COOPERATIVE MULTI TARGET TRACKING USING MULTI SENSOR NETWORK

Ahmed M. Elmogy , Fakhreddine O. Karray
Electrical and Computer Engineering Dept., University of Waterloo,
Ontario, Canada

Abstract– Sensors provide a key feedback link allowing robotic and autonomous systems to react to their environments. Without this feedback, robotic and autonomous systems will operate in an uncontrolled manner, since they don't have the ability to perceive and respond to their environments. The limited capabilities of static sensors especially in complex applications and environments force the use of multiple sensors operating dynamically. This paper addresses the development of multiple objects tracking system using multiple mobile sensors. For the purposes of surveillance and security, trackers use an Extended Kohonen neural network to track the moving targets in their environments. The proposed tracking algorithm can be used for single and multiple target tracking. A clustering algorithm is used in order to minimize the number of active trackers over time and hence save energy. An auction based algorithm is used for the purpose of optimizing the cooperation between trackers. Quantitative and qualitative comparisons with other recent multi target tracking approaches show that our proposed tracking algorithm can provide a good coverage, and a better energy saving.

Index terms: Mobile sensors, target tracking, Kohonen neural network, clustering

I. INTRODUCTION

In autonomous systems, there is an increasing need for more accurate and reliable sensors as they are continuously being applied to new, more complex and demanding tasks. A sensor network is one of the frameworks that have been proposed recently to improve the capabilities of a sensing system. Such a network, consisting of multiple similar and/or dissimilar sensors that work in tandem for a common surveillance task, is also commonly referred to as a distributed sensor system.

Many security, surveillance, and reconnaissance tasks require autonomous observation of the movements of targets navigating in a bounded area of interest. A key research issue pertaining to these problems is that of sensor placement: determining where sensors should be located to maintain the targets in view. In the simplest version of this problem, the number of sensors and sensor placement can be fixed in advance to ensure adequate sensory coverage of the area of interest. However, in more complex applications, a number of factors may prevent fixed sensor placement in advance. For example, there may be little prior information on the location of the area to be observed, the area may be sufficiently large that economics prohibit the placement of a large number of sensors, the available sensor range may be limited, or the area may not be physically accessible in advance of the mission. In the general case, the combined coverage capabilities of the available robot sensors will be insufficient to cover the entire terrain of interest. Thus, the above constraints force the use of multiple sensors dynamically moving over time. Mobile sensor networks can be very effective in overcoming these problems.For instance, the troops and/or vehicles in the battlefield can carry biochemical sensors while doing their normal daily activities. These mobile sensing devices can sample the environment at potentially several different locations, exchange the information with other nodes, and collaboratively make a decision. Although mobile nodes in a sensor network have many advantages, there are also several challenges. First, there must be a collaboration mechanism among nodes to coordinate the sensing operations. Without collaboration, performance of the network is expected to be significantly degraded. Second, the mobile nodes must be deployed in the environment in such a way as to achieve full coverage of the environment, do the required tasks with minimum energy consumption, minimize the interference between the mobile nodes as possible, and minimize the cost of node deployment.

Motivated by all these challenges, this paper presents an energy efficient multi target tracking framework that can be used to track multiple moving targets using multi mobile sensors. The contributions of this work can be outlined in two phases.

The first phase is the development of an Extended Kohonen neural network for the purpose of target tracking. This is done by using supervised learning technique to get the initial weights of unsupervised Extended Kohonen Map instead of random initialization. Selecting the initial weights of the unsupervised Extended Kohonen Map is very challenging because it will affect the speed of convergence during self organization of the Extended Kohonen Map and also will increase its Mapping accuracy. The second phase is the development of an energy-efficient multi target tracking algorithm. The key idea of this algorithm is the introduction of target clustering before tracking so as to reduce the number of trackers needed to track the moving targets. A hybrid subtractive K-means clustering technique will be used for this purpose. Also, an auction-based algorithm is used as a cooperation methodology between trackers during tracking. The used auctioneer in this algorithm is always changing during tracking other than using one auctioneer as proposed in [1]. By changing the auctioneer during tracking, our proposed algorithm is considered as a distributed energy-efficient multi target tracking algorithm and so it is robust and expandable.

The rest of this paper is organized as follows. Section 2 gives a summary of the state of the art on mobile sensor network and target tracking. Section 3 presents the target tracking algorithms including robot and target detection, clustering targets, target reaching, and trackers cooperation. Section 4 reports our simulations on single target and multi target tracking using supervised and unsupervised Kohonen Map respectively. Section 5 concludes and highlights the future work.

II. Related Work

One of the fundamental issues that arise in a mobile sensor network is coverage. Traditionally, network coverage is maximized by determining the optimal placement of static sensors in a centralized manner as seen in the class of art gallery problems [2]. However, recent investigations reveal that mobile sensors can self organize to provide better coverage than static sensors [3,4]. Mobile sensors are often desirable, since they can patrol a wide area and can be repositioned for better surveillance [5].

A recent article on mobile sensor networks [6] presented a distributed and scalable potential field-based approach for the deployment of mobile sensors. The fields are constructed such that each sensor is repelled by both obstacles and by other sensors, thereby forcing the network to spread itself through the environment. In [7], algorithms for controlling a group of sensing vehicles to achieve full coverage in a dynamic environment are proposed. Nevertheless, collision avoidance and the effect of measurement errors can't be guaranteed. In [3], the authors proposed an autonomic mobile sensor architecture using an antlike scheme to self-organize nodes to track unknown time-varying target distributions. Hoe and Varchney [4] proposed energy efficient deployment algorithms for a mobile sensor network.

Existing target tracking approaches can be classified into two categories: single target tracking, and multi target tracking. Most of the research in the area of target tracking has focused on the single target tracking category [8,9,10,11,12,13]. However, in order to work in security, and surveillance applications, it is more needed to use multiple sensors in order to track multiple moving targets.

In [14], the authors deal with the surveillance problem by computing the motion of one or more robot observers in order to maintain visibility of one or several moving targets. The targets are assumed to move unpredictably, and the distribution of obstacles in the workspace is assumed to be known in advance. The main idea of the algorithm is to maximize the shortest distance the target must move in order to escape from the observer visibility region. In [15], Parker investigated the use of a cooperative team of autonomous sensor-based robots for applications in the domains of surveillance, and reconnaissance. The primary focus of her work is on developing the distributed control strategies that allow the team to attempt to minimize the total time in which targets escape observation by some robot team member in the area of interest, given the locations of nearby robots and targets. In another work [16], she described the implementation of this weighted-force vector approach for fault-tolerant multi-robot cooperation. In this article, she focused on the analysis of this approach. The proposed approach is called A-COMMT (cooperative observation of multiple moving targets.

Kolling and Carpin [17,18] presented another version of the Parker work called B-COMMT to overcome some of the difficulties exist in Parker work. One of these situations was when one robot followed two targets moving in opposite directions, eventually losing both. Our work in this paper differs from all of these approaches by decoupling the tracking algorithm from the cooperation strategy between trackers and also by considering the energy optimization during tracking the moving targets.

III. Target Tracking Approach

The objective of this paper is to develop a generalized methodology for tracking multiple moving objects. This methodology will be energy efficient one by minimizing the number of active trackers over time. In this context, the overall problem of tracking is a multi task process:

1) Detecting every target within a given scene.
2) Distinguishing and categorizing objects obstacles or objects of interest
3) Find the centre of gravity of targets within the scene.
4) Tracking the centre of gravity of the targets using Extended Kohonen Maps.
5) Tracking the exit targets by the best suitable trackers using an auction- based approach.

Our goal is to develop an algorithm that maximizes the following metric:

$$B(t) = b_{ij}(t) = \begin{cases} 1 \text{ if robot } i \text{ is observing target } j \\ 0 \qquad\qquad \text{otherwise} \end{cases} \tag{1}$$

The goal is to develop an algorithm that maximizes the following metric:

$$A = \sum_{t=1}^{t_e} \sum_{j=1}^{n} \frac{g(B(t), j)}{t_e} \tag{2}$$

where

$$g(B(t), j) = \begin{cases} 1 \text{ when there exist } i \text{ such that } b_{ij}(\mathrm{t}) = 1 \\ 0 \qquad\qquad \text{otherwise} \end{cases} \tag{3}$$

n, and t_e are the number of targets and execution time respectively. In other words, the problem aims to maximize the number of targets that are observed by trackers. Our target tracking approach consists of four fundamental stages: robot and target detection, clustering targets inside tracker's sensing range, target reaching, and trackers cooperation.

A. Robot and Target Detection

Our target tracking approach is based on two fundamental assumptions: (1)robot team members would be able to passively observe (e.g., through visual image processing) nearby robots and targets to ascertain their current positions. So, we assume that the positions of targets are known for one robot if they lie within its sensing range; (2)the field of view of the trackers is omnidirectional. Each tracker will have two ranges; the inner range which is the sensing range of the robot within which it executes the tracking algorithm to maintain observation of the targets within its range. The outer range called the predictive tracking range, which is the range within which the targets are out of the sensing range but still observed (i.e., the target starts to leave the robot's sensing range).

B. Clustering Targets inside the Sensing Range

In order to make our approach dependent on the distribution of the targets rather than the density of targets as in [19], we chose to cluster the targets inside the tracker sensing range. Clustering the targets make our approach an energy efficient one because not all the trackers will be active at all the time. Out of the numerous available clustering techniques, two were selected, subtractive, and K-means techniques. The reason behind using K-mean clustering technique is its high level of accuracy [20]. However, K-mean clustering technique has the problem of selecting the initial locations of clusters, which will affect the speed of convergence and the accuracy of the algorithm. So, we propose using the subtractive clustering technique to find the initial number and locations of the clusters centers to be fed into the K-mean clustering technique in order to find the final exact locations of clusters centers.

C. Target Reaching

The target is reached by adopting a representation of the sensory input vector $u_p = (\theta, d)$ where θ and d are the angle difference and distance between the tracker and the target. Each tracker uses an Extended Kohonen Map (EKM) [3,21] in order to reach the target. The Extended Kohonen Map is an extension of Kohonen Map [22], and is considered as one of the most famous unsupervised learning neural network. Extending the Kohonen Map, which is done by adding fan-in input weights to its input layer gives the map the ability to learn by supervised learning. However, this is not always the case; unsupervised learning could still be used. Each neuron i in the EKM has a sensory weight vector $w_i = (\theta_i, d_i)$ that encodes a region in the workspace centered at w_i. Figure 1 shows the supervised learning process in the Extended Kohonen Map.

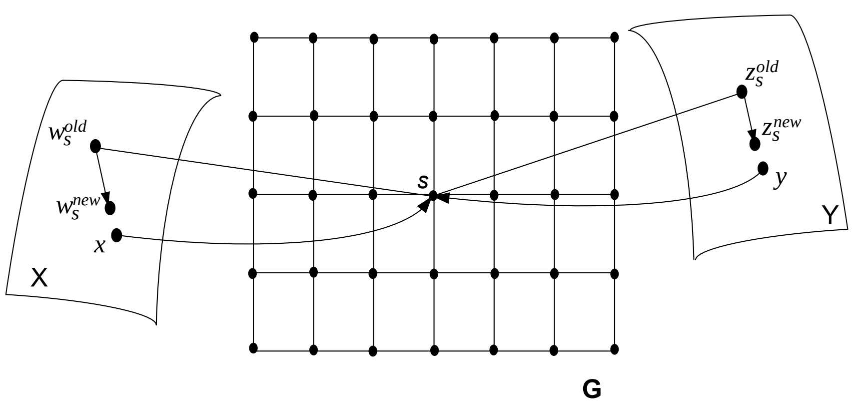

Figure 1: Supervised Extended Kohonen Map learning

Where w_s^{old}, w_s^{new} are the old and new (after learning) fan-in weight vectors for the winning neuron, z_s^{old}, z_s^{new} are the old and the new fan-out weight vector for the winning neuron, and x, y are the training input and output. The winning neuron is the neuron, which has the closest fan-in weight vector to the training input x. Again as in K-mean clustering technique, unsupervised EKM has the problem of selecting the initial neurons weights. Selecting the initial weights will affect the accuracy and speed of mapping from the space of sensory data to the space of motor commands for tracking purposes. In this paper, we propose to use the supervised EKM parameters (fan-in and fan-out) as the initial parameters of unsupervised EKM in order to increase the accuracy and speed of convergence of unsupervised Map. The target is reached as follows:

1) Determine the winning neuron for each sensory input $u_p = (\theta, d)$of a target:

$$D(u_p, w_s) = \min_{i \in B(\theta)} (u_p, w_i) \tag{4}$$

The difference$D$ is taken over the set $B(\theta)$of neurons encoding very similar angles asθ. In other words, the direction from the tracker to the target has a higher priority than the distance.

1) Determine the output activity(s_r, s_l) (the right and left wheel speed) of the winning neuron and move the robot.
2) Compute the actual displacement $v$of the tracker, which is the difference between the new sensory input and the old one.
3) Use v as a training input and adjust the input weights in the neighborhood of the winning neuron:

$$\Delta w_i = \alpha G(s, i)(v - w_i) \tag{5}$$

4) Adjust the output weights in the neighborhood of the winning neuron in order to minimize the error between the actual activity of the tracker and the output of the EKM.
5) Repeat from step 1 until self-organization is reached.

D. TRACKERS COOPERATION

In multi-target tracking systems, tracking performance can be improved by maximizing cooperation between robots in response to the changes in target motion. There are two kinds of cooperation: uncertainty reduction and task allocation. The second type of cooperation is considered in this paper. The trackers used in this work are assumed to be equipped with high bandwidth communications and an array of sensors and actuators, which give the robots the ability to achieve cooperative behavior at the group level. We propose using an auction-based method in [1] to guarantee that the help call coming from the robot that detects a target about to exit its sensing range (or in its predictive tracking range) is answered by only one robot. The auctioneer in our method can be changed rather than the central auctioneer proposed in [1]. The tracker that detects an exit target will do the task of an auctioneer. This increases the robustness of our algorithm because there is no central point of failure in this case. Using an auction-based algorithm will guarantee that the most suitable robot will track the exit target. In other words, there is no need to explore the environment or to check the answered help calls as in [17,18]. This makes our proposed method a more energy-efficient one than the method in [18]. The auction-based method proceeds as follows:

1) ***Help announcement***: the robot that needs help (detects an exiting target) broadcasts a help call to its teammate. One robot can issue multiple help calls according to the number of targets about to be lost. Each help call includes the position of the target to be lost.
2) ***Bid submission***: after each robot receives the help call, they send their bids to the auctioneer (the robot that issued the help call). The bids include the distances of the bidders to the target.
3) ***Close of auction***: the auctioneer processes the bids, determines the winner, and notifies the bidders with a message which indicates who is the winner.
4) ***Task execution***: the winner will proceed by orienting itself to face the target (Using EKM) and move with its maximum speed to put the target inside its

sensing range.

The existence of the auctioneer doesn't mean that the system is completely centralized. The system is still distributed and the function of the auctioneer is only to start the action of tracking.

IV. ASSESSMENT OF THE FRAMEWORK

As mentioned above, the target tracking algorithm for an individual target is decoupled from the cooperative tracking algorithm for a multi-tracking system. So, we first present simulation results for our single robot tracking system as a basis layer of the cooperative multi-target system. The target tracking algorithm design depends on targets, sensors, and environments. Target motion recognition is one of the fundamental capabilities that a mobile robot must have in order to operate in an environment. Therefore we designed a single tracker, which tracks and reports the positions of moving targets in the vicinity of a robot. The simulation results of two types of trackers are presented (supervised and unsupervised Extended Kohonen Maps) using mobot simulator [23]. The tracking performance is judged by both accuracy of tracking and speed of convergence. We also present the simulation results for a cooperative multi-target tracking.

A. SINGLE TARGET TRACKING

In our simulations, we use 30x30 neurons in the structure of the EKM. Figures 2,3 show the results of tracking a single target using both supervised and unsupervised EKM. The small circle and square are the initial positions of the target and the tracker respectively. The indicated arrows show the direction of movement of both, the target and the tracker.

As seen from the trajectories of the target and the tracker (figures 2,3), the unsupervised learning EKM has provided a better tracking performance in terms of accuracy and tracking speed than supervised learning EKM.

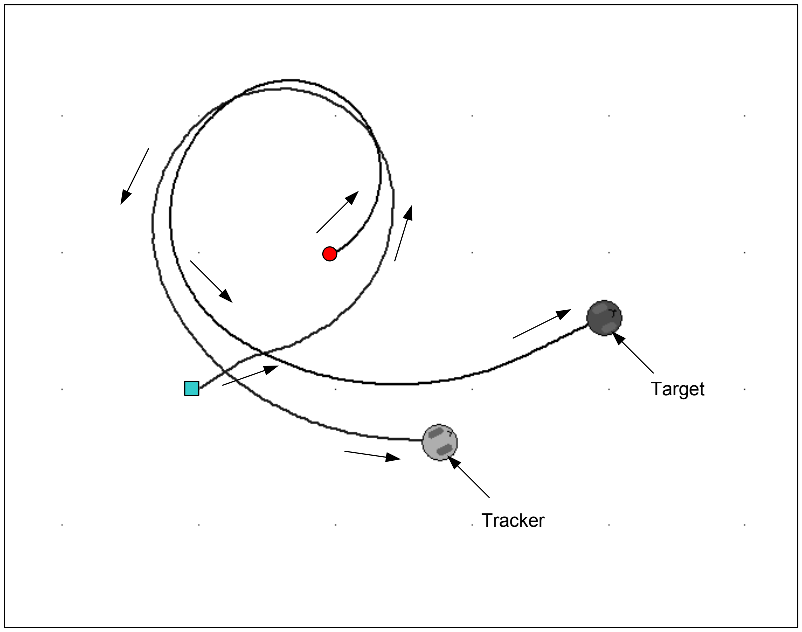

Figure 2: Single robot tracking using supervised learning EKM

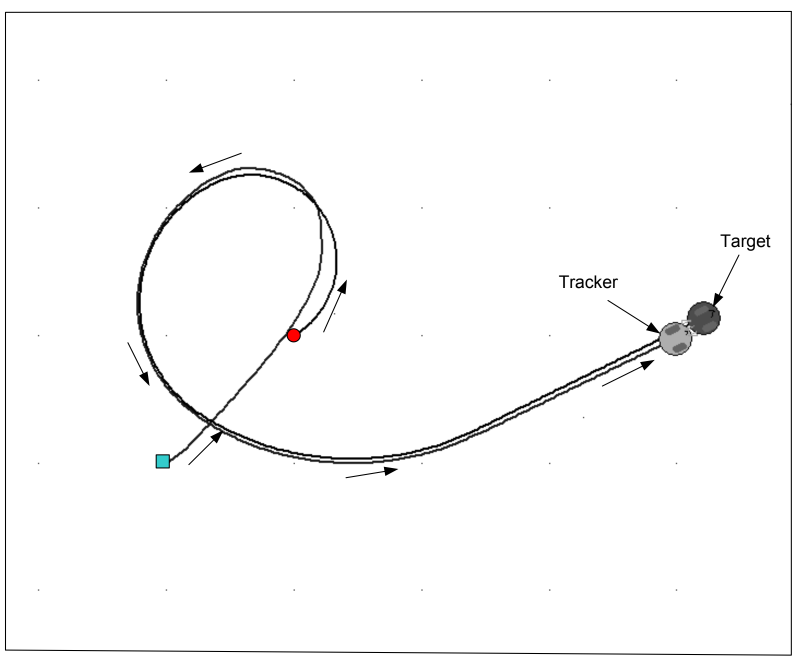

Figure 3: Single robot tracking using unsupervised learning EKM

B. COOPERATIVE MULTI TARGET TRACKING

In order to validate the proposed multi-target tracking algorithm mentioned in the last section, extensive simulations have been performed with mobot simulator [23]. The experiments presented in the following should be interpreted as preliminary findings, and the collection of data with real robots will be considered as a part of our future work. The proposed algorithm is analyzed in various configurations. The environment was designed to be a 6m x 9m rectangular shape. The robots and targets were initially randomly deployed in the environment. Robot sensing range was set to be 1.5m. The cooperative multi target algorithm performance is judged by two parameters: the average coverage A (eq. 1) over time and the average energy saving over time E (eq. 6). The energy saving can be measured by considering the number of busy and asleep trackers over time. In order to do that, three different cases are analyzed. In the first case, the number of trackers n is equal to the number of targets m and in the second and third cases, the number of trackers is 3/4 and 1/2 the number of targets respectively. In each case we did extensive simulations by changing the locations of trackers and targets, the speed of targets and trackers, the direction of targets and trackers, and the number of clusters. We recorded the average coverage and average energy saving for around 25 trials in each case. The average coverage and the average energy saving for all the cases are shown in figures 4 and 5 respectively. Each point shows the average coverage or the average energy saving obtained in 25 simulated runs.

$$E = \sum_{i=1}^{t_e} \frac{s}{n} * \frac{1}{t_e} * 100 \tag{6}$$

Where s is the number of asleep trackers, n is the total number of the trackers, and t_e is the execution time of the algorithm.

We can more effectively evaluate the performance of our approach by comparing it with four different approaches with different observation policies: (1) Local approach [1], (2) A-COMMT approach [1], (3) B-COMMT approach [17], and (4) Modified B-COMMT [18]. The Local approach controls the robot motion by

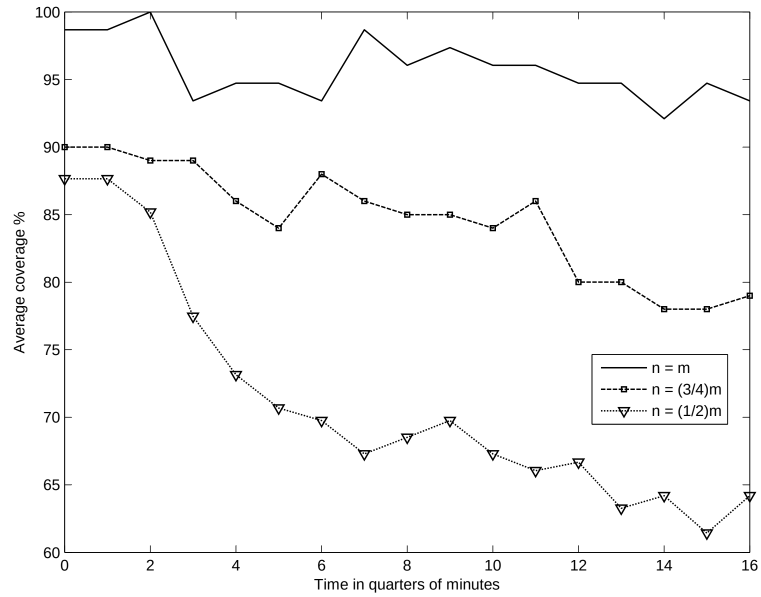

Figure 4: Comparison over time between EKM average coverage for different n and m ratios

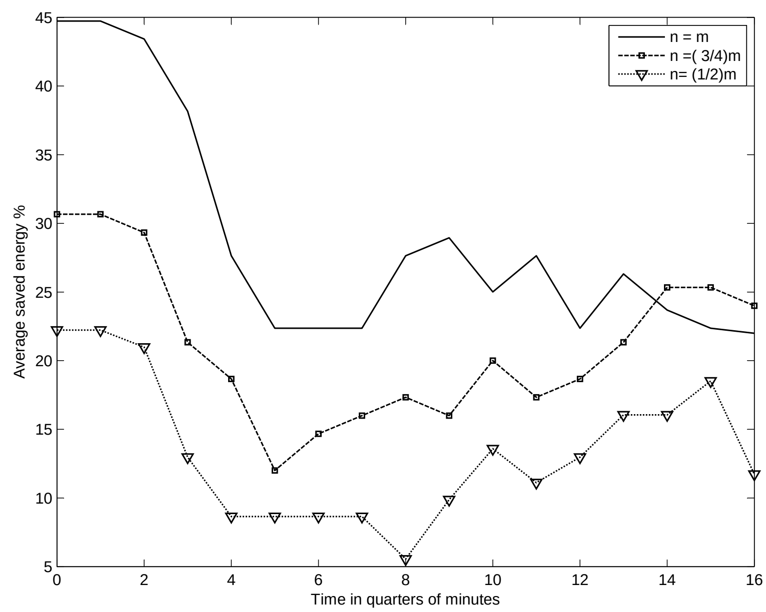

Figure 5: Comparison over time between EKM average energy saving for different n and m ratios

computing the summation of the attractive forces coming from nearby targets and the repulsive forces coming from nearby robots. The A-COMMT approach was studied to determine the effectiveness of weighting the force vectors coming from the nearby targets. Adding the weights to the force vectors in A-COMMT cause the robots to be less attractive to targets that are already observed by other robots. B-COMMT approach [18] is essentially proposed to overcome some problematic situations that may arise in A-COMMT approach. More detailed discussions of these situations can be found in [17,18]. The most important difference between A-COMMT and B-COMMT is that the force vectors coming from nearby robots are weighted as well. B-COMMT approach is improved by introducing more refined techniques for target loss prediction in [18].

We compared our approach with these four approaches by measuring the metric *A* (eq.1) during the execution of the algorithm. Figure 6 summarizes the results of this comparison with different m/n ratios (every point is the average coming from 100 simulated runs). These results show the near equivalence performance of our proposed algorithm and the improved B-COMMT approach for small m/n ratios, but the improved performance of our approach for larger m/n ratios. Although, we didn't prove that the simulation results would hold for larger m/n ratios, it is expected that results similar to what we did will continue for larger m/n ratios.

More interesting is the detailed comparative performance of our approach with the improved B-COMMT for m/n equal to one. As shown in figure 7, our proposed algorithm provides a good coverage performance compared to the B-COMMT algorithm. Furthermore, our proposed algorithm provides average energy savings between 8% and 45% as shown in figure 5, compared to 0% energy saving in COMMT. This is because in B-COMMT, all trackers are always busy even if there are no targets to track (the trackers explore the environment searching for targets even if there are no targets to track).

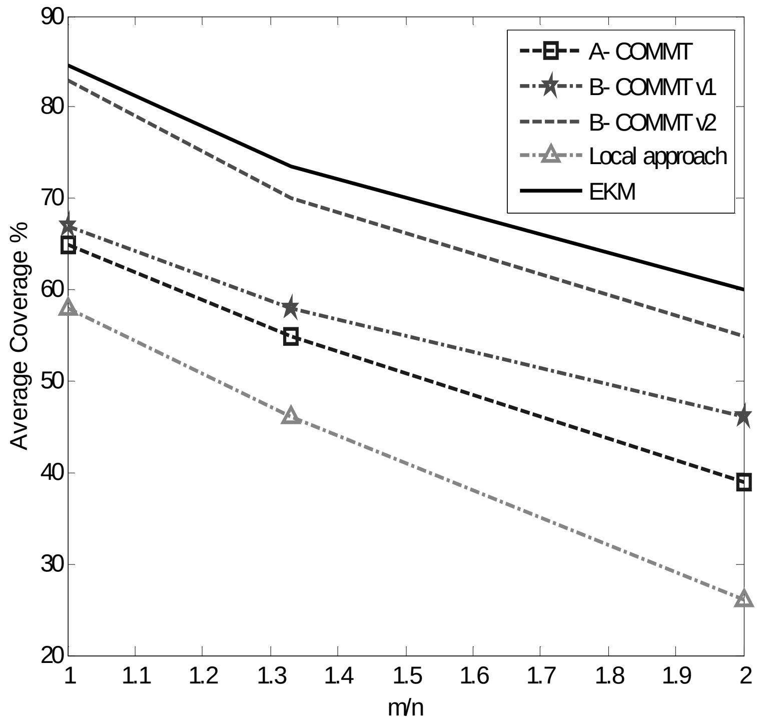

Figure 6: Simulation results of five approaches to cooperative tracking for various $n = m$ ratios

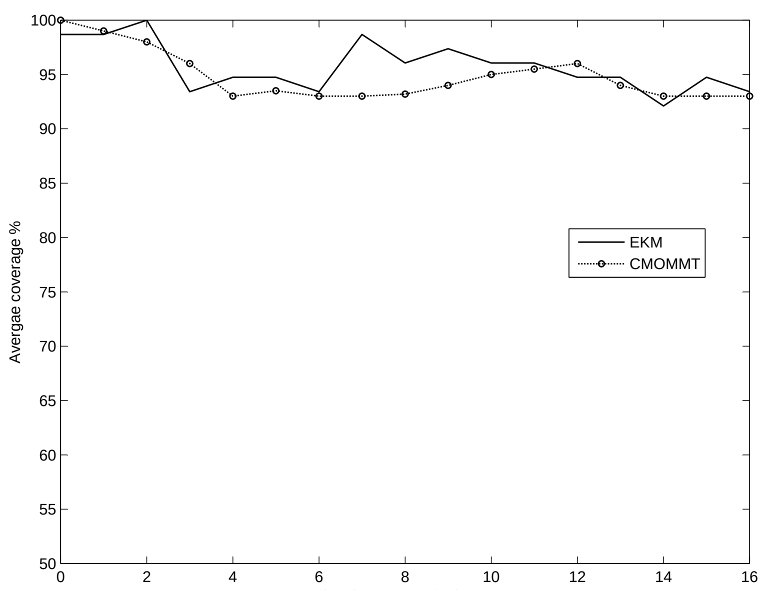

Figure 7: Comparison over time between EKM and COMMT average coverage for $n = m$

V. Conclusions

In this paper, multiple target tracking using multiple mobile sensors has been studied. There are two sub-problems: the single target tracking problem, and the multi-robot cooperation problem. The first problem is challenging, and is considered the core of any tracking system, whether it is a single target or a multi-target tracking system. The Extended Kohonen Map has been proposed to solve this problem. The simulation results of both supervised and unsupervised cases have shown that EKM has some promise in solving the tracking problem. For surveillance and security applications, a multi-target tracking system has been proposed. The EKM tracker is decoupled from the cooperative algorithm, which enhances the robustness of the proposed system. A hybrid subtractive K-means clustering technique has been utilized to cluster the targets, and then the tracking system can track the clusters' locations. An auctioneer-based approach has been proposed to solve the cooperation problem in the multi-target tracking system. The key idea of using clustering alongside an auction-based algorithm is to make our algorithm energy efficient one. The simulation results have revealed that the proposed system provides better coverage performance to other well-known techniques [15,17,18]. Also the simulation results have shown that our algorithm is much better than these techniques in terms of energy saving.

On the other hand, although the proposed cooperative tracking system has shown encouraging results, the work reported here only marks the beginning of our study into multi target tracking domain. While the evaluation metrics and the type of environment we have studied so far serve the purpose of evaluating and comparing the performance of our tracking system with alternative methods. It remains a challenge to maintain the robustness and adaptability of our framework in more complex real world problems. Our future work will include the development of the proposed system to be more generic framework to cope with a variety of complex and dynamic environments. Further research will also investigate the effect using combinations of stationary and mobile sensors on the performance of the tracking system. Additionally, the development of our framework to work into areas such as cooperative multi-tasking in which groups of robots work on individual tasks, and then form different groups to perform other assignments will be considered.

REFERENCES

[1] B. P. Gerkey, and M. J. Mataric, " Sold!: Auction Methods for Multirobot Coordination", IEEE Transactions on Robotics and Automation, Vol. 18, No. 5, pp. 785-768, Oct. 2002.

[2] J. O'Rourke," Art Gallery Theorems and Algorithms", London, U.K.: Oxford Univ. Press, 1987.

[3] K. Hsiang, W. Leow, and M. Ang," Autonomic Mobile Sensor Network With Self- Coordinated Task Allocation and Execution", IEEE Trans. On SMC- Part C, Vol. 36, No. 3, pp. 315-327, May 2006.

[4] N. Heo, and P. Varsheny," Energy Efficient Deployment of Intelligent Mobile sensor Networks", IEEE Transactions on SMC- Part A, Vol. 35, No. 1, pp. 78-92, Jan. 2005.

[5] H. Qi, S. S. Iyengar, and K. Chakrabarty," Distributed sensor fusion-a review of recent research", J. Franklin Inst., Vol. 338, pp 655-668, 2001.

[6] A. Howard, M. J. Mataric, and G. S. Sukhatme," Mobile sensor network deployment using potential fields: A distributed, scalable solution to the area coverage problem", in Proc. 6th Int. Conf. Distributed Autonomous Robotic Systems, Fukuoka, Japan, pp 299-308, 2002.

[7] J. Cortes, S. Martínez, T. Karatas, and F. Bullo," Coverage Control for Mobile Sensing Networks", IEEE Transactions On Robotics and Automation, Vol. 20, No. 2, pp. 243-255, April 2004.

[8] Y. B. Shalom, and T. E. Fortmann," Tracking and data Association", Academic Press, Inc., Orlando, Florida, 1988.

[9] P. L. Bogler," Radar principles with applications to tracking systems", John Wiley & Sons, New York 1990.

[10] F. Gustafsson, F. Gunnarsson, K. Bergman, U. Forssell, J. Jansson, R. Karlsson, and P. J. Nordlund," Particle filters for positioning, navigation, and tracking", IEEE Transactions on Signal Processing, Vol. 50, No. 2, pp 425-437, Feb. 2002.

[11] M. Isard, and A. Blake," Condensation- conditional propagation for visual tracking", International Journal of Computer Vision, Vol. 29, No. 1, pp 5-28, 1998.

[12] D. Liu and L. C. Fu," Target tracking in an environment of nearly stationary and biased clutter", In Proceedings of the 2001 IEEE/RSJ International Conference on Intelligent Robots and Systems, pp 1358- 1363, Maui, Hawaii, Oct. 2001.

[13] W. Zhang, and G. Cao," Optimizing free reconfiguration for mobile target tracking in sensor network", In Proceedings of the IEEE International Conference on Computer Communication, pp. 2434-2445, March 2004.

[14] R. Murrieta, H. G. Banos, and B. Tavar," A reactive motion planner to maintain visibility of unpredictable targets", In Proceedings of IEEE International Conference on Robotics and Automation, pp 4242-4247, Washington DC, May 2002.

[15] L. E. Parker," Distributed algorithms for multi-robot observation of multiple moving targets", International Journal of Autonomous Robots, Vol. 12, No. 3, pp 231-255, 2002.

[16] L. E. Parker," Cooperative robotics for multi-target Observation", Intelligent Automation and Soft Computing, special issue on Robotics Research at Oak Ridge National Laboratory, Vol. 5, No. 1, pp 5-19, 1999.

[17] A. Kolling and S. Carpin," Multi-robot cooperation for surveillance of multiple moving targets - a new behavioral approach", In Proceedings of the IEEE International Conference on Robotics and automation, pp 1311-1316, 2006.

[18] A. Kolling, and S. Carpin," Cooperative observation of multiple moving targets: an algorithm and its formalization", International Journal of Robotics

Research, Vol. 26, No. 9, pp 935-953 , Nov. 2007.

[19] B. Jung, and G. S. Sukhatme," Tracking targets using multiple robots: The effect of environment occlusion", Autonomous Robots, Vol. 13, No. 3, pp 191-205, 2002.

[20] T. Kanungo, D. M. Mount,N. S. Netanyahu, C. D. Piatko, R. Silverman, and A. Y. Wu," An Efficient k-Means Clustering Algorithm: Analysis and Implementation", IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 24, No. 7, pp. 881-891, July 2002.

[21] L. M. Gambardella, C. Versino", Learning The Visuomotor Coordination Of A Mobile Robot By Using The Invertible Kohonen Map", From Natural to Artificial Neural Computation, International Workshop on Artificial Neural Networks Proceedings, pp. 1084-1091, Berlin, 1995.

[22] T. Kohonen," Self-Organization and Associative Memory", Springer Series in Information Sciences,Vol. 8, Berlin, 1988.

[23] G. R. Mir," Mobot simulator", http://www.mobotsoft.com/mobotsim.htm.