Dynamic Sensors Selection for Overlapped Multiple-Target Tracking using Eagerness

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***Abstract*—Efficient target tracking applications use active sensor nodes collaboratively to track multiple moving targets by balancing the trade-off between the quality of tracking and network's lifetime. In this paper, we propose a low-energy dynamic sensor selection (LEDS) scheme to track multiple targets by estimating energy consumption of sensors and information utility projection of the targets on sensors to calculate the eagerness in tracking. Eagerness represents the eligibility of a sensor node to be selected for tracking, considering relative profiles of other sensors and location of all the targets in its vicinity. LEDS enables an even distribution of energy consumption among the nodes to prolong their remaining energies. Our results show that the proposed scheme can significantly improve the network lifetime over the existing methods while maintaining the high tracking accuracy in congested areas where multiple concurrent targets overlap.**

Keywords- Target tracking; Sensor selection; Information utility; Energy resources; Network lifetime.

I. INTRODUCTION

Multiple-target tracking applications, for tracking of mobile intruders, enemy attack, or animals movements, need to use wireless sensor networks (WSNs) intelligently to capture environmental conditions. The sensor nodes for these applications do not directly interact with physical property of interests, e.g., temperature but detect changes due to moving targets in terms of: presence, location, speed, or angle. In target tracking applications, dense deployment of sensors in a region ensures longevity and reliability of the tracking. However, due to constrained power resources, not every sensor in the sensing field needs to be active at all the times, so a set of active sensors need to be selected for energy efficient tracking. The choice of active sensors is specially very challenging when the sensing areas of multiple targets overlap and Quality of Service (QoS) requirements (e.g. coverage degree and energy consumption) must be met. The coverage degree in the context of mobile targets is the number of active nodes to track a target at any time which strikes optimal trade-off between the quality of tracking and energy consumption. Quality of tracking could improve with increasing number of measurements by sensors but this could lead to a shorter network lifetime due to the excessive use of energy by more involved sensors in tracking. Also, when the sensing areas of multiple targets overlap, a sensor node may cover multiple concurrent targets and could run out of energy quickly. Thus, a sensor selection scheme should efficiently establish the QoS parameters' trade-off.

Multiple-target tracking schemes aim at data association strategies [1-3], or improving energy efficiency in localization by incorporating the network and sensors properties [4-6]. On the other hand, existing sensor selection schemes do not explicitly support concurrent tracking of multiple targets. Most of these techniques used information utility principles in selecting the best subset of sensors to track a single target in order to minimize: the entropy of measurements [7], Root Mean Squared Error (RMSE) [8-10], Cramer-Rao Lower Bound (CRLB) [11, 12], or maximize the information gain [13, 14]. Here, RMSE and CRLB represent the level of uncertainty in the estimation and lower bound of tracking error, respectively. Wei et al. proposed a Weighted Distance (WD) [13] sensor selection scheme to find a leader node, whose measurement should maximize the information utility for given prior distribution of a target. This method suffers from a low tracking accuracy as it is based on the measurements from a single node. Methods for selecting more than one sensor were addressed in [8, 21] for better quality of tracking. Global Node Selection (GNS) [8] was proposed to minimize the expected filtered RMSE for a given value of coverage degree using the global knowledge of nodes' locations. Based on this approach, an active set of sensors is determined by selecting those sensors that are not collinear with the target's location. Niche Overlap-based Selection (NOS) scheme [21] dynamically selects a varying degree of sensors in dealing with energy-quality trade-off. This scheme is a greedy approach where nodes with higher Niche overlap measurements are selected until the required level of accuracy is achieved.

In [15], optimal selection of sensors for multiple targets was done through an efficient search technique to obtain the small subset of available nodes among a large network of sensors in order to optimize the tracking performance. However, the core assumption of this work is that multiple targets are well separated over the network and they do not overlap through their trajectories. Concurrent tracking of multiple overlapping targets [16] using Sleep Scheduling algorithm for Multiple-Target Tracking (SSMTT) can reduce the number of active sensors by limiting the area of tracking contour along the direction of the targets, and awakening the nodes within the contour based on the proposed sleep pattern. This approach reduces cost of overlapping by awakening nodes once. SSMTT did not consider the number of selected active nodes, and as a result, network suffers from high energy consumption by overly utilization of the sensors.

In this paper, we present a low-energy dynamic sensor selection (LEDS) scheme motivated by conservation of resources and quality of target tracking, concomitantly. This paper makes the following contributions: (1) our proposed scheme, LEDS considers sensor selection problem in multiple-

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target tracking to deal with the energy-quality trade-off, where the sensing areas of targets overlap with each other; (2) we introduce a new metric "eagerness" as a criteria of selection. Eagerness represents the eligibility of a node to be selected at any time. LEDS scheme utilizes residual energy, energy consumption rate, and information utility of sensors as well as the global knowledge of concurrent targets to calculate sensors' eagerness in tracking. Moreover, LEDS employs the Particle Filtering algorithm presented in [1] to track the targets, and (3) LEDS utilizes the CRLB [17] to dynamically select active subsets of sensors of varying coverage degrees for lower tracking error. Although, the use of CRLB as an objective function is not new, the novelty lies in the selection of sets of dynamic coverage degrees. Our study shows that use of eagerness criteria can significantly outperform the schemes proposed in [8, 13, 16, 21] by a margin of 30%-70% in terms of network lifetime when the tracking area is largely congested by targets. Additionally, our results show a good performance in sparse targets as compared with other methods.

This paper is organized as follows; Section II describes our system model and problem statement. Section III provides a brief overview of estimation theory and localization strategy. The proposed sensor selection scheme is presented in Section IV, followed by simulation parameters and results in Section V. Finally, Section VI concludes the paper.

II. SENSORS-TARGETS ASSIGNMENT PROBLEM

In our network model, we consider n sensors, $S = \{s_1, s_2, \dots, s_n\}$ randomly deployed in a rectangular region. Each sensor has a sensing range R_s that is assumed circular and is same for every node. Initial energy, E of every node is same at the time of deployment, and every sensor s_i is aware of its current residual energy $e_t(s_i)$. We assume that m targets, $R = \{r_1, r_2, \dots, r_m\}$ traverse the region for the lifetime of the network (T), and there is a subset of sensors with property $S'_{j,t} = \{s_i | d(s_i, r_j) \le R_s\} \subseteq S$ to cover every target r_j at time $t \in T$ and $d(s_i, r_j)$ being the distance between sensor s_i and target r_j.

Sensors can detect targets by measuring the energy signals, e.g., the angular direction of the magnetic field. Energy consumption in a sensor is characterized by sensing, processing, and communication units [18]. Power analysis of sensor nodes indicate that the energy consumption of the sensing unit is very negligible so it can be ignored, but communication unit consumes the most of the energy for data transmission [18]. We consider the energy dissipation model in LEACH protocol [19] to calculate the energy that a node consumes in covering targets per time unit. Let E_{elec} denotes the energy required for radio circuit, while E_{mp} and E_{fs} represent the amplifier energy for multi-path and free space model, respectively. Then the total energy consumption, $C_t(s_i)$ for a sensor s_i per time unit is as follows:

$$C_t(s_i) = E_{tx}(l, d) + E_{rx}(l) \tag{1}$$

where $E_{rx}(l) = lE_{elec}$ is the energy used to receive an l-bits message and $E_{tx}(l, d) = \begin{cases} l(E_{elec} + E_{fs}d^2) & d < d_0 \\ l(E_{elec} + E_{mp}d^4) & d \ge d_0 \end{cases}$ is the energy used to transmit an l-bits data message over a distance d to another node. If the distance is less than the critical distance d_0, free space model (fs) is used; otherwise, multi-path model (mp) is used [19]. The network lifetime, T is defined as the elapsed time since the launch of the sensor network until the first node dies, i.e., its residual energy becomes zero. Finally, the data collected upon tracking is equal to l bits and is proportional to number of covered targets.

Definition 1. Target Dynamic Coverage Degree: at any time, target r_j is tracked by varying number of sensors nk such that $1 \le nk \le |S'_{j,t}|$.

The coverage degree impacts the energy-quality trade-off in target tracking, so the problem can be defined as following:

Problem Statement: Low-Energy Dynamic Sensor Selection (LEDS): Given n sensors and m targets with overlapping sensing areas, determine the best subsets of sensors to track the targets, which maximizes the network lifetime and maintains the high quality of tracking.

III. LOCATION ESTIMATION USING PARTICLE FILTERING

Accurate tracking of a moving target can be done by estimating the state of the target using localization algorithms. Target's state is a physical true location of the target X_t and $\hat{X}_t$ is the estimated location. Target dynamic model $p(X_t|X_{t-1})$ is based on Wiener velocity model [20] and follows a linear equation $X_t = A_{t-1}X_{t-1} + q_{t-1}$ where A is the transition matrix, and q is a zero-mean Gaussian process noise with variance Q. Measurement model $p(Z_t|X_t)$ is non-linear and is an azimuth angle from a sensor's platform to a target. The azimuth angle of a sensor s_i located at (x_s, y_s) from target r_j located at (x_t, y_t) at a time t is given by:

$$\theta_t^i = arctan\left(\frac{y_t - y_s}{x_t - x_s}\right) + w. \tag{2}$$

The measurement error $w \sim N(0, \Delta\theta)$ follows an additive white Gaussian noise model where the standard deviation of the error ($\Delta\theta$) is isotropic at all the nodes. In order to track a target under Bayesian framework, we need to calculate the prior and posterior distribution of a target's state. Prior distribution is used to compute predictive distribution of the state before obtaining any measurements from the target at current time and is expressed as:

$$p(\hat{X}_t|Z_{1:t-1}) = \int p(X_t|X_{t-1}) p(\hat{X}_{t-1}|Z_{1:t-1}) dx_{t-1}. \tag{3}$$

Posterior distribution is then to update the predictive distribution after obtaining measurements at time t:

$$p(\hat{X}_t|Z_{1:t}) = \frac{p(Z_t|X_t) p(\hat{X}_t|Z_{1:t-1})}{p(Z_t|Z_{1:t})} \tag{4}$$

where $p(Z_t|Z_{1:t})$ is a normalizing parameter and can be presented as: $p(Z_t|Z_{1:t}) = \int p(\hat{X}_t|Z_{1:t-1})\, p(Z_t|X_t) dx_t$.

Particle Filtering (PF) [2] refers to general class of methods to solve (3) and (4), where closed-form computation of statistical quantities is replaced by drawing *np* samples (particles) from the distribution, i.e. $\hat{X}_t^{i=1:np}$, and estimating the quantities by sample averages. Each particle is associated with a uniform weight (w_t^i). Associated weights correct the difference between the actual target's location and the estimation obtained from the posterior distribution.

Theoretically, in estimation theory the lower bound on the tracking error is expressed by Cramer-Rao Lower Bound (CRLB). In the simplest form, the lower bound states that the covariance of estimator is at least as high as the inverse of the Fisher Information [17]. Mathematically, the predicted covariance denoted by cov_t has a lower bound as $cov_t \geq J_t^{-1}$ where J_t^{-1} is the inverse of Fisher Information matrix J_t and can be computed recursively as following [17]:

$$J_t = D_t^{22} - [D_t^{12}]^T (J_{t-1} + D_t^{11})^{-1} D_t^{12}$$

where

$$D_t^{11} = A^T Q^{-1} A, D_t^{12} = -A^T Q^{-1}, D_t^{22} = Q^{-1} + \mathbb{E}(\hat{H}_t^T \Delta\theta^{-1} \hat{H}_t)$$

and $\hat{H}_t$ is the Jacobean of (2) by sensor s_i evaluated at the estimated location of a target. Finally, the responding $CRLB_j$ of target r_j at every step of recursion is computed as the trace of J_t^{-1}:

$$CRLB_j = [J_t^{-1}]_{1,1} + [J_t^{-1}]_{2,2}. \quad (5)$$

IV. Low-Energy Dynamic Sensor Selection Scheme

Our proposed sensor selection scheme assumes that only the communication unit of every node is able to switch either to active mode or to sleeping mode. Therefore, every sensor can sense the environment and determine if a signal is environmental noise, existing target, or a new target. To determine the source of a signal, and targets' locations estimation, a localization algorithm called Rao-Blackwellized particle filtering [1] is used. We assume that a centralized remote base station (BS) can coordinate all the nodes, and LEACH [19] algorithm is used to transmit data from sensors to BS. The problem of sensor selection can be accomplished as follows: All the sensors that detect new target(s) will report to the BS. The BS performs sensor set selection and then broadcasts the active schedule to every selected node. After receiving the active schedule, only the selected nodes will communicate the locations estimation results to the BS.

A. Algorithm Description

The sensor set selection scheme LEDS presumes that BS knows the location of all the sensors in addition to the updated location of all targets at every time. Then, BS calculates the prior distribution according to (3) to estimate the predicted location of the targets at the next time. Next, BS computes the information utility, $I_{j,t}(s_i)$ gained by every node $s_i \in S'_{j,t}$ for every target r_j based on the method in [13]. As received signals by sensors attenuate with the distance from the targets, so, information utility is proportional to the distance.

In order to decide which nodes are more eligible to be selected, we introduce a new metric as eagerness. Eagerness represents the willingness of a sensor to be selected at any time. In order to compute the eagerness, we first denote the maximum information utility projection of target r_j as $I_{j,t}^{max}$. Next, we calculate the probability that sensor $s_i \in S'_{j,t}$ is selected conditional to the information utility and the residual energy as $p_{j,t}\left(s_i \middle| I_{j,t}(s_i)\right)$, and $p_{j,t}\left(s_i \middle| e_t(s_i)\right)$, respectively:

$$p_{j,t}\left(s_i \middle| I_{j,t}(s_i)\right) = 1 - \frac{I_{j,t}^{max} - I_{j,t}(s_i)}{I_{j,t}^{max}},$$

$$p_{j,t}\left(s_i \middle| e_t(s_i)\right) = \frac{e_t(s_i)}{E}.$$

It is possible that a sensor is covering multiple targets, so assigning a sensor to multiple targets can result in shorter lifetime due to more energy consumption. In this case, the algorithm checks the sensors in $\bigcup_{j=1:m} S'_{j,t}$. If there exists a sensor s_i covering multiple targets, the algorithm will prioritize the assignment of s_i to a target with higher $p_{j,t}\left(s_i \middle| I_{j,t}(s_i)\right) \times p_{j,t}\left(s_i \middle| e_t(s_i)\right)$. If there exists assignments having the same priorities, the assignment of higher $I_{j,t}(s_i)$ will be considered first. Targets covered by s_i will then be sorted in a priority set V_i based on the calculated priority levels. Let $L_j(s_i)$ denotes the assignment priority level of s_i to $r_j \in V_i$.

The value of eagerness $G_{j,t}(s_i)$ is a trade-off among $p_{j,t}\left(s_i \middle| I_{j,t}(s_i)\right)$, $p_{j,t}\left(s_i \middle| e_t(s_i)\right)$, and E_{tx} where energy consumption rate for transmission is proportional to $L_j(s_i)$:

$$G_{j,t}(s_i) = \frac{p_{j,t}\left(s_i \middle| I_{j,t}(s_i)\right) \times p_{j,t}\left(s_i \middle| e_t(s_i)\right)}{L_j(s_i) \times E_{tx}\left(l_{for\ one\ target}, d\right)}, \quad \forall r_j \in V_i. \quad (6)$$

$L_j(s_i)$ represents the number of targets that has been covered so far by sensor s_i. Finally, sensors will be sorted in a descending order based on the eagerness values into a candidate set, $CS'_{j,t}$ for every target r_j. The pseudo-code of LEDS is presented in Algorithm 1.

Consider the example shown in Fig. 1 where $R = \{r_1, r_2, r_3\}$, $S = \{s_1, s_2, s_3\}$, $S'_{1,t} = \{s_1, s_2\}$, $S'_{2,t} = \{s_1, s_3\}$, $S'_{3,t} = \{s_1\}$. Suppose the residual energies, $e_t(s_1)$, $e_t(s_2)$, and $e_t(s_3)$ are 9, 8, and 10 units, respectively, and information utilities gained by every node for every target, $I_{1,t}(s_1)$, $I_{2,t}(s_1)$, $I_{3,t}(s_1)$, $I_{1,t}(s_2)$, and $I_{2,t}(s_3)$ are 0.2, 0.2, 0.3, 0.3, and 0.15 units, respectively. In this example, we assume that the energy that one sensor spends on data transmission for one target, $E_{tx}\left(l_{for\ one\ target}, d\right)$ per time unit is 1, and initial energy of sensors, E at the time of deployment was 10 units. Following the Algorithm 1, $V_1 = \{r_3, r_2, r_1\}$ will be constructed by satisfying the calculated priority levels for assignment of sensor s_1. Considering V_1, eagerness values for every node, $G_{1,t}(s_1)$, $G_{2,t}(s_1)$, $G_{3,t}(s_1)$, $G_{1,t}(s_2)$, and $G_{3,t}(s_3)$ according to (6) will be 0.198, 0.45, 0.9, 0.8, 0.75, respectively. Finally candidate sets will be sorted as: $CS'_{1,t} = \{s_2, s_1\}$, $CS'_{2,t} = \{s_3, s_1\}$, $CS'_{3,t} = \{s_1\}$.

In fact, not all the sensors in candidate sets will contribute to the quality of tracking. Generally, we want to select nk sensors that minimizes the $CRLB_j$ for every target r_j, which leads to the following optimization problem:

$$AS'_{j,t} = \arg \min_{\cup\, s_i \in CS'_{j,t}} CRLB_j(s_i)\,. \tag{7}$$

Given the prior distribution, the algorithm starts to calculate the $CRLB_j$ recursively for all the sensors $\cup\, s_i \in CS'_{j,t}$ according to (5) for every target r_j. Next, we distinguish the index of a sensor $s_i \in CS'_{j,t}$ with minimum $CRLB_j$. The distinguished index represents the dynamic coverage degree, nk at time t to track target r_j. Collaboration among sensors with indices equal or less than nk will result in the most contribution in tracking error reduction of target r_j. By performing the above steps for every target, we get finite active joint-sets of the dynamic coverage degrees.

B. Algorithm Complexity

LEDS algorithm terminates in time $O(mn)$, where m and n are the number of targets and sensors, respectively.

Proof: The algorithm total running time is $O(T_S + T_C + T_A)$, where T_S is the time to form the subset of available sensors for every target $S'_{j,t}$ (lines 1&2), T_C is the time for candidate set formation $CS'_{j,t}$ (lines 3-8), and T_A is the time for selecting active sets of sensors $AS'_{j,t}$ (lines 8-11). The algorithm consists of three separated loops for T_S, T_C, and T_A which every loop will take no longer than $O(mn)$.

V. Performance Evaluation

We conducted Matlab simulations to evaluate the performance of our proposed scheme. The simulations were carried out for different network configurations. Network configurations varied in terms of initial locations of deployed nodes, number of moving targets, and trajectory of targets.

A. Simulation Settings

Simulation scenarios consisted of 200 randomly deployed stationary sensors within a 1 km×1 km square region. We considered random initial topologies for sensors with transmission range of 250 m. We considered dynamic environments where targets arrived over time, travelled through different trajectories and had different travel durations.

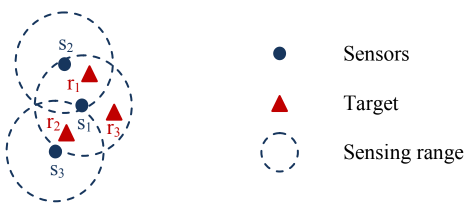

Fig. 1: An example of three sensors and three targets

Algorithm 1: Low- Energy Dynamic Sensor Selection (LEDS)

Input: dataset of network configuration, predicted estimation of targets

while all sensors are alive

1. **for** every target r_j
2. Form $S'_{j,t}$
3. **for** every $S'_{j,t}$ & every $s_i \in S'_{j,t}$
4. Compute $I_{j,t}(s_i)$, $p_{j,t}\left(s_i \middle| I_{j,t}(s_i)\right)$, $p_{j,t}(s_i|e_t(s_i))$
   // **** Candidate sets formation *******
5. Calculate the assignment priority levels, $L_j(s_i)$ and form V_i for $s_i \in \cup\, S'_{j,t}$,
6. Calculate eagerness, $G_{j,t}(s_i)$ for $s_i \in S'_{j,t}$
7. Form $CS'_{j,t}$ based on $G_{j,t}(s_i)$
8. **for** every $CS'_{j,t}$
9. Compute $CRLB_j$ recursively for $\cup\, s_i \in CS'_{j,t}$.
10. Mark $s_i \in CS'_{j,t}$ with minimum $CRLB_j$ as nk sensor in the list $CS'_{j,t}$
11. Add $\cup_{i=1:nk}\, s_i \in CS'_{j,t}$ to $AS'_{j,t}$

end while

Output: sets of active sensors, $AS'_{j,t}$ $\forall r_j \in R$

We ran the experiments for 10, 15, and 20 moving targets. We defined more scattered trajectories in the case of 10 targets, i.e., less targets overlapped; whereas the scenarios for 15 and 20 targets were highly overlapped. We chose to keep most of the parameters given in Rao-Blackwellized particle filtering [1] as our employed localization algorithm. These parameters included the process noise (Q), measurement noise ($\Delta\theta$), and number of PF samples. As mentioned in Section III, target trajectory is modeled according to the Wiener velocity model [20]. Note that our goal is mainly to investigate the efficiency of our proposed sensor selection algorithm to perform the localization rather than the efficiency of localization algorithm. One can refer to [1] for further reading on efficiency of Rao-Blackwellized algorithm under different settings of Q and $\Delta\theta$. Energy parameters included the energy dissipated for transmitter and receiver electronics (E_{elec}, E_{mp}, and E_{fs}) as in [19].. Finally, each data point in the results represents an average of 100 simulation runs for different network configurations.

We compared our energy-efficient LEDS scheme with the GNS [8], WD [13], NOS [21], and SSMTT [16]. For all the simulation scenarios, coverage degree for GNS was set to two sensors. Our purpose to compare with GNS, WD, and NOS is to evaluate the efficiency of LEDS with algorithms that could handle multiple targets separately through single target tracking. Table 1 offers an overview of the parameters used in the ensuing simulations. Parameters were set the same value for all the schemes otherwise stated.

B. Simulation Results

In Fig. 2 we compare the four schemes in the network lifetime under various target densities. The network lifetime is defined as the elapsed time since the launch of the sensor network until the first node dies, i.e., its residual energy becomes zero. We observe in Fig. 2 that in the case of 10 targets where trajectories were sparsely defined, WD has the longest lifetime, whereas its performance degrades as more targets overlap in the case of 15 and 20 targets.

Table 1: Parameters and their settings

Parameter		Setting
no. of sensors (n)		200
no. of targets (m)		10, 15, 20
targets' trajectory model		wiener velocity model
targets' arrival and travel time		dynamic
no. of PF samples		100
process noise (Q)		0. 1
measurement noise ($\Delta\theta$)		0.01
E_{elec}, E_{mp}, E_{fs}		**50** nJ, **0.0013** pJ/bit/m4, **10** pJ/bit/m^2
data message ($l_{for\ one\ target}$)		400 bytes
initial energy of sensors (E)		10 J
coverage degree	LEDS	dynamic
	NOS	dynamic
	WD	fixed at **one** leader node
	GNS	fixed at **two** nodes
	SSMTT	contour-based selection

The reason for the better lifetime of WD in sparse targets can be explained by the selection of only one leader node as well as assignment of sensors to track a single target in many instances due to the fact that targets are scattered in the field. We observe that given the knowledge of residual energy and energy consumption rate in addition to information utility, LEDS outperforms the other schemes by 30%-70% in lifetime for 20 targets. We further see in Fig. 2 that LEDS provides a good lifetime in sparse targets despite the employed dynamic coverage degree. We see in Fig. 2 that SSMTT has the shortest lifetime in all the scenarios. As explained in Section I, SSMTT reduces the number of active sensors by limiting the area of tracking as a contour and it does not consider any particular sensor selection method. As a result, SSMTT suffers from a high consumption by overly utilizing of sensors.

Fig. 3 shows the total tracking error, i.e., $RMSE_{tot}$, for all target densities. We defined the $RMSE_j$ as the expected distance between the estimated and actual locations of a target:

$$RMSE_j = \sqrt{\frac{\sum_{t=1}^{T}\left(\hat{X}_t - X_t\right)^2}{T}}, RMSE_{tot} = \frac{\sum_{j=1:m} RMSE_j}{m}.$$

To show LEDS performance in tracking accuracy and to do a logical comparison, we ran the simulations for the same period equal to the shorter lifetime for every target density scenario. So, we chose the lifetime of SSMTT scheme as the basis of comparison. We see in Fig. 3 that LEDS is as efficient as NOS scheme with a negligible loss in tracking error reduction. NOS selects the best set of informative nodes to minimize the tracking error, and as a result provides the best tracking performance among all schemes. Although, the tracking uncertainty reduction is greatly affected by the relative geometric specifications of the targets and sensors, but this could lead to continuous selection of only most informative nodes if information utility is the only criteria of concern. Therefore, NOS shows a shorter lifetime in congested scenarios because it repeatedly utilizes the same best informative sensors for an optimized tracking whereas LEDS can distribute the energy load by rotating between sensor nodes (Fig. 2). In order to evaluate the distribution of energy load among the available sensors for tracking, we introduced a metric as Repetition Frequency (RF). RF explains the frequency that a node is subsequently selected for tracking a target. We defined it as the number of subsequent times over the overall time that a particular sensor is selected. Results for RF in Fig. 4 confirm that using LEDS there are no overly utilized nodes that will run out of energy before the others.

Next, we discuss the performance results of four schemes for 10 targets. Fig. 5 demonstrates the tracking error for every target in the field, i.e., $RMSE_j$. The results in Fig. 5 closely confirm the fact that LEDS maintains the low tracking error as NOS with negligible performance loss. Fig. 5 demonstrates a higher tracking error for few targets throughout the network lifetime. This variance can be explained by the fact that sensors are randomly deployed in the region and they remain stationary afterward. As a result, some sub-regions of the field are affected by coverage loss due to unavailability of sensors. Fraction of times that a target is not captured by any sensor is shown in Fig. 6, where the results explicitly illustrate the behavior of tracking error in Fig. 5.

Finally, Fig. 7 shows the average coverage degrees for every target throughout the network lifetime. Note that coverage degree for WD was a single leader node and for GNS was fixed to two sensors at all the times. We see that in LEDS, approximately two sensors are enough to minimize the $CRLB_j$ in (7) most of the times. We also notice that considering the energy metrics in eagerness computations does not cause a considerable difference in the number of nodes that are needed for high quality of tracking. As a result, LEDS performs efficiently in keeping up an acceptable accuracy while prolonging the network lifetime.

VI. Conclusion

This paper presented a scheme for low-energy dynamic sensor selection in multiple-target tracking where the sensing areas of the targets overlap with each other.

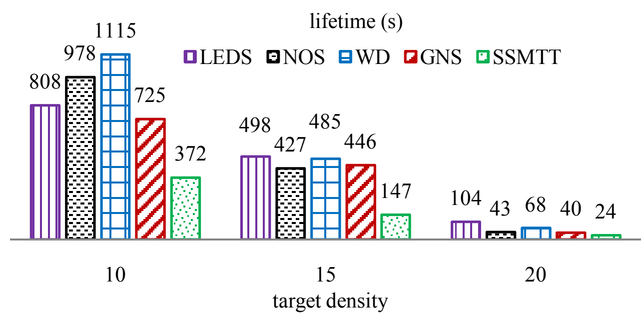

Fig. 2: Lifetime comparison under different target densities

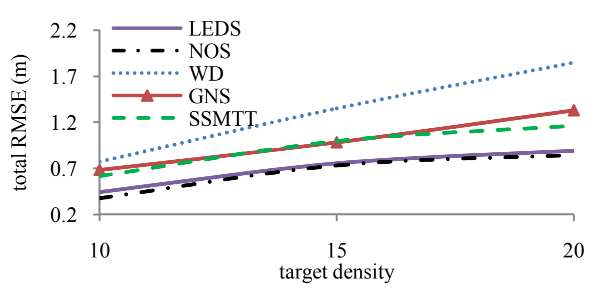

Fig. 3: Total error ($RMSE_{tot}$)- simulations were run for SSMTT lifetime

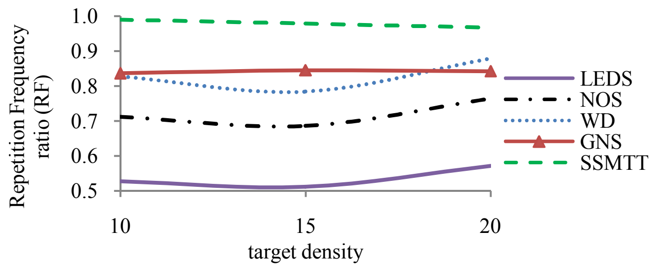

Fig. 4: Repetition Frequency ratio- simulations were run for SSMTT lifetime

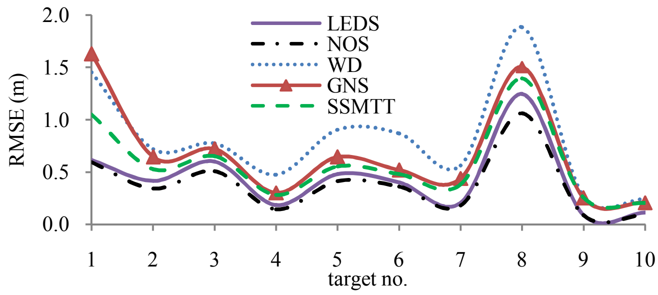

Fig. 5: Tracking error ($RMSE_j$) of 10 targets, simulations were run for SSMTT lifetime

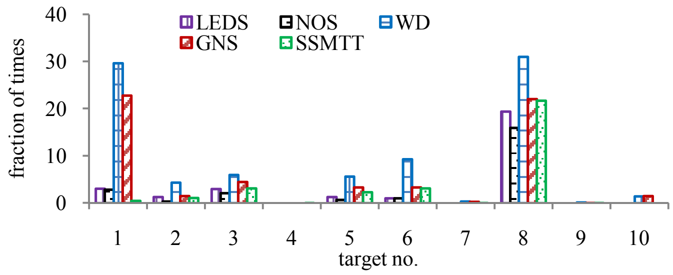

Fig. 6: Fraction of times that targets are not captured by any sensor

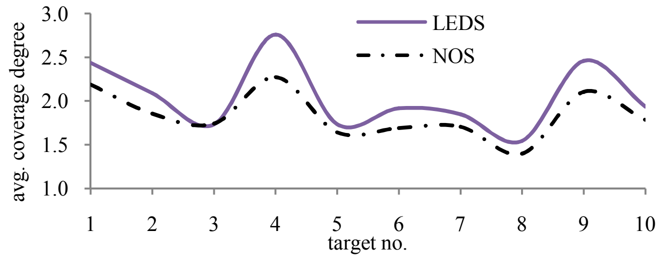

Fig. 7: Average coverage degree over the network lifetime for 10 targets

The scheme utilizes residual energy, energy consumption rate, and information utility projection of targets on sensors as well as the global knowledge of concurrent targets to evaluate the eligibility of sensors for selection. Our results demonstrate that with the use of eagerness criteria, our scheme can outperform the other existing schemes namely WD, GNS, NOS, and SSMTT by a margin of 30%-70% in network lifetime, while maintaining the high tracking accuracy. LEDS employs a central decision making in order to accurately achieve the global knowledge about the number of concurrent targets in the field and schedule the active sensors accordingly. Although a central approach is more reliable, but a distributed approach can make more efficient use of communication channel thereby saving considerable energy. Our future work will focus on extending LEDS to a distributed approach and comparing with central-based LEDS.

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