s_j\| \), with boundaries of 1 at \( d = 0 \) and 0 at \( d = \infty \). The covariance model can be defined using the power exponential form as \[ \rho_{PE}^{\theta_2}(d) = e^{-(d/\theta_1)^{\theta_2}}; \theta_1 > 0, \theta_2 \in (0, 2] \]

As mentioned in (2), the model is able to behave either exponentially (\( \Theta = 1 \)), or squared-exponentially (\( \Theta = 2 \)). Since, the physical event information (i.e. electromagnetic waves) follows an exponential autocorrelation function, (1) can be written as

\[ D_E(M) = \sigma_S^2 - \frac{\sigma_S^2}{M(\sigma_S^2 + \sigma_N^2)} \sum_{i=1}^{M} \rho_{S,i} - 1 + \frac{\sigma_N^2}{M^2(\sigma_S^2 + \sigma_N^2)^2} \sum_{i=1}^{M} \sum_{j \neq i}^{M} \rho_{i,j} \]

where \( \sigma_S^2 \) and \( \sigma_N^2 \) are the variances of the event information and observation noise, respectively.

As a result, the minimum number of active sensors for a given distortion constraint should be determined according to the application. Therefore, the minimum number of sensors may be defined as

\[ M^* = \arg \min_M \{ D(M) < D_{\text{max}} \}, \]

where \( D_{\text{max}} \) is the maximum distortion allowed by the sensor application.

**III. SENSING RANGE MODIFICATION FOR HIGH SPEED TARGET**

In the Spatial Split algorithm which is based on spatial correlation, the position of sensors with respect to the target must be given. By the assumption of knowing sensors position, the target position is estimated by tracking algorithm. Therefore, the sensing area defined by a circle whose center is the estimated target position and its radius presents the sensing range, is the estimation of the actual sensing area. When the speed of the target is low, the error of the target position estimation is negligible. In this case the estimated sensing area corresponds to the actual sensing area. As a result, since selected active sensors are in the actual sensing range, they
may more effectively sense the target. However, for high speed target, as illustrated in Fig. 2, the error of the target position (the distance between the center of the estimated and actual sensing area) increases proportionally to the target speed. Then, the overlap of these two areas decreases.

![Figure 2. RMS position error of the target versus different speeds.](image)

Therefore, the most active selected sensors are not in the actual sensing range and this can cause intensification in error estimation of the target position in the next instants. Then, after several instants there will be no overlap between the two estimated and actual sensing areas. This problem is illustrated in Fig. 3, wherein a target moves in a straight line with the speed of 10m/s. In this case, the estimation has diverged, and at last, active sensors are selected out of the sensing range. Then, the algorithm fails to the track the target.

![Figure 3. Example of a failed target tracking.](image)

To resolve this problem, the overlap of the two estimated and actual sensing areas must be somehow increased. For high speed targets, we propose to increase the radius of the estimated sensing area. As seen in Fig. 4, although there is an error in estimating the target position by increasing the estimated sensing radius, the overlap of the two estimated and actual areas is also increased and the probability of selecting active sensors in the actual sensing range is increased.

![Figure 4. Example of target tracking by modification of sensing range.](image)

IV. SIMULATION RESULTS

It is assumed that the network has been initialized so that the sensors can communicate with each other and share some accumulated statistics. Each sensor knows its position and the sensors share common information such as a prior density and motion model.

The target is considered as a point-object moving in a two-dimensional plane. In this work, we consider a quite general, nonlinear motion model [13], i.e., the coordinated turn rate model. \( t \) shows the discrete-time index and \( \Delta \tau \) denotes the length of a time step. In the present model, it is deemed that the target speed which can move with an unknown turn rate is almost constant. Then, the state of the target \( x(t) \) is defined as [13]

\[
x(t+1) = \begin{pmatrix} 1 & \sin \rho(t) \Delta \tau & -1 - \cos \rho(t) \Delta \tau \\ 0 & \cos \rho(t) \Delta \tau & -\sin \rho(t) \Delta \tau \\ 0 & -1 - \cos \rho(t) \Delta \tau \rho(t) & 1 - \rho(t) \Delta \tau \rho(t) \\ 0 & \sin \rho(t) \Delta \tau & \cos \rho(t) \Delta \tau \\ 0 & 0 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \\ \end{pmatrix} x(t)
\]

\[
\begin{pmatrix} \Delta \tau^2 \\ \frac{2}{\Delta \tau} \\ 0 \\ 0 \\ 0 \\ \Delta \tau \\ 0 \\ 1 \\ \end{pmatrix} u(t)
\]  

(5)
where \( x(t) = \{ \dot{x}_1(t), \dot{x}_2(t), x_1(t), x_2(t), \rho(t) \} \) shows the target state and contains the coordinates \( x_1, x_2 \), the velocities \( \dot{x}_1, \dot{x}_2 \), and the turn rate \( \rho \). Also, \( u(t) \) is the corresponding motion noise with \( u(t) \sim N\left(0, \text{diag}\left[\sigma_1^2, \sigma_2^2, \sigma_3^2\right]\right) \).

In many sensors, measurements are a function of the relative distance between the sensors and the target (e.g., radar, acoustic sensors, sonar, etc.).

We consider a typical example where the sensors measure the power of the radiated signal from a target. The received power typically decays exponentially with the relative distance. In logarithmic scale, the target-originated measurements are modeled by [14],

\[
\begin{align*}
    h_d(d) &= K - 10\eta \log_{10}(d), \\
    z_k(t) &= h_d(d_k(x(t))) + w_k(t)
\end{align*}
\]

where \( w_k(t) \) is a zero-mean i.i.d. Gaussian observation noise with variance of \( R_k \) which accounts for the shadowing effects and other uncertainties. The sensor noise is assumed uncorrelated, \( K \) is the transmission power, and \( \eta \in [2, 5] \) is the path loss exponent. These parameters depend on the radio environment, antenna characteristics, terrain, and etc. Note that \( \eta = 2 \) corresponds to the free space transmission and serves as a lower limit.

The sensor density in the network is one sensor over a field of \( 20 \times 20 \text{m}^2 \). It is assumed that there is no communication loss and the sensors are synchronized. For all simulations, we take the following parameters into account. The transmission power for each sensor is \( K = 9\text{dBm} \), the path loss index is \( \eta = 3 \), the time step is \( \Delta\tau = 1 \) (sec.), the process noise covariance is \( Q = 0.001^2I_3 \), and the observation noise variance (shadowing effects and other uncertainties) is \( R_k = 0.5 \). The prior estimate is \( \hat{x}(0|0) = x(0)+x_{bias} \), where \( x_{bias} \) represents a strong bias on the position drawn from a uniform distribution on a square of length 30m centered on \([0,0] \).

In order to compare the effectiveness of different sensor selection algorithms in target tracking, the straight trajectory shown in Fig. 5 is considered. The criteria considered for comparison purposes are the MSE of the target position, mean number of active sensors, and the failure tracking percentage. Table I summarizes the simulation results for different algorithms obtained via averaging over 2000 ensembles. As the DEIF algorithm uses all sensors for estimating the target position, its MSE and failure tracking percentage compared to other algorithms are optimum with the lower error bound. Among the sensor selection algorithms, the Spatial-Split algorithm has also the closest performance to the DEIF. This is due to efficient utilization of correlation coefficients \( \rho_{i,j} \) and \( \rho_{N,j} \) in selection of active sensors.

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Speed (m/s)</th>
<th>Sensing radius (m)</th>
<th>Mean NO. of active sensors</th>
<th>MSE (m²)</th>
<th>Failed tracking (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>DEIF</td>
<td>0.3</td>
<td>50</td>
<td>4.59</td>
<td>2.16</td>
<td>0.6</td>
</tr>
<tr>
<td>MINS</td>
<td>0.3</td>
<td>50</td>
<td>4.74</td>
<td>2.08</td>
<td>3.57</td>
</tr>
<tr>
<td>Closed sensors</td>
<td>0.3</td>
<td>50</td>
<td>4.59</td>
<td>1.59</td>
<td>2.0</td>
</tr>
<tr>
<td>Spatial-Split</td>
<td>0.3</td>
<td>50</td>
<td>4.59</td>
<td>1.59</td>
<td>2.0</td>
</tr>
</tbody>
</table>

![Figure 5. Tracking a target in straight line.](image)

The position estimation error as a function of sensing range variations is investigated for different target speeds. Visual inspection in Fig. 6 reveals that for the Spatial Split algorithm, the larger the sensing range is, the less the error of the position estimation will be. This phenomenon is due to the increasing of the overlap between the two actual and estimated sensing areas. It is also seen that if the sensing range more increases, the error of the position estimation will correspondingly begin to increase. In fact, by increasing the sensing range and selection of the sensors far from the target, the SNR decreases which causes a negative feedback on the position estimation filter.

As a result, for the sensing range larger than a specific value (called the optimum sensing range), the negative effect of decreasing of the SNR overcomes the positive effect due to increasing the overlap between the two actual and estimated sensing areas. Another advantage is that with increasing the target speed, the optimum sensing range is also increased.

The effect of the number of active sensors on the position estimation error is illustrated in Fig. 7. It is shown that as the number of active sensors increases, the RMS position error decreases and this remains similarly for different target speeds.

TABLE I Comparison of target trackers for different algorithms.
Figure 6. Position estimation error versus sensing range for target speeds 10, 15 and 20m/s

Figure 7. Position estimation error versus number of active sensors for target speeds 10, 15 and 20m/s

V. CONCLUSIONS

The problem of sensor selection based on spatial correlation was investigated for target tracking in WSN. The proposed approach includes a decentralized estimation method based on the extended information filter for target tracking and the spatial-split algorithm based on spatial correlation for sensor selection. The effect of target speed on the spatial-split algorithm was also investigated and led to proposing a modification on the sensing range due to the increase of the position estimation error for high speed targets. For low speed targets, the proposed approach showed a better tracking accuracy. Also, modifying the sensing range for high speed targets retains the tracking accuracy.

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