A Multi-modality Framework for Energy Efficient Tracking in Large Scale Wireless Sensor Networks

Lizhi Yang, Chuan Feng, Jerzy. W. Rozenblit, Jianfeng Peng

Abstract— **This paper considers the problem of tracking real-world objects in a large scale area using distributed wireless sensor networks. Due to the limited power supply of wireless sensors, prediction based tracking mechanisms have been commonly used to conserve the energy consumption of the tracking algorithm. On the other hand, in order to preserve the quality of tracking (QoS), appropriate recovery approaches have to be incorporated into the tracking algorithm since the prediction may fail due to network topology changes, blind areas, the uncertainty and unpredictability of real-world objects' motion, etc. In this paper, a multi-modality tracking framework is proposed and an n-step prediction tracking algorithm is evaluated in the framework. The proposed framework is suitable for the tracking system in which sensors are randomly deployed. This paper exhibits how the network of multi-modality wireless sensors can reduce the power consumption of the tracking and preserve the quality of tracking as well.**

I. INTRODUCTION

In the paper, we consider the problem of tracking real-world objects in a large scale area using distributed wireless sensor networks (DWSNs) in which sensors are randomly deployed. The sensors have abilities to sense the environment in various modalities, process the information, and forward it to a certain node for further processing[11]. Compare to a single-modality sensor network that can only provide partial information of the environment, a multi-modality sensing system can obtain more complete descriptions of the monitored environment through combining the fused data from various sensors with different capabilities and strengths[10]. Thus, a multi-modality wireless sensor network architecture can offer more flexibility and more resources for various tracking applications.

However, when designing a tracking algorithm for specific tracking applications such as border control, battle field surveillance or traffic flow measuring, there are several constraints that are needed to be considered. Some of these constraints are inherent from the nature of wireless sensors, e.g., the sensors may have a limited power supply, a limited communication bandwidth or a limited computational power. Therefore, the algorithm must be designed to expend as little energy as is possible in order to maximize network's lifetime. Moreover, since surveillance and tracking systems are likely to be deployed in a critical or hostile environment where functional failures are vital sometime, the design priority should be given to the quality and the reliability of tracking[1]. Thus, in order to improve the energy efficiency of the tracking algorithm as well as preserve the quality of tracking, it is necessary to develop an integrated framework that takes into account some specific important issues of wireless sensor system design.

Lizhi Yang, Chuan Feng, Jerzy W. Rozenblit and Jianfeng Peng are with the Department of Electrical and Computer Engineering, University of Arizona, Tucson, AZ 85721, USA (phone: 520-626-2117; fax: 520-626-2117; email: {lyang, fengc, jr, jpeng}@ece.arizona.edu).

A. Decentralized wireless sensor network architectures

A fully decentralized sensor network is defined in [12] as a system in which the data is processed by local sensors and global results are available locally. While a centralized architecture is theoretically optimal and also conceptually simple[8], it is not suitable in a large scale area because of the limited communication bandwidth of wireless sensors. Moreover, the failure of the fixed superior node may imply the failure of the entire system. On the other hand, given a decentralized architecture, it is able to utilize dynamic head selection techniques to enhance the robustness of tracking since there is no local point of failure leading to the global failure. While each sensor node has a limited communication bandwidth, it is capable of coordinating with other nodes to have the global results. In addition, each wireless sensor has its own processors to fuse the data from diverse sensors with a lighter processing load. Consequently, a decentralized architecture offers more scalabilities than a centralized architecture, i.e., it is more adaptive to large scale tracking applications.

B. Sensor deployment strategies

A deployment strategy decides how to deploy sensors including where and how many to deploy in a specific area and may vary with the application considered. It is critical for tracking applications since the positioning of sensor nodes affects sensing coverage, communication and computing cost[15]. A strategy can be predetermined or undetermined respectively when the environment is known or unknown[3]. In this paper, we focus our attention to the application of tracking real-world objects, e.g., tracking moving targets using huge numbers of sensors with a small detection range. Typically, sensors are distributed randomly, in a large scale region to be monitored. The possible scenario can be short range micro sonar sensors or acoustic sensors deployed in a country border to detect and track illegal intrusions. Ideally, sensors will be dropped from aircrafts or vehicles without any further adjustment. In many such contexts it will be far easier to deploy larger numbers of nodes initially than to deploy additional nodes or additional energy reserves at a later date [2]. Nevertheless, a random deployment strategy may lead to severe coverage problems subject to sensors' communication and detection constraints.

1-4244-0065-1/06/$20.00

Moreover, the tracking performance of the tracking algorithm will be dramatically deteriorated due to the existing of blind areas. Here the blind areas represent areas fully or partially uncovered by any sensor node. In addition, while the position of the sensor is usually fixed after deployment, the network topology and membership may frequently change due to a functional failure, physical damage, lack of power or new sensors just joining the network [14]. In other words, the DWSN for tracking objects may be ad hoc.

C. Prediction based tracking mechanisms

As a commonly used strategy to reduce the power consumption of the sensing system, turning off unnecessary sensors can effectively enhance the lifetime of the entire system since the energy consumption increases significantly during the periods of activities[15]. However, in a randomly deployed sensor network there is a need for an activation mechanism to accurately decide which sensors are necessary to be activated for the quality of tracking purpose [14]. Moreover, especially in a decentralized architecture, the activation mechanism has to be accommodated with head node selection schemes which have to reply on communications between sensor nodes. In [4], [13] and [11], a prediction based triangulation approach is proposed to precisely calculate the positions of the target under tracking. The key idea of this approach is that the lifetime of tracking systems can be dramatically enhanced by using a liner prediction activation mechanism.

In this paper, we propose a multi-modality tracking framework (MmTF) for energy efficient tracking in large scale wireless sensor networks and evaluate an n-step prediction (nsP) tracking algorithm which is the updated version of the algorithm in [4], [13] and [11] in this framework. In MmTF, diversities of sensors such as seismic, acoustic, sonar, etc., can be integrated to generate a multi-level wireless sensor network for energy sensitive tracking applications. In such a multi-level wireless sensor network, some of sensor nodes will be assigned as the communication nodes that are responsible for transmitting fused data to a remote control center; some will be the sentries to detect the appearance of objects; some will be the coordinators for activation tasks; and some will be the computation nodes for high load computation tasks. We will show how the MmTF can be used to enhance the performance of the nsP algorithm.

D. Organization of this paper

The organization of the rest of the paper is as follows. In section 2, the problem is discussed with respect to the energy efficiency and the quality of tracking. Section 3 presents the underline concept of the multi-modality tracking framework and shows how MmTF can be used to improve the performance of the prediction based tracking algorithms. In section 4, we present the details of the n-step prediction algorithm. In section 5, we present the simulation and its results. Section 6 concludes the paper and outlines directions for future work.

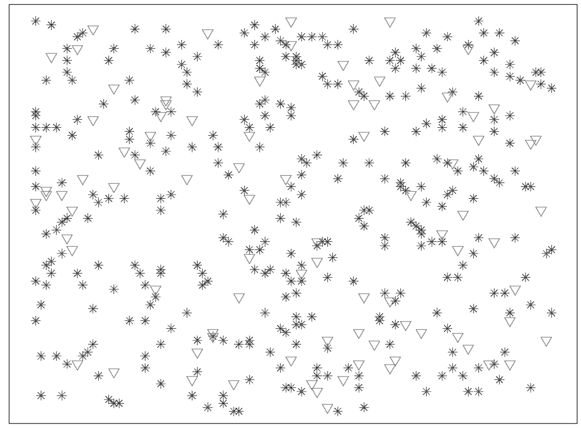

Fig. 1. A multi-modality surveillance system example. The triangle symbols represent sensors equipped with a GPS receiver and the star symbols represent acoustic sensors.

II. Problem description

A large scale environment, in which we are performing tracking and surveillance tasks, is presented by a two-dimensional zone. Multi-modality sensors are dropped uniformly to cover the dimensions of the zone. One example of multi-modality surveillance systems is shown in Fig. 1 in which the star and the triangle symbols represent different types of sensor nodes respectively. In general, with a unlimited power supply, a given large scale area can be monitored perfectly. However, due to the limited power supply of wireless sensors, the quality of monitoring becomes inversely proportional to the life time of the network[4].

In order to save the power usage of sensors, in [4], [13] and [11], a prediction based mechanism, through which most of sensors can be in the sleep status, has been proposed. Making use of this mechanism with the sensed data from active sensors, the system is able to predict the next position of the target under tracking, with the time series trajectory of its path. Based on the predicted position values, the active sensors activate an appropriate set of sensors in that region. It is clear that the fewer nodes that are active, the less power that is consumed.

However, due to the uncertainty and unpredictability of real-world objects' motion, existing of blind areas and ad hoc proprieties of DWSNs, predictions may fail. From a spatial perspective, the number of active sensors governs the distribution of the sensing range. Given a randomly deployed sensor network, some areas that are completely or partially out of the sensing scope of any sensor. Moreover, the situation may be getting worse due to the uncertainty of objects' behaviors and node failures. In addition, the activation of sleep sensors relies on the prediction results. Due to the environment noise and the measurement noise, the measured results such as the position of the target under tracking will be imprecise. Thus, the prediction based on such results will be imprecise too.

In this paper, in order to enhance the performance of the prediction based tracking algorithms, we propose a multi-modality tracking framework. Making use of multi-modality sensors, the low power sensors such as seismic sensors can be activated first based on the predictions. Once the presence of the target is detected by these sensors, the high power sensors such as acoustic sensor arrays can be activated to get the position information of the target. If the predictions fail, the more low power sensors will be activated to cover a relative larger area to find the target. The lower power sensors can also be used to generate the communication layer and the coordinating layer for the entire tracking system. Thus, this framework provides high flexibilities for implementing energy efficient tracking algorithms.

III. THE MULTI-MODALITY TRACKING FRAMEWORK

1) The tracking system model: Consider a 2-dimensional sensing field. Let $\mathcal{A}$ represent a unique type of sensors. Assume that the sensing system with N multi-modality sensors are randomly dropped into the sensing field, then $\mathcal{A}$ can be defined by

$$\mathcal{A} = \{\int_i | \int_i \in \mathcal{A}, i \in [1, N]\} \tag{1}$$

where $\int_i$ represents a single sensor node. Assume that there are $\mathcal{K}$ types of sensors, which are uniformly deployed in the sensing field. Thus, $\mathcal{S} = \bigcup_{j=1}^{\mathcal{K}} \mathcal{A}_j$ represents the entire tracking system in the sensing field.

Typically, for each sensor in $\mathcal{S}$ at time t, the power consumption will vary under various states. There are four power usage modes for each active sensor, namely, *idle, sensing, transmitting and receiving*. Otherwise, the sensor node will be in the power down mode as sleeping. In [14], a comprehensive power usage model is defined by

$$p = W_{\mathcal{I}} \cdot t_{\mathcal{I}} + W_{\mathcal{E}} \cdot t_{\mathcal{E}} + B_r \cdot W_{\mathcal{R}} \cdot t_{\mathcal{R}} + B_t \cdot W_{\mathcal{T}} \cdot t_{\mathcal{T}} + W_{\mathcal{D}} \cdot t_{\mathcal{D}} \tag{2}$$

and the power consumption matrix can be represented by

$$\mathcal{P} = \begin{pmatrix} t_{1\mathcal{I}} & t_{1\mathcal{E}} & B_r \cdot t_{1\mathcal{R}} & B_t \cdot t_{1\mathcal{T}} & t_{1\mathcal{D}} \\ t_{2\mathcal{I}} & t_{2\mathcal{E}} & B_r \cdot t_{2\mathcal{R}} & B_t \cdot t_{2\mathcal{T}} & t_{2\mathcal{D}} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ t_{n\mathcal{I}} & t_{n\mathcal{E}} & B_r \cdot t_{n\mathcal{R}} & B_t \cdot t_{n\mathcal{T}} & t_{n\mathcal{D}} \end{pmatrix} \times \begin{pmatrix} W_{\mathcal{I}} \\ W_{\mathcal{R}} \\ W_{\mathcal{E}} \\ W_{\mathcal{T}} \\ W_{\mathcal{D}} \end{pmatrix} \tag{3}$$

where $W_{\mathcal{I}}$, $W_{\mathcal{E}}$, $W_{\mathcal{D}}$, $W_{\mathcal{R}}$ and $W_{\mathcal{T}}$ are denoted as the power usage of a sensor under different working modes. $t_{\mathcal{I}}$ is the time length for a sensor in the idle status, $t_{\mathcal{E}}$ denotes the time required for the sensor to optimally estimate the position of an object, $t_{\mathcal{D}}$ is the time length for the sensor in the power down status, $t_{\mathcal{T}}$ is the time required for the sensor to send out an unit packet, $t_{\mathcal{R}}$ is the time required for the sensor to recept an unit packet, B_r and B_t represent the size of packet that are received and transmitted by the sensor (respectively).

According to the results presented in [5], some observations can be summarized as in Fig.2. Note that the actuation energy is the highest and the communication cost is the next important issue. Thus, one possible approach to reducing the power consumption is to reduce times of the operations of the actuation and the communication load of sensors. Moreover, for different types of sensor nodes, the power consumption for each main component may vary. For example, a node with seismic sensors can only be used to decide the presence of the target under tracking. Thus, it may consume less power than the node with sonar sensors which is used to calculate the position and the moving orientation of the target.

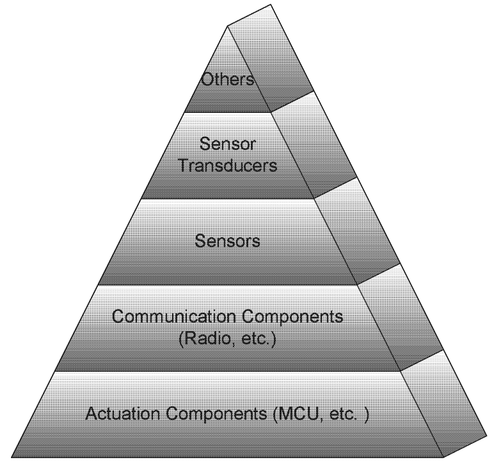

Fig. 2. The power consumption diagram. The actuation energy is the highest, the communication cost is the next important issue, the sensor energy is less important and the other power consumptions are negligible.

2) The Framework Overview: The multi-modality tracking framework, shown in Fig.3, provides an integrated framework for the decomposition of the requirements of the energy efficient tracking algorithm design. The sentry nodes at the bottom of the framework can be deployed along the boundaries of the sensing field. They are always active and all other sensors can be initially asleep. Once the presence of objects is detected by the sentry nodes, the appropriate coordinating nodes will be activated. Note that the execution of the activation task has to reply on the position information of the wireless sensors. Thus, a number of localization nodes are needed to provide the position information for other nodes. Generally, a localization node is a seed node equipped with a GPS receiver. Such nodes have knowledge of their absolute locations[6][7]. Thus, other nodes are able to calculate their own locations through communicating with seed nodes.

The coordinating nodes are a set of sensors which are responsible for activating sensors with specific functionalities. For example, in order to get the position values of a moving object in a 2-dimensional zone, theoretically three sonar sensors are needed. Thus, the coordinating nodes are required to activate appropriate sonar sensors on the right locations to get such information (Fig.4) in tracking. The levels of fidelities can be defined based on the needs of applications. Thus, the following rules can be incorporated into the tracking algorithm design:

1) Most of sensors should be asleep for the majority of the

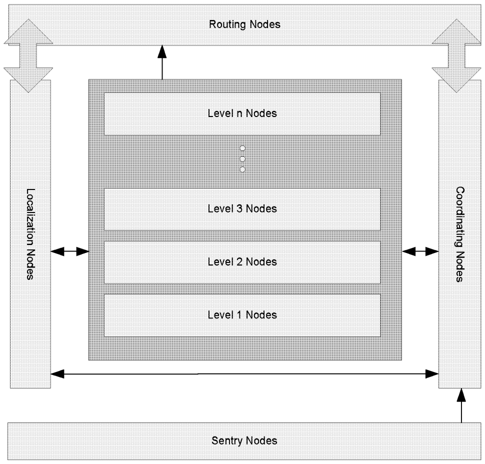

Fig. 3. The multi-modality tracking framework

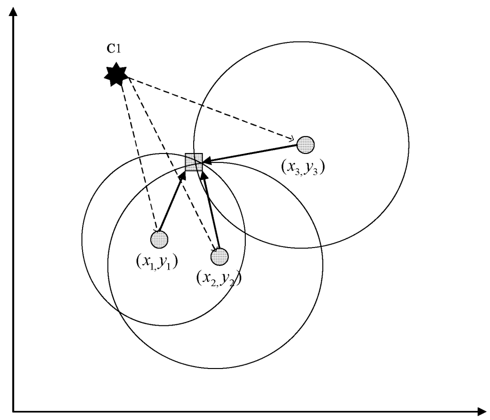

Fig. 4. A triangulating fusion example. The star symbol represents a coordinating sensor and the dot nodes represent sonar sensors. Three sonar sensors are needed to compute the target's position.

time. The sentry nodes can be always active. The entire sensing filed will be a closed zone, i.e., any intrusion can be detected be the sentry nodes.

2) Lower power sensors will be activated first to save the power of high power sensors.
3) Lower power sensors execute message passing, data routing and coordinating tasks.
4) Lower power sensors will be used to help system recover from prediction failures.

IV. The N-step Prediction Algorithm

In this section, we describe the details of the n-step prediction tracking algorithm.

A. The generic prediction model

Suppose that at time t, the position of the object is detected as $(x(t), y(t))$. Then after Δt seconds, the position can be predicted as $(x(t+\Delta t), y(t+\Delta t))$. We assume that there are $T(T < N)$ wireless range detection sensors (sonar sensors) deployed in the sensing field. Initially, all of them are in the sleep status. In [11], we use the previous position of the target $(x(t-\Delta t), y(t-\Delta t))$ and the current position $(x(t), y(t))$ to calculate the velocity (V) and the moving direction (θ) of the target under tracking, then the next position $(x(t + \Delta t), y(t + \Delta t))$ can be given by

$$\begin{aligned} x(t+\Delta t) &= x(t) + V \times \cos\theta \times \Delta t \\ y(t+\Delta t) &= y(t) + V \times \sin\theta \times \Delta t \end{aligned} \quad (4)$$

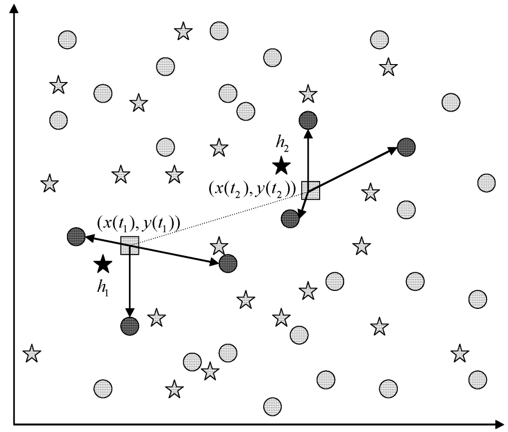

Fig. 5. A head node selection example. The star symbols represent the coordinating sensors (e.g., seismic sensors) with low power consumption and the dot symbols represent the specific functionality nodes (e.g., sonar sensors) with a high power consumption. A coordinating node, h_1, is a low power sensor node that is selected as a head node at time t. After ΔT seconds, h_1 predicts that the target will move to the position $(x(t_2), y(t_2))$. Since h_2 is the closest coordinating node to the predicted position, it is selected as the next head node to sense the presence of the target. Once the target is detected by h_2, another three high power sensors will be activated to calculate the position of the target.

B. The heuristic head node selection scheme

One of the key ideas of the n-step prediction tracking algorithm is to select the appropriate low power sensors as the head nodes based on the prediction results. Assume that at given time t_1, h_1 is the head node and the target is detected on the position $(x(t_1), y(t_1))$. Based on the generic prediction model, from equation 4 we can estimate the next position as $(x(t_2), y(t_2))$. Given the predicted position, the current head node h_1 will select the node h_2 to be the next head node (Fig.5). Once the node h_2 detects the presence of the target, three sonar sensors will be activated to calculate the position values.

Let $\mathcal{H}$ be the set of head nodes and a head node selection criteria is heuristically defined by the shortest distance between the predicted position and the position of the sensors. Thus, the head node set $\mathcal{H}$ can be given by

$$\mathcal{H} = \{h_i \mid h_i \in \mathcal{S}, minimal\ D(P(\int), P(x)), i \in [1, N]\}. \quad (5)$$

where $minimal\ D(P(\int), P(x))$ is the evaluation function. In Fig.5, since h_2 is the closest node to the predicted position $(x(t_2), y(t_2))$, h_2 is selected as a head node by h_1.

C. Improvements

The n-step prediction tracking algorithm is based on the generic prediction model. As we discussed in the problem

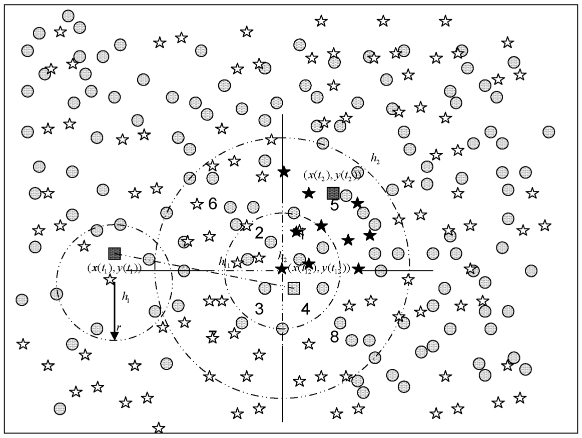

Fig. 6. A prediction failure recovery example. The node h_2 splits the spatial space of its communication range into several partitions and randomly activate the low power nodes within each partition to detect the presence of the target under tracking.

description section, when using the prediction based tracking algorithm, the quality of tracking may be dramatically deteriorated due to prediction failures which can be caused by the uncertainty and unpredictability of real-world objects' motion, existing of blind areas, environment noises and measurement noises, etc. In this paper, we propose two approaches that can be incorporated into the prediction based tracking algorithm to improve the tracking performance.

1) The n-step prediction process: As shown in Fig.5, the predicted position $(x(t+\Delta t), y(t+\Delta t))$ can be obtained from Eq.(4). In [14], the simulation results show that the time interval Δt will affect the quality of tracking, i.e., a large Δt will lead to a high ratio of prediction failures. Thus, the Δt has to be adjusted when tracking different objects with various velocities. Moreover, when the Δt is set to be small, more power will be consumed since the communication load between sensors is much higher. In our n-step prediction model, the prediction will be made based on n times measurements rather than 2 times measurements. Thus, the accuracy of predicting will be much higher.

2) The ring partition scanning process: The ring partition scanning process is used to help system recover from prediction failures. As shown in Fig. 6, given the predicted position $(x(t_{12}), y(t_{12}))$, the sensor node h_2 is selected as the head node to sense the target. As we see in Fig. 6, the target is not detected since the target is on $(x(t_2), y(t_2))$. In other words, the prediction fails. Thus, the node h_2 splits the spatial space of its communication range into several partitions and randomly activate the low power sensors within each partition to detect the target under tracking. Finally, the target is detected by sensors in partition 5. The procedure of the nsP algorithm is shown in Table. I. We denote $D(P(\int), P(x))$ as the distance between the target and sensor nodes. M represents the number of low power sensors within the communication range of a head node.

TABLE I

THE N-STEP PREDICTION TRACKING ALGORITHM

Procedure *The N-step Prediction Tracking*

1 **Set** $P(x_1) = current\ position,\ P(x_2)$ = *(0,0)*;
2 /*Calculate the predicted position $P(x_2)$ based on n times
3 measurements*/
4 then $P(x_2) = (x(t_2), y(t_2))$;
5 **Set** *distanceST = 0, temp = 0, sensorID = 0* ;
6 **For** $(i = 0; i < M; i++)$
7 /*search local position tree till the end*/
8 *temp* $= D(P(\int_i), P(x_2))$;
9 **If** $(distanceST > temp)$
10 $\{$*distanceST* = temp;
11 *sensorID = i*;
12 $\}$
13 **End;**
14 /*$\int_{sensorID}$ is selected as a head node to activate other three sonar
15 sensors to get the position information of the target*/
16 **For**$(i = 0; i <\ the\ number\ of\ ring\ partition; i++)$
17 randomly activate sensors once within the partition of the ring;
18 **If** (detected);
19 break and go to step 6;
20 **End**;

V. SIMULATIONS

In order to evaluate the performance of the n-step prediction tracking algorithm in the multi-modality tracking framework, we use MATLAB to present a simulation of targets tracking.

A. The simulation configuration

In our simulation, the sensing field is of 100 meters times 100 meters. Assume that the low power sensors (e.g., seismic sensors) which are used as the coordinating sensors have a 10 meters effective detection scope and the high power sensors (e.g., sonar sensors) which are used as specific functionality sensors have a 6 meters detection range. Both of them have a 360 degrees covering angle. 500 seismic sensors and 1000 sonar sensors are uniformly deployed in this sensing field. The target traverses in this field with a speed which varies from 0m/s to 40m/s. The energy consumption of sensors is measured in Watt (W).

Fig. 7 shows a snapshot of the simulation for tracking a target. The blue colored symbols represent the sensors in the sleep status and the red colored symbols represent the active sensors. The circle (o) shows the position of the target and the triangle (∇) indicates the predicted position. The solid line (- -) represents the original moving track of the target under tracking and the dotted line (...) represents the predicted path.

B. Simulation result

The tracking procedure and the performance of the nsP algorithm are presented as in Fig. 7. The simulation results show that the ratio of prediction failures drops from 25% to 5% and almost 20% power is saved comparing to a 2-step prediction algorithm.

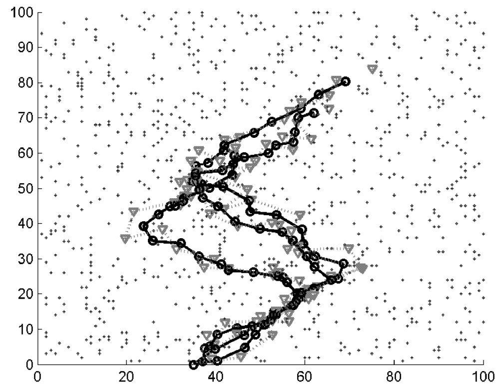

Fig. 7. Snapshots of the simulation for tracking targets

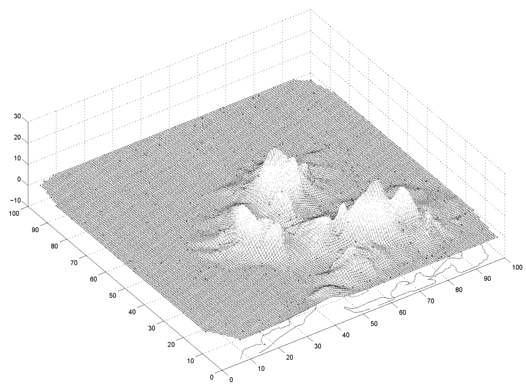

Fig. 8. The diagram of the energy consumption

VI. CONCLUSION

In this paper, we have proposed a multi-modality tracking framework which is suitable for energy sensitive tracking applications. The prediction based tracking algorithms can be seamlessly implemented in this framework and the quality of tracking can be remarkably improved. Making use of this multi-modality tracking framework, a wireless sensor network, which is used for tracking objects in a large scale area, can be designed as a multi-level network in which the tasks of coordination, communication and computation are distributed into diverse sensors. Thus, this framework provides more space for real implementations. In addition, if the functionality of the multi-modality sensor network is well harnessed, it is able to provide diverse levels of fidelities for various applications. Thus, the next step of our research will be building a test bed to validate this approach.

REFERENCES

[1] B. S. Rao and H. Durrant-Whyte, "A Decentralized Bayesian Algoritm for Identification of Tracked Targets," *IEEE Trans. on Systems, Man, and Cybernetics*, Vol. 23, No. 6, pp. 1683-1698, Nov. 1993.

[2] A. Cerpa and D. Estrin, "ASCENT: Adaptive Self-Configuring Sensor Networks Topologies," in *Proceedings of IEEE INFOCOM 2002*, pp. 1278-1287, 2002.

[3] T. Clouqueur, V. Phipatanasuphorn and K. K. Saluja, "Sensor Deployment Strategy of Target Detection," *AACM WSNA'02*, pp. 42-48, 2002.

[4] C. Gui and P. Mohapatra, "Power Conservation and Quality of Surveillance in Target Tracking Sensor Networks," in *Proceedings of The Ninth International Conference on Mobile Computing and Networking (MobiCom) 2004,* pp. 129-143, Sep. 2004.

[5] J. Hill, R. Szewczyk, A. Woo, S. Hollar, D. Culler, and K. Pister, "System architecture directions for network sensors," in *Proceedings of the 9th International Conference on Architectural Support for Programming Languages and Operating Systems (ASPLOS-IX),* pp. 93-104, Nov. 2000.

[6] L. Hu and D. Evans, "Localization for Mobile Sensor Networks," in *Proceedings of the Ninth International Conference on Mobile Computing and Networking (MobiCom) 2004,* pp. 45-57, Sep. 2004.

[7] T. He, C. Huang, B. Blum, J. Stankovic, and T. Abdelzaher, "Range-free localization schemes in large scale sensor networks", in *Proceedings of the Ninth International Conference on Mobile Computing and Networking (MobiCom) 2003,* pp. 81-95, Sep. 2003.

[8] M. E. Liggins, C. Chong, I. Kadar, M. G. Alford, V. Vannicola and S. Thomopouls, "Distributed Fusion Architectures and Algorithms for Target Tracking," in *Proceedings of the IEEE,* Vol. 85, No. 1, pp. 95-107, Jan. 1997.

[9] S. Pattem, S. Poduri, B. Krishnamachari,"Energy-Quality tradeoff for Target Tracking in Wireless Sensor Networks," *2nd Workshop on Information Processing in Sensor Networks, ISPN*, Apr. 2003.

[10] S. Shetty, A. T. Alouani, "A Multisensor Tracking with an Image-based Maneuver Detector," *IEEE Trans. on Aerospace and Electronic Systems*, Vol. 32, No. 1, pp. 167-181, Jan. 1996.

[11] D. Vaidya, J. Peng, L. Yang and J. Rozenblit, "A Framework for Sensor Management in Wireless and Heterogeneous Sensor Network," in *Proceedings of 12th IEEE International Conference and Workshops on the Engineering of Computer-Based Systems*, pp. 155-162, Apr. 2005.

[12] T. Vercauteren and X. Wang, "Decentralized Sigma-Point Information Filters for Target Tracking in Collaborative Sensor Networks," *IEEE Trans. on Singal Processing*, Vol. 53, No. 8, pp. 2997-3009, Aug. 2005.

[13] H. Yang and B. Sikdar, "A protocol for tracking mobile targets using sensor networks," in *Proceedings of the First IEEE International Workshop on Sensor Network Protocols and Applications*, pp. 71-81, May. 2003.

[14] L. Yang, C. Feng, J. W. Rozenblit and H. Qiao, "Adaptive Tracking in Distributed Wireless Sensor Networks," accepted by *13th IEEE International Conference and Workshops on the Engineering of Computer-Based Systems*, March 2006.

[15] Y. Zou and K. Charkrabarty,"Sensor Deployment and Target Localization in Distributed Sensor Networks," *ACM Trans. on Embedded Computing Systems,* Vol. 3, No. 1, pp. 61-91, Feb. 2004.