Adaptive Multi-Target Tracking
in Heterogeneous Wireless Sensor Networks

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ABSTRACT: Energy efficient multiple-target tracking is an important application of Wireless Sensor Networks (WSNs). Most prior studies consider tracking multiple targets as an extension of executing a single target tracking algorithm multiple times, and use a single parameter for energy efficiency. We consider various factors such as multiple targets tracked by the sensor, remaining energy of the sensor and relative location of the sensor with respect to a target's motion, in order to decide the tracking state of a sensor in a distributed environment. Further, we explore and identify the effective combination of these parameters to optimize energy usage, depending on specific network conditions. We then propose the Adaptive Multi-Target Tracking (AMTT) algorithm that can recognize the network condition based on local information without centralized coordination, and uses effective parameters to achieve energy efficiency.

I. INTRODUCTION

Wireless Sensor Networks (WSNs) find their use in applications like target tracking in battlefields, and monitoring hazardous chemicals or wild life while they are in transit. In target tracking applications, the sensors sense the targets present in their sensing range, and send the collected target signatures to the base station where data collected by all sensors is processed and used, for example, to estimate the next position target might go to. These sensors however, have energy limitation as they typically stay on with batteries. One way to mitigate this problem is to use sensors responsibly as and when required and schedule them to operate in different operational states to save their energy.

As the targets move around in the environment, it is difficult to keep monitoring them at all times with a limited number of static sensors. Practically, sensors may be incrementally deployed and a limited portion of mobile sensors may be used to improve the tractability. This leads us to consider heterogeneity in sensor networks where partial amount sensors are capable of being mobile. Having mobility heterogeneity helps in keeping deployment costs low. However, in terms of operation, mobility requires extra energy consumption of sensors. Thus, it is important to decide carefully as to when and which mobile sensors should be moved to track the targets.

In the target tracking problem we tackle, there are multiple targets in a network and each target is monitored by at least n sensors ($n \geq 1$), as required in many practical scenarios such as trilateration for target localization, or corroborating results for better accuracy. The sensors can change their operating state among SLEEP, READY, ON and MOVE states, for better energy utilization.

Most of prior studies consider tracking multiple targets as an extension of executing a single target tracking algorithm multiple times, and consider a single or a few parameters such as a sensor's remaining energy for energy efficiency and/or network lifetime. Furthermore, to the best of our knowledge, network density has not been considered. In this paper, we investigate the impact of various factors including multiple targets tracked by a sensor, remaining energy of a sensor and relative location of the sensor with respect to target's motion, under different network conditions. Further, we explore and identify the effective combination of these parameters to optimize energy usage, depending on specific network conditions. We then propose the Adaptive Multi-Target Tracking (AMTT) algorithm that can recognize the network condition based on local information without centralized coordination, and uses effective parameters to achieve energy efficiency. We validate each step of our approach using extensive simulations.

The remainder of this paper is organized as follows. In Section II we summarize the related work. We discuss our approach in Section III with validation and evaluation. We conclude the paper in Section IV.

II. RELATED WORK

A lot of research has being carried out in the field of target tracking using WSNs. Some of the significant works that deal with target tracking include [2], [10], [6], [7], [9]. Many recent works aim at exploiting network heterogeneity in the wireless sensor network by introducing both static and mobile sensors in the network [13], [4], [8], [11], [14]. In accordance with these works, we introduce mobility in some of the sensors in our environment to facilitate better target tracking and focus on making this activity as energy efficient as possible. Recently game theory approaches have been taken for solving and strategizing mobility prob-

(a)Considering multiple-targets tracked by a sensor

(b)Considering remaining energy of a sensor

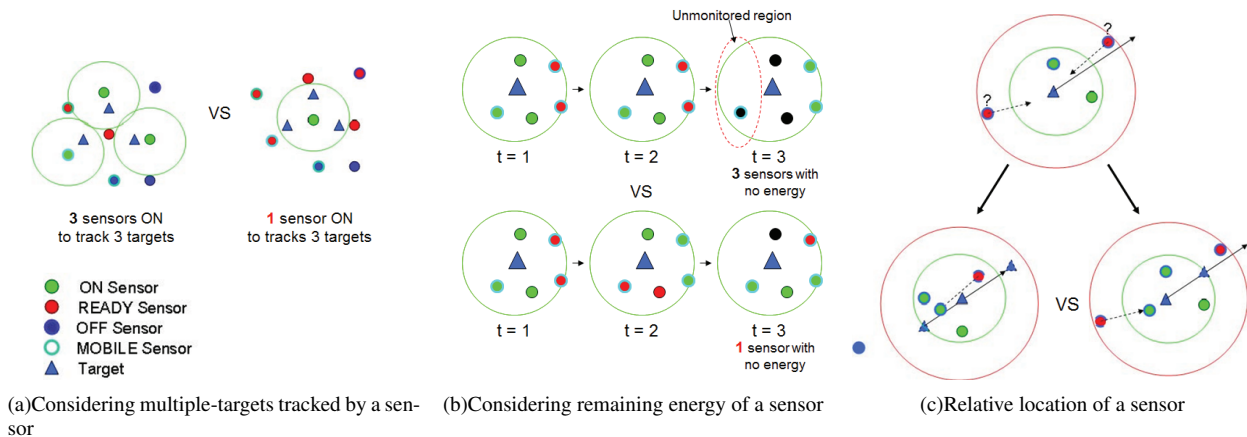(c)Relative location of a sensor

Fig. 1. Performance of individual factors

lems of sensors in the WSNs [3], [12], [5]. Below, we discuss some of the above mentioned in brief, with regards to the contributions of these approaches, their shortcomings and how our work helps in overcoming them.

In the work done by Abdelkader, et. al. [2], a multi-target tracking framework is proposed that is based on use of Voronoi tessellations. Two mobility models are proposed to control the coverage degree according to target presence [2]. Their goal is to allow the detection of targets using multiple sensors and to discover redundant sensors. Their approach helps them in determining the locations where the probability of the occurrence of a target is more as compared to rest of the area. They also propose a way to discover redundancies in the network to improve the cost effectiveness of the overall wireless sensor network. Simulations carried out by them are in favor of their approach. The main drawback of this study is that it does not extend to multiple targets and it fails to consider a very important criterion while carrying out sensor motion - the battery power. It is essential to consider this factor while moving sensors because it consumes a lot of battery power and can lead to leaving the sensors in a depleted energy state.

Kim, Mechitov, et. al. [10], study the feasibility in using binary proximity sensors for tracking targets. They propose a system in which the sensor output is used to estimate individual positions in the path of the target in the near past and find a line that gives an estimate that best fits the path points. This is, in turn, used to find out the current location of the target. Though the approach used is novel and effective for single target tracking, the main drawback of this work is its inability to track multiple targets. The ability to track multiple targets by a single sensor goes a long way in the efficient use of the network resources and helps, to a great extent, in increasing the network lifetime and robustness.

In [7], the authors propose two sleep-awake protocols that help in achieving a high quality of surveillance and reducing the overall power consumption in the components of the network. They also suggest a set of pointers to efficiently deploy sensors in target tracking applications. Their approach of having the sensors operate in different working modes is exploited by us in deciding which nodes need to be in a ready state to track a target. Again, the major drawback of this study is that it does not take into consideration target tracking for multiple targets.

In the work done by Xing, et. al. [13], the authors explore efficient use of mobile sensors to address limitations of static WSNs for target detection. Their proposed data-fusion based detection model allows static and mobile sensors to collaborate in target detection. They also propose an optimal sensor movement scheduling algorithm to minimize the total moving distance of sensors while achieving a set of spatiotemporal performance requirements that include a high detection probability, low system false alarm rates and a bounded detection delay. While scheduling their sensors for moving to a new location their complete focus is on minimizing the total distance traveled by the sensors. Because of this, a node that lies in the path of the target's motion and that can potentially track a target in near future is moved to a new location. It's necessary to avoid such scenarios. Our proposed algorithm specifically tries to avoid moving a sensor that can possibly track a target at later stage.

In [12] and [5], the sensors' movement is used to improve surveillance quality. However, the power consumption of locomotion is not explicitly considered [3]. Chin, et. al. [5], propose a coordinating protocol for sensors to collaboratively track targets in sensor networks. The sensors form a cohort opportunistically to limit the target's degree of freedom in escaping detection. They also minimize the overlap in the spatial coverage of this cohort's members. Though this technique is effective, it fails to extend to a heterogeneous type of sensor network. Having all sensors with mobility can be expensive and a heterogeneous model can solve that problem. Also, the authors fail to consider the cost of these operations in terms of energy consumed

which is an important factor in such networks.

We can observe that efficient sensor scheduling for mulit-target tracking has been less explored and energy efficiency is considered from a single factor of sensors like the sensor's remaining energy or its relative location in the network. Also network conditions like local density of sensors and presence of multiple targets has not been considered.

III. OUR APPROACH

In this section, we first discuss various factors to be considered for a multi-target tracking problem. Secondly, we investigate the impact of those factors on energy usage, individually as well as the combination of the factors. Then, we develop an Adaptive Multi-Target Tracking (AMTT) algorithm.

A. Factors for Energy Efficiency

Sensors may interact with neighbor sensors to decide their tracking state: SLEEP, READY, ON or MOVE. Sensors can be in a SLEEP state where no or minimal energy is used and they awake from the state periodically. Sensors in a READY state do not sense a target, but they can communicate with neighbor sensors within a communication range. ON state is where sensors are sensing a target(s) and actively collect target signatures. If sensors are mobile, they may be in a MOVE state in which sensors move to a new location closer to targets for sensing. Scheduling the state of the sensors' operational mode is the key issue to save individual sensor's energy as well as to maximize the network lifetime.

We discuss various factors to make the decision on the sensor state, such as multiple-targets tracked by the sensor, the remaining energy in the sensor, and the relative location of the sensor with respect to the targets path of motion.

A.1 Multiple-targets Tracked by an Individual Sensor

Unlike a single target tracking problem, there may be multiple targets around a sensor. In practice, sensors spend almost the same energy to track single or multiple targets. We point out that if multiple targets can be tracked by a single sensor, the total number of sensors to be turned ON would be reduced, leading to significant savings of energy compared to the case where each target is tracked separately. It is illustrated in Figure 1(a). In the first (left) case, the 3 sensors nearest to each of the 3 targets are turned ON to track them. However, there is one sensor available that can track all three of them at the same time. If we turn the center sensor ON, the other three sensors can be just in a READY state. We expect that the opportunity of a single sensor tracking multiple targets would occur more often in a dense network.

MaxPower	100 J
SensingEnergy	0.1 J
ReadyEnergy	0.01 J
TransmittingEnergy	0.12 J
ReceivingEnergy	0.12 J
MovingEnergy	0.1 J

TABLE I

ENERGY MODEL USED IN SIMULATIONS

A.2 Remaining Energy of a Sensor

The remaining energy of a sensor is often taken into account in order to extend a network's lifetime. If a same set of sensors is used again and again, those sensors will die out much sooner as compared to other sensors. In a sparse network environment, this can lead to empty holes in the network where the target may be present and cannot be tracked. The scenario is depicted in Figure 1(b). We expect that the remaining energy would play an important role especially in a sparse mode network in the aspect of a network lifetime.

A.3 Sensor's Relative Location

We note that it is important to have a target tracked by sensors that lie the closest to its path of motion as well as the closest to the target's location. This way, the sensors can track a target(s) for a maximum time possible, and the overhead of turning sensors ON and OFF repeatedly can be reduced. Also, while moving sensors to a new location to track targets not tracked by enough sensors, the sensors that lie farthest from target's path of motion should be moved. The reason for this is that if sensors that lie in the path of the target are moved, those sensors could potentially track the target at a later time, and may have to move back again to track the target. This increases the amount of movement carried out which is an expensive operation. It has been illustrated in Figure 1(c).

B. Impact of the Factors

We investigate the impact of the factors on average energy used in sensors and network lifetime in Figures 2(a) and 2(b), respectively, while varing network density. In Figure 2(a), it can be observed that using only the Remaining Energy as an impacting parameter leads to worst performance in terms of overall energy savings. Multiple-targets tracked by a sensor gives an improved performance in the mid to high sensor densities. The parameter Relative Location of Sensor with respect to targets motion performs best individually. However, the factor Remaining Energy cannot be ignored as it is an important factor in improving the network lifetime, especially at low network densities, as can be seen from Figure 2(b).
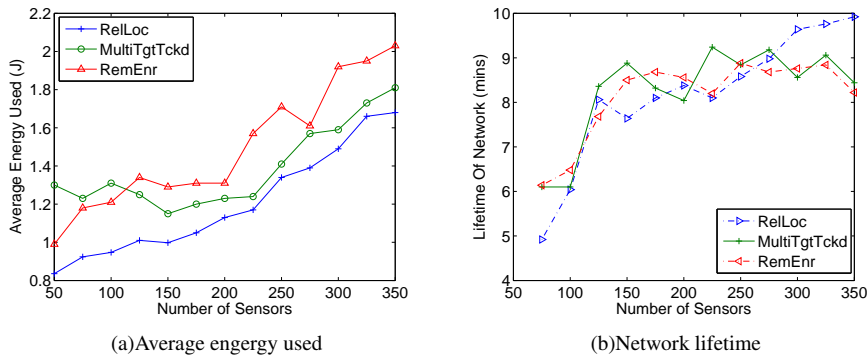
(a)Average engergy used

(b)Network lifetime

Fig. 2. Performance of individual factors

(a)Remaining Energy and Relative Location

(b)Multi-target Tracked and Remaining Energy
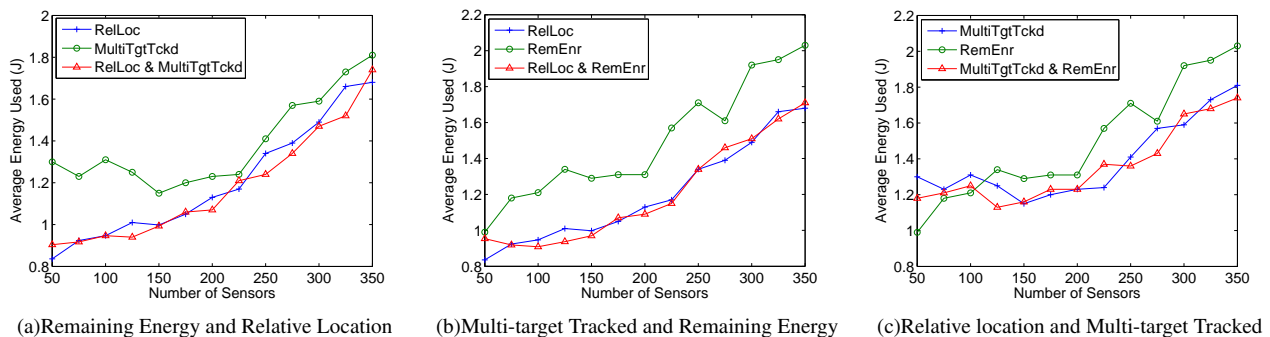
(c)Relative location and Multi-target Tracked

Fig. 3. Individual vs. combining factors

C. Impact of Combining the Factors

Next, we evaluate the performance when multiple factors are combined using simulation. The simulations are carried out in Matlab. The network is of 100 * 100 square units in area. The number of sensors is varied from 50 to 350 with increments of 25. If a sensor can contact 3 or more neighbor sensors, it perceives the network as dense network or else it perceives it as a sparse mode network. The number of targets is 5. All the targets start at a random location in the WSN with a linear movement pattern and have no correlation with movement patterns of other targets. The WSNs heterogeneity is set at 75%. This means that 75% of the sensor nodes can be mobile. Depending on weather it is a dense mode or a sparse mode network, the sensors exchange the following information with their neighbor sensors: maximum number of targets the sensor can track, sensors location and its remaining battery power. For the network lifetime evaluation the standard energy model for CC 2420 has been used. The power consumed for locomotion depends on the amount of distance traveled by the sensor. As it is an expensive activity, we consider its value for one unit distance of locomotion same as one sensing activity. The energy consumption model can be found in the available data sheet [1]. The values used for energy consumption is summarized in Table I.

Figures 3(a), 3(b), and 3(c) show that combining the two

impacting factors leads to the energy savings in most cases, and at least as good as using the best performing individual factor. From Figure 3(a), we find that combining Relative Location and Multiple-targets tracked by sensor gives the best performance in mid to high network densities. Meanwhile, from Figure 3(b), it can be seen that using Relative Location and Remaining Energy gives the best performance in low to mid network densities.

Comparing the performance of different combinations, Figure 4(a) shows that Relative location and Remaining Energy perform the best for low to mid network densities and Relative Location and Multiple-targets tracked by sensor performs the best for mid to high network densities. So to achieve optimal performance across all network densities, we have to bridge this transition.

In summary, we find that using a combination of these can result in a better performance in terms of energy savings as compared to using single parameters, or the performance is at least similar to that of the best performing parameter for different network densities. For low to mid dense networks, a combination of Remaining Energy and Relative Location of Sensor performs optimally while in the mid to high density networks, a combination of Multiple Targets a Sensor can track and Relative Location of Sensor performs optimally. This leads us to conclude that to obtain an overall optimal performance, the designed algorithm has

to select the correct combination of parameters based on its local network conditions.

D. Adaptive Multi-Target Tracking (AMTT) Algorithm

Based on the observations above, we develop Adaptive Multi-Target Tracking (AMTT) algorithm, where all the factors discussed above are used with adaptive weights as below.

$$Priority = \alpha M + \beta S \times T \cos(\theta) + \gamma R \qquad (1)$$

where M is the number of targets tracked by the sensor, S is a Sensor Vector, T is a Target Vector, $\theta = TargetAngle - SensorAngle$, and R is the Remaining Energy. All the values are normalized between 0 and 1, so that the weights would be comparative. The main factors to choose sensors to track targets are adaptively decided based on the local network condition - dense or sparse mode. The sensors locally choose their operational mode, either dense or sparse, based on the number of neighbor sensors they can contact. If a sensor can contact many neighbor sensors above a certain threshold, the sensor perceives the network as a dense one. Otherwise, the sensor operates on a sparse mode. After extensive simulations, we found the value of this threshold as 3 for our environment. In a dense mode, AMTT uses high weights on the combination of Relative Location of a sensor and Multiple Targets a sensor to determine its tracking state, and puts high weights on the Remaining Energy and Relative Location of a sensor in a sparse mode. As can be seen from Figure 4(b), AMTT achieves its desired performance pattern achieving the best performance throughout the network condition.

E. Evaluation

In order to compare the performance AMTT, we consider a baseline system. This baseline system also is a distributed system to track multiple targets where each target is tracked by n sensors. The main difference from our proposed algorithm is that random sensors are chosen to track the targets without specific criteria. In case n sensors are not available to track the targets, the required numbers of mobile READY sensors move in to track the targets in a random fashion.

Figure 5(a) shows that the AMTT performs better than the baseline system in the average energy used. Especially as the execution time increases, the performance benefit of AMTT becomes higher significantly. The performance of network lifetime is exhibited in Figure 5(b). The definition that we consider for network lifetime is as the time from the start time to the time of the first instance when any of the targets is not monitored by n sensors. There are various definitions for network lifetime in the literature. Our consideration for the above definition is based on the need for the target to be at least tracked during the lifetime of the network.

IV. CONCLUSIONS

We have proposed and an energy efficient algorithm, called AMTT to track multiple targets in a heterogeneous wireless sensor network. We have identified different factors that affect the performance and energy consumptions in heterogenous WSNs based on different network conditions. These factors are the multiple-targets tracked by a sensor which is significant in high network densities, the remaining energy in the sensor which is significant in the low network densities, and the relative location of the sensor which is significant across all network densities. Also the combination of these parameters can show better performance or is at least as good as the best performing individual parameter. The proposed AMTT algorithm can identify the optimal combination of impacting parameters based on the local network conditions of a sensor and lead to significant energy savings and a longer network lifetime.

As for future work, we plan to include existing prediction models for targets' movement in our algorithm and have more realistic constraints on sensor's movements. We plan to explore more thorough metrics to identify the correct network threshold and find the optimal percentage of sensor heterogeneity required.

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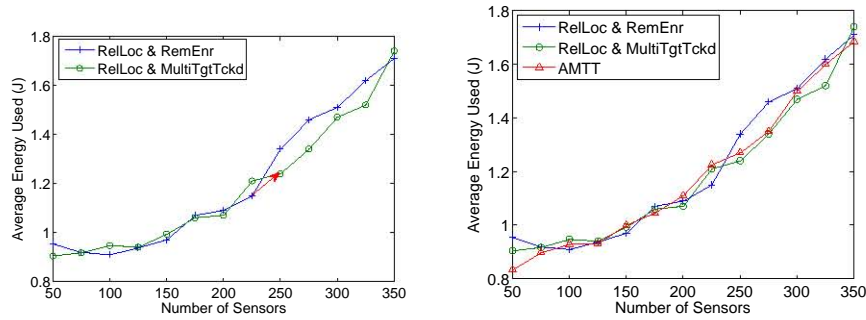
(a)Finding optimal factors depending on network (b)AMTT: achieving the best of the two performance density

Fig. 4. Finding optimal factors to consider - AMTT
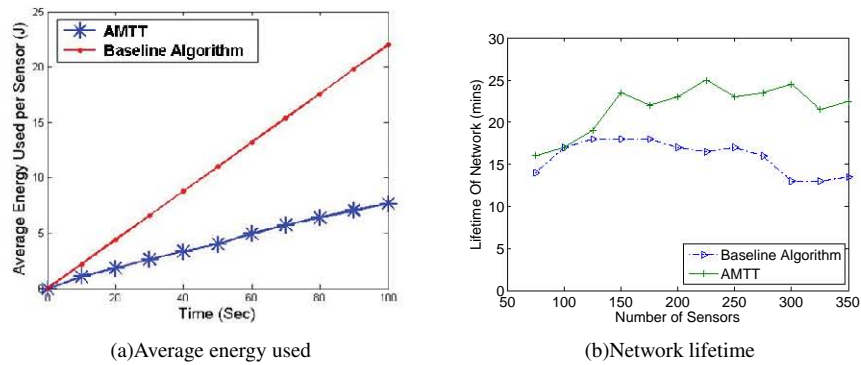
(a)Average energy used

(b)Network lifetime

Fig. 5. Comparison of AMTT and Baseline

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