Lightweight Target Tracking Protocol Using Ad-hoc Sensor Network

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***Abstract*— In this paper, we present a protocol, Lightweight Target Tracking Protocol Using Ad-hoc Sensor Network, for one of the most likely applications of sensor networks: tracking moving targets. The protocol uses a clustering based approach for scalability and a prediction based tracking mechanism to provide a distributed and energy efficient solution. The protocol is robust against node or prediction failures that may result in temporary loss of the target and recovers from such scenarios quickly and with very little additional energy use. Analysis regarding the protocol's performance and energy consumption is presented. We use simulation to examine the the protocol's necessary handover frequency and the target loss rate.**

I. Introduction

One of the important areas where the advantages of sensor networks can be exploited is tracking mobile targets. Scenarios where such networks may be deployed can be both military (tracking enemy vehicles, detecting illegal border crossings) and civilian (tracking the movement of wild animals in wildlife preserves). In this paper we propose a distributed and scalable prediction based algorithm (the Lightweight Target Tracking Protocol, which we hereafter denote as LTTP) to accurately track the mobile target using sensor networks. Unlike previously proposed protocols that focus on signal processing, our protocol aims at the communication aspects and providing efficient and continuous target tracking, including lost target recapture scheme. With power conservation as one of the key design guidelines of this protocol, most of the sensor nodes stay in the hibernation mode (with their communication and sensing circuit shutdown) for most of the time. Given a target to track, the protocol provides a distributed mechanism for locally determining the set of sensors suitable for the task. Only these nodes are then activated, minimizing the energy consumption on tracking.

The problem of tracking targets with sensor networks has received attention from various angles. In [2], the authors consider the case where a set of k targets need to be tracked with 3 sensors per target from the resource requirement viewpoint. They show that the probability that all targets can be assigned 3 unique sensors shows phase transition properties as the level of communication between the sensors increases. In [6] an information driven sensor collaboration mechanism is proposed. The basic idea is for a network to determine participants in a "sensor collaboration" by dynamically optimizing the information utility of data for a given cost of communication and computation. Multiple definitions of information utility are introduced and compared. Collaborative signal processing aspect for target classification in sensor networks is addressed in [3]. Tracking based on relations in the targets is discussed in [7]. Techniques for locating targets using a variety of mechanisms have been proposed in [1], [5], [4]. However, these work do not address the issue of a scalable architecture for coordinating a sensor network for the purpose of target tracking. A fully decentralized, light-weight, dynamic clustering algorithm for target tracking is devised in [8]. The sensor network is assumed to be hierarchical and consists of (a) a static backbone of sparsely placed high-capacity sensors that will act as cluster heads; and (b) low-end sensors whose function is to provide sensor information to the cluster heads upon request. A cluster head volunteers to become active when it detects presence of a target. The tracking of a mobile target is treated in a discrete manner in that the tracking of current instant is independent from results of previous instants. Lack of continuity in tracking results in a larger target loss probability. It will also be difficult to put sensors into sleep mode since cluster heads are only sparsely deployed and target detections have to rely on the large amount of low-end sensors. Authors of [13] also assume one high-end sensor as the cluster head for each cluster consisting of low-end sensors. The target's positions are predicted based on a Kalman filter and suitable sensors for the further tracking instants are alerted. This scheme is essentially similar to [9], [10], [11]. Authors of [12] propose a tree-based approach for facilitating sensor nodes to collaborate in detecting and tracking a mobile target. In these schemes, sleeping of nodes is not taken into consideration.

II. LTTP: Lightweight Target Tracking Protocol Using Ad-hoc Sensor Network

For ease of deployment, sensors are assumed to be uniformly distributed across the network. Each sensor has two sensing radii, normal beam r and high beam R. The sensor network is organized into clusters with cluster heads (CH). Regarding the clustering algorithms, the only assumption is that each cluster head has the following information about all sensors belonging to its cluster: (1) identity, (2) location and (3) energy level. Dynamic rotating of cluster heads can be easily accommodated in LTTP. The target is assumed to enter the monitored area from outside.

The fundamental guideline that we followed throughout the design of the LTTP algorithm is to keep the operation complexity of the tracking procedure as low as possible. This will alleviate both the computation and the communication load for sensors and clusters, thereby reducing the energy consumption rate of the nodes and prolonging the whole network's lifetime.

1) Protocol Description: The LTTP algorithm comes into play after sensors are deployed and clusters are formed. LTTP distinguishes between the border nodes, sensors located within a given distance of the border, and non border nodes in terms of their operation. While border sensors are required to keep sensing all times in order to detect the targets that enter the sensing region, a non-border sensor's sensing device hibernates unless it is specifically asked to sense by its cluster head. Since the target is assumed to move from outside into the sensing area, it will be detected by the border sensors when it trespasses the border. The non-hibernating border sensors will sense the first several locations of the target. After that a sequence of tracking operations in the order of "sensing-predicting-communicating-sensing" are carried out distributively by a series of clusters (cluster heads/sensors) that are located along the target's track. Here we introduce the notation of "upstream cluster head" and "downstream cluster head", which are defined according to the cluster heads' relative locations along the target's moving track. Let $CH_1, CH_2, CH_3, \cdots, CH_i, \cdots, CH_N$ denote the sequence of cluster heads that become involved into the tracking of the target as it proceeds from its very first location to the last. The major tracking procedure after the target is detected is shown in figure 1 and described as follows:

- CH_i receives target description information from its upstream cluster head neighbor CH_{i-1}. The target's estimated showing-up location is enclosed;
- Based on sensors' residue energy and distance to the aimed location, CH_i find the optimal sensor triplet that are able to cover the target's estimated location;
- At the current tracking instant, if the sensor triplet successfully captures the target, each sensor will stay awake and every τ units of time report the target information to CH_i. After time T when the target is estimated to move out of the sensing range of the sensor triplet with a large probability, CH_i will predict the target's next location based on available information. If the target still stays in its cluster CH_i will reconstruct the sensor triplet to track the target. Otherwise CH_i sends the target description information to CH_{i+1}, which is the cluster head nearest to the target's estimated location; The target will be handed over to the sensor triplet woken up by CH_{i+1} and operations listed above will be repeated by CH_{i+1};
- If the sensor triplet fails to detect the target, a failure recovery procedure (described in following section) will be started to recapture the lost target. Once the target is re-captured the procedure above will be repeated.

In LTTP described above a predictor is necessary to predict the target's future locations. LTTP is specifically designed to

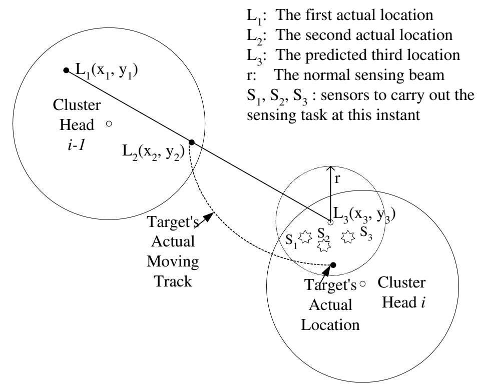

Fig. 1. Handover of target tracking among sensor triplets

accommodate various predictors to obtain best performance under different circumstances. In the simulation section we utilized the first order linear predictor to examine LTTP's performance.

2) Failure Recovery: As described previously, each upstream cluster head relays the target related information to the downstream cluster head that will be involved. If the upstream cluster head does not get any confirmation from the downstream cluster head after a given period of time, then it assumes that the downstream cluster head is no longer available and the target has been lost. Another type of failure occurs when the target changes its direction or speed so abruptly that it moves significantly away from the predicted location and falls out of the detectable region of the sensor-triplet selected for the sensing task at this instant. In both of these failure scenarios a straight forward solution is to let all 3 sensors switch to high beam and sense again. The lost target will be re-located if it is within R distance to all 3 sensors.

If target is still missing even when all sensors are in high beam, we have to wake up all sensors within a given area to detect it. The "woken-up area" is calculated based on the target's previous actual location. If we use V_e to denote the target's estimated speed, and t_e the time elapsed since the target is last sensed, here we define a "re-capture" radius R_σ as:

$$R_\sigma = V_s \times t_e \quad (1)$$

We describe our recovery scheme here as follows. The scheme is designed to re-locate the lost target and minimize the communication and computation cost. The recovery process is broken into various levels:

1) First level of recovery: let the currently selected sensor-triplet switch to high beam if they were using the normal beam previously. If the target is detected, this failure recovery procedure ends successfully. After this the system will go back to normal "sense-predict-communicate-sense" cycle .
2) Second Level of recovery: Figure 2 shows the basic operation of the second level of recovery. If the first

level of recovery fails, as indicated in Figure 2, a group of sensors whose distances from the target's last known position are within $R_\sigma \pm \delta$ will be activated. The parameter δ can dynamically adjusted according to sensors' density. The higher the density, the smaller the δ. The sensors will try both normal beam and high beam to re-capture the lost target before this level of recovery is declared to be failed.

3) N^{th} level of recovery: If the second level of recovery does not succeed, then another group of sensors that are about $(R_\sigma + 2r \pm \delta)$ distance away from the target's last known location are activated to locate the target, where r is sensor's normal sensing beam. Similarly, if the $(N-1)^{\text{th}}$ level of recovery does not succeed even with high beam, then a group of sensors that are $(R_\sigma + 2Nr \pm \delta)$ meters away from L_i are activated to locate the target.

It is apparent that the second or higher level of recovery costs much more energy than the first level. Using simulations, we have verified that the failure probability of the first level recovery is quite low if the tracking resolution is appropriate. Thus the energy consumed is not significant.

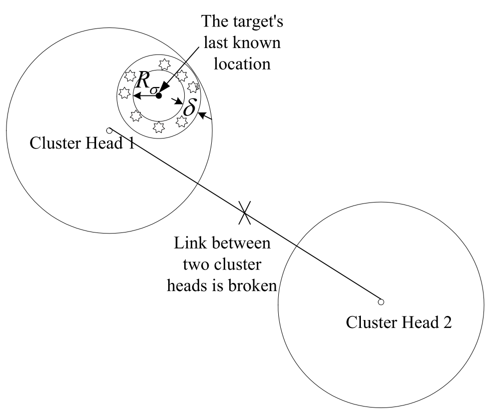

Fig. 2. 2nd level of failure recovery

III. Protocol Analysis

The fact that communication only occurs within a cluster or among neighbor clusters makes LTTP scale. Note that in procedure above there are three important parameters that affect LTTP's accuracy and effectiveness: sensor density λ, sensor triplet's report interval τ and the target's handover interval T. The sensor density should be large enough so that a sensor triplet can be successfully found with a large probability to track the target. τ is an application dependent parameter and higher accuracy demands smaller τ. T can be adjusted according to the target's moving speed and it is critical to avoid target loss. Too large value of τ or T will result in loss of target, while too small a value will incur excessive power consumption. Our paper addresses this problem by analyzing the target's loss probability and the energy consumption associated with each sensor triplet.

A. Node Density

The choice for the number of required sensors per target per tracking instant intrinsically decides the sensor density λ nodes/m^2 of the sensing network. To minimize the likelihood of missing a target, the probability $\mathcal{P}$ that an arbitrary point inside the sensor network can be sensed simultaneously by at least 3 sensors with their normal beams should be close to 1. Since the sensors are assumed to be uniformly distributed over the sensing region and the number of sensors is large, the distribution of the number of nodes in any given area A is Poisson distributed with rate λA. The probability that there are 3 or more sensors within the low beam sensing range of any arbitrary point is proved to be:

$$\begin{aligned} \mathcal{P} &= \sum_{i=3}^{\infty} \frac{e^{-\lambda \pi r^2} (\lambda \pi r^2)^i}{i!} \\ &= 1 - e^{-\lambda \pi r^2} \left(1 + \lambda \pi r^2 + \frac{\lambda^2 \pi^2 r^4}{2} \right) \end{aligned} \tag{2}$$

From the expression above, substituting a desirable value for $\mathcal{P}$, say 0.99, the required node density λ can be easily obtained.

B. Tracking Resolution

The target is continuously "captured" and "handed over" between sensor triplets. An "outage" event occurs when the target moves out from the range of any of the 3 sensors that are currently tracking it. Since the target is handed over between sensor triplets, in our paper we investigate the outage probability $\mathscr{B}_o$ when a target is under tracking by a sensor triplet.

In reality the target's movement is usually unknown, which makes random walk an attractive and appropriate model for analysis of the target. The target's two dimension coordinates are given as:

$$x_{i+1} = x_i + v_i \times \tau \cos(\theta) \tag{3}$$

$$y_{i+1} = y_i + v_i \times \tau \sin(\theta) \tag{4}$$

θ in equation above is a random variable that is uniformly distributed over $(0, 2\pi)$. v_i is the target's instantaneous speed when it is tracked by the ith sensor triplet. τ represents the tracking accuracy desired by the application.

Denoting the probability that the target stays in one sensor's sensing range R_t after time T as $\mathscr{B}_c(T, r)$

Claim 1: If $t/\tau \geq \sqrt[3]{\frac{3r^4}{16\epsilon d^4}}$ then Prob$\{R(t) \leq r\}$ follows a Rayleigh distribution with parameter $nd^2/2$.

Proof: In an interval t, the sink changes its direction $n = t/\tau$ times and its final position is the sum of n random phasors of magnitude d. The x and y coordinates of this position are given by: $X_n = \sum_{i=1}^{n} d \cos \theta_i$ and $Y_n = \sum_{i=1}^{n} d \sin \theta_i$. As n becomes large, the use of central limit theorem implies that the distribution of X_n and Y_n become Gaussian with mean 0 and variance $nd^2/2$. Transforming the joint distribution of X_n

and Y_n to polar coordinates then gives the pdf of $R(t)$. In the case where n may not be large enough to satisfy the central limit theorem, in [14] it is shown that the pdf of $R(t)$ is given by

$$p(r) = \frac{2re^{\frac{-r^2}{\alpha}}}{\alpha}\left[1+\frac{3}{8n}\left(\frac{E[d^4]}{E[d^2]^2}-2\right)\left(\frac{r^4}{2\alpha^2}-\frac{2r^2}{\alpha}+1\right)\right] \quad (5)$$

where $\alpha = nE[d^2]$. Note that the term outside the square braces is the Rayleigh distribution and thus for $p(r)$ to be within ϵ of this distribution

$$\left|\frac{3}{8n}\left(\frac{E[d^4]}{E[d^2]^2}-2\right)\left(\frac{r^4}{2\alpha^2}-\frac{2r^2}{\alpha}+1\right)\right| \le \epsilon \qquad (6)$$

For our random walk model where the step size is fixed, $E[d^4] = d^4$ and $E[d^2] = d^2$. Using these in Eqn. (6):

$$\frac{3}{8n}\left(\frac{r^4}{2n^2d^4}-\frac{2r^2}{nd^2}+1\right) \le \epsilon \qquad (7)$$

which can be simplified to

$$3r^4 \le 16\epsilon n^3 d^4 - 6n^2 d^4 + 12nr^2 d^2. \qquad (8)$$

When n is large, we have $n^3 \gg n^2 \gg n$ and we can approximate the equation above be neglecting the lower order terms. Then we have

$$n \ge \sqrt[3]{\frac{3r^4}{16\epsilon d^4}}. \qquad (9)$$

■

Thus for large enough n the PDF of the distance traveled by the sink is Rayleigh and is given by

$$\text{Prob}\{R(t) \le r\} = 1 - e^{-\frac{\tau r^2}{td^2}}, \qquad 0 \le r \le \infty \qquad (10)$$

Now consider the target in the sensing range of sensor i with the location of the target being equally likely anywhere within the circle describing the sensor's transmission region. Then from the results in [15], the probability β that the target is still within the range of the sensor after time T is given by

$$\beta = \sum_{k=1}^{\infty} \frac{(a)_k z^k}{(b)_k k!} \qquad (11)$$

where $a = 1/2$, $b = 2$, $z = -4\tau R_t^2/(Td^2)$ and $(a)_k$ and $(b)_k$ are Pochhammer symbols: $(a)_k = a(a+1)(a+2)\cdots(a+k-1)$ and $(a)_k = b(b+1)(b+2)\cdots(b+k-1)$. Ideally once the current sensor triplet becomes incapable of tracking the target, it should be handed over to a new constructed sensor triplet to continue the tracking. Thus, we define the "handover frequency" $\mathscr{F}_h = 1/T$. For the desired target capture probability $\mathscr{B}_c$ after T units of time, the two equations above can be solved to obtain the required handover frequency $\mathscr{F}_h$.

Since 3 sensors collaborate in the tracking of the target at a given instant, The outage probability $\mathscr{B}_o$ that the target stays captured by all 3 sensors after time T is proved to be:

$$\mathscr{B}_o = 1 - \mathscr{B}_c(T, r)^3$$

TABLE I
PARAMETERS USED IN EQN. 11

Parameters	Definitions
e_s, e_r	e_s is the energy consumption for a sensor to send k bits to its cluster head that is d distance away. e_r is the energy consumption of a sensor to receive l bits from its cluster head. Using the first order radio model we have: $$e_s(k,d) = E_{elec}k + \epsilon_{amp}kd^2$$ $$e_r(l) = E_{elec}l$$ where $E_{elec} = 50nJ/bit$ and $\epsilon_{amp} = 100pJ/bit/m^2$
$\mathscr{B}_o, \mathscr{B}_h$	The occurrence probability of "outage" event $\mathscr{B}_o$ could be calculated based on Eqn 11. $\mathscr{B}_h$ is the probability that the lost target is recaptured when the sensor triplet switches to high beam and we have: $\mathscr{B}_h = 1 - \mathscr{B}(T,R)^3$n
$\mathscr{F}_r, d$	$\mathscr{F}_r = 1/\tau$. It is the frequency that the sensor triplet reports the target's information to their cluster head. This frequency is determined by applications and represents the tracking granularity and accuracy. d is the target's displacement each τ unit of time. It is estimated by LTTP's predictor.
λ, k, l, r	λ is the sensor density calculated from Eqn. **??**. k is the length of the target information report sent from the sensor triplet to their cluster head. l is the length of the sensor's wake-up message and r is the low beam sensing radius

C. Energy Consumption

Since communication consumes the largest amount of energy in a sensor network, we investigate the energy depletion $\mathscr{E}$ (table I defines parameters in equations below) between handover events. . $\mathscr{E}$ consists of following components:

1) Energy consumed to wake up the sensor triplets $3e_r$;
2) Energy consumed by the sensor to report the target information to the cluster head;
3) Energy to recover from tracking failure.

If the target stays captured by the sensor triplet, the energy consumption for the sensor to report the target information to the cluster head is $3\mathscr{F}_r e_s$. If the target gets lost, the sensor will try to re-capture it by switching to high beam. The incurred energy consumption is $3\mathscr{B}_h e_s$. If the target still remains lost and is re-captured via nth order of failure recovery, the energy consumption incurred is:

$$\mathscr{E}_f = \sum_{i=1}^{n} \lambda\pi[(ir+\delta)^2 - (ir)^2](e_s + e_r) \quad n = 1, 3, 5\cdots$$

Thus, this energy consumption $\mathscr{E}$ is shown to be:

$$\begin{aligned}\mathscr{E} \;&=\; \mathscr{F}_r e_s + e_r + \mathscr{B}_o\mathscr{B}_h e_s \\ &\quad + \mathscr{B}_o(1-\mathscr{B}_h)\mathscr{E}_f \end{aligned} \qquad (12)$$

IV. SIMULATION RESULTS

As addressed in previous sections, there are two parameters that are very important to guarantee LTTP's effectiveness and efficiency: the handover frequency and the LTTP's failure rate. In this section we present the simulation results regarding these parameters.

In figure 3 the target movement is assumed to obey random walk with its speeds shown by the x-axis. The y-axis shows the time that it takes for the target to escape from the circular areas with different radii (20m, 40m , 60m). Since the sensor triplet's positions are known to the cluster head, it is possible to calculate the size of the region that is covered by the sensor triplet currently. Successful tracking will hand over the target to the next one before the target escapes from the current covered region that the target resides. Thus, when estimation of the target speed is available, the handover frequency can be dynamically adjusted to minimize the target loss.

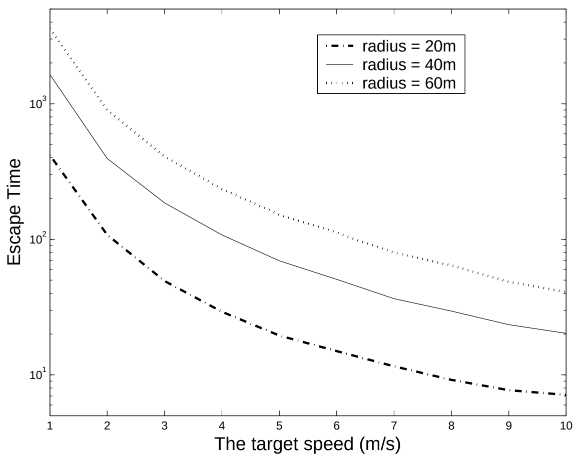

Fig. 3. The time that it takes the target to move out of the monitored area

We also investigate the occurrence rate of failures caused by inaccuracy of the predictor. LTTP protocol can actually integrate various predictors to achieve the best performance under different circumstances. In this simulation we use the first order linear predictor with LTTP to predict the target's future locations, whose movement is still described by random walking with its speed indicated by the x-axis in figure 4. The monitored area is of $500m \times 500m$ with the sensors uniformly distributed in it. The sensor's distribution density is $\lambda = 0.01$ and the sensor's sensing radius 50m. The y-axis indicates the failure rate with different target speeds. Figure 4 describe the failure rate when the tracking resolution is 0.1s. As we can see that with 0.1s as the tracking resolution, the failure rate stays at 0 even when the target's speed reaches above 15m/s. This suggests that if no estimation of the target's speed is available, the tracking resolution can be adjusted to achieve satisfied performance.

V. Conclusion

In this paper a lightweight target tracking scheme using sensor network is presented. The scheme is designed to be scalable and can adapt to a range of target speeds. The tracking resolution and the target handover frequency are designed to be adjustable to obtain best performance under different circumstances. The simulation results shows that the target can be accurately tracked by choosing appropriate parameters.

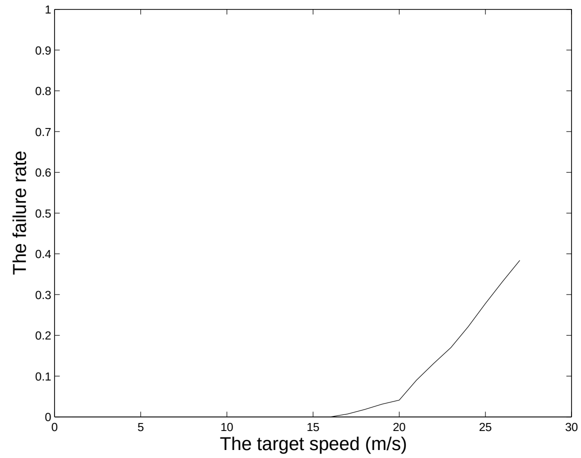

Fig. 4. The tracking failure rate of LTTP with 0.1s as the tracking resolution

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