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A Protocol for Tracking Variable Targets with Sensor Networks

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Abstract: ith continuous advances in sensor fabrication technology, the deployment of large-scale sensor networks for pervasive monitoring and control of physical systems has become increasingly feasible. Scalability, low overhead, and distributed operation are among the key requirements for protocols designed for such networks. In this paper, a Distributed Predictive Tracking (DPT) algorithm is proposed to address the problem of tracking mobile targets in wireless sensor networks. The proposed algorithm employs a cluster-based architecture to improve scalability and energy efficiency, while a lightweight prediction mechanism is used to estimate the future position of moving targets. Based on these predictions, only a limited set of sensors along the expected target trajectory are activated, allowing the remaining nodes to remain in a low-power state. The DPT algorithm is designed to be fully distributed and resilient to node and prediction failures, and it incorporates an efficient recovery mechanism to rapidly re-acquire lost targets with minimal additional energy consumption. Simulation results demonstrate that the proposed algorithm can accurately track targets with random movement patterns over a wide range of target speeds while maintaining low energy overhead.

Keywords: Sensor Networks, Mobile Targets, Tracking.

I. INTRODUCTION

Advances in sensor fabrication and the integration of sensing and communication technologies have facilitated the deployment of large-scale sensor networks. Due to their capability for pervasive monitoring, control of physical systems, and cost-effective large-scale deployment, sensor networks have significant potential in both commercial and military applications. However, the design and deployment of such networks pose several challenges arising from scalability requirements and inherent limitations, including constrained energy resources, distributed coordination, and ad hoc deployment conditions. In addition, application-specific communication and system requirements may impose further constraints on network coordination and scheduling[1].

In this work, we address the problem of scalable coordination and operation of a large sensor network specifically designed for tracking mobile targets. Target tracking represents one of the primary application domains where the advantages of sensor networks can be effectively exploited. Deployment scenarios include both military applications, such as tracking hostile vehicles and detecting illegal border crossings, and civilian applications, such as monitoring wildlife movement in natural reserves[2].

Accurate target tracking typically requires the simultaneous involvement of at least two sensors per target, which introduces coordination challenges. Moreover, to minimize energy consumption resulting from communication and sensing activities, it is desirable to activate only the minimum number of sensors required for tracking, while keeping the remaining nodes in a sleep or idle state. Achieving energy efficiency and high overall system performance simultaneously necessitates large-scale management and coordination mechanisms. These challenges are further exacerbated by unpredictable target movements, which require dynamic coordination of the most appropriate sensors over time.

To address these issues, we propose a planning and management framework for sensor networks used in mobile target tracking. Although designed for tracking applications, the proposed architecture is flexible and can be readily adapted to other sensor network applications.

Target tracking using sensor networks has been studied extensively. In [3], the authors analyze a scenario in which k targets are tracked using three sensors per target and show that the probability of successful tracking increases with higher

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correlation among the sensors. A data-driven collaborative sensor framework is proposed in [4], where sensing decisions are based on information utility metrics. Cooperative signal processing techniques for target classification in sensor networks are discussed in [5], while correlation-based target tracking approaches are explored in [6]. Various localization and tracking techniques have also been proposed in [7], [8], and [9].

Despite these efforts, the problem of designing a scalable and flexible architecture for coordinating sensor networks specifically for target tracking remains largely unresolved. Issues such as feasibility, minimizing computational and communication overhead, and understanding system trade-offs have not been sufficiently addressed. This paper aims to fill these gaps.

In this study, we propose a Distributed Predictive Tracking (DPT) algorithm that enables accurate tracking of mobile targets using sensor networks. The algorithm employs a cluster-based architecture to enhance scalability and robustness. Since energy efficiency is a primary design target, most sensor nodes remain in sleep mode at any given time. Upon detecting a target, the protocol dynamically determines the optimal set of sensors required for tracking and activates only those nodes, thereby minimizing energy consumption[10].

Furthermore, the protocol incorporates a predictive mechanism that informs neighboring cluster heads of approaching targets. Based on these predictions, cluster heads proactively activate suitable sensors before the target arrives, reducing the likelihood of target loss while allowing most sensors to remain inactive. Simulation results show that the protocol effectively tracks randomly moving targets across a wide range of speeds. Additionally, the proposed architecture includes an efficient recovery mechanism that rapidly reacquires lost targets caused by prediction or node failures, with minimal energy overhead.

The remainder of this paper is organized as follows. Section II reviews related work. Section III presents the proposed tracking algorithm, and Section IV evaluates its performance through simulations. Finally, Section V concludes the paper and outlines directions for future research.

II. RELATED WORK

Target tracking in wireless sensor networks is a critical research area due to its importance in applications such as surveillance, environmental monitoring, and battlefield awareness. Early target tracking approaches were primarily centralized, relying on transmitting sensor measurements to a fusion center for processing. Although centralized methods can achieve high localization accuracy, they suffer from poor scalability, excessive communication overhead, and high energy consumption, making them unsuitable for large-scale sensor networks.

To overcome these limitations, distributed and collaborative tracking techniques have been extensively investigated. Zhao et al. proposed a data-driven collaborative sensor framework in which sensing actions are dynamically coordinated based on information utility measures, enabling adaptive tracking with reduced communication cost [11]. Similarly, Li et al. explored distributed detection, classification, and tracking techniques based on in-network signal processing to reduce energy consumption while maintaining acceptable tracking performance [12].

Clustering-based architectures have been widely adopted to improve scalability and energy efficiency. Lin and Gerla introduced a mobility-adaptive clustering mechanism for wireless networks [8], while Banerjee and Khuller proposed a hierarchical clustering scheme for scalable control in multi-hop wireless networks [13]. These clustering techniques provide localized coordination and reduce routing complexity, forming the foundation for many tracking protocols. However, most existing clustering schemes are generic and do not explicitly address the dynamic requirements of target tracking.

Several studies have also analyzed sensing coverage, sensor density, and their effects on tracking reliability. Krishnamachari et al. investigated phase transition phenomena in sensor networks and demonstrated how connectivity and coverage influence the probability of tracking multiple targets [14]. Probabilistic and maximum-likelihood estimation techniques have been proposed to enhance localization accuracy [15], [16], but these methods often incur significant computational and communication overhead.

Prediction-based tracking has emerged as an effective approach for reducing energy consumption by activating only sensors likely to observe the target. Zhang and Cao proposed a dynamic convoy tree-based collaboration framework that exploits motion prediction to improve tracking efficiency [17]. Brooks et al. examined distributed target classification and tracking using local collaboration among sensors [18]. However, advanced prediction models such as Kalman filtering typically increase computational complexity and communication cost.

Overall, existing research lacks a lightweight, fully distributed, and failure-resilient tracking architecture that simultaneously achieves scalability, energy efficiency, and robustness to unpredictable target motion and node failures. Few studies integrate clustering, prediction, adaptive sensor activation, and recovery mechanisms into a unified framework [19]. The proposed Distributed Predictive Tracking (DPT) protocol addresses this gap by providing a cluster-based, prediction-driven architecture that supports efficient tracking of variable-speed targets with low communication overhead and rapid recovery from tracking failures.

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III. PROPOSED METHOD

A. Challenges

Deploying a large-scale sensor network introduces several design challenges arising from constraints inherent to sensor-based environments. This section examines these challenges and establishes the foundation for the proposed tracking protocol. Any practical sensor network protocol must address issues related to scalability, coordination, energy efficiency, and deployment flexibility.

Sensor networks face challenges due to limited energy resources, large-scale deployment, and ad hoc operation. These constraints must be carefully considered to ensure the feasibility and effectiveness of any proposed design.

1) Scalable Coordination:

A typical sensor network deployment may consist of hundreds or thousands of nodes. At such scales, manual configuration of individual nodes is infeasible. Nodes may fail, new nodes may join the network, and physical access to nodes may be limited. Therefore, scalable coordination and management mechanisms are essential to ensure robust network operation. In target tracking scenarios, coordination must scale with network size, the number of targets, and the number of active tracking tasks.

2) Tracking Accuracy:

An effective tracking system must maintain high accuracy and minimize the probability of missing targets. The system should also provide a wide operational range while maintaining low latency, robustness to noise, and resilience to node failures.

3) Ad Hoc Deployability:

One of the defining characteristics of sensor networks is their ability to be deployed in an ad hoc manner [3]. Sensors may be randomly deployed in inaccessible or hazardous environments, such as disaster areas or remote regions [4]. Consequently, sensor nodes must be capable of self-organization and autonomous operation without human intervention or predefined communication structures.

4) Computational and Communication Costs:

Any sensor network protocol must consider both computational and communication overhead. Since communication typically consumes more energy than local computation [2], protocols should minimize communication requirements whenever possible.

5) Energy Constraints:

Due to the difficulty of recharging sensor batteries, energy availability is severely limited. Energy-aware protocols that reduce power consumption and adapt to remaining energy levels are therefore highly desirable. Whenever possible, inactive nodes should be placed into low-power sleep modes.

In the following section, we present the proposed architecture for scalable and accurate mobile target tracking. The protocol emphasizes minimizing communication and management overhead through a cluster-based approach.

B. A Distributed Algorithm for Predictive Tracking

This section describes the proposed Distributed Predictive Tracking (DPT) protocol for efficiently tracking mobile targets in sensor networks. The DPT algorithm is specifically designed to address the challenges outlined above while maintaining high tracking accuracy. The protocol operates without a centralized control entity, eliminating single points of failure and improving robustness against node failures.

Tracking is performed in a fully distributed manner by sequentially activating sensors located along the predicted path of the moving target. A cluster-based architecture is adopted to ensure scalability and energy efficiency. While numerous clustering algorithms have been proposed in the literature [1], [8], the proposed protocol is independent of the specific clustering mechanism employed. Any suitable clustering algorithm may be used, as the DPT protocol imposes no restrictions on cluster formation or maintenance.

1. **Assumptions of the DPT Algorithm**

   In this section, we present the assumptions made by the Distributed Predictive Tracking (DPT) algorithm. Although no specific assumption is imposed on the

clustering algorithm itself, it is assumed that each Cluster Head (CH) maintains essential information about all sensor nodes belonging to its cluster. This information includes:

(1) sensor identity,
(2) sensor location, and
(3) current energy level.

These data form the basis of the cluster head's decision-making process during target tracking, particularly when selecting the most appropriate sensors to activate for tracking a moving target.

The assumptions regarding the sensor nodes are listed below. These assumptions are practical and are intended to minimize energy consumption while extending the operational lifetime of the entire network.

Homogeneous Sensors: All sensor nodes are assumed to have identical hardware and functional characteristics.
Uniform Deployment: Sensor nodes are randomly and uniformly distributed over the sensing region.
Dual Sensing Radii: Each sensor is equipped with two sensing ranges: a low sensing radius $R_L$and a high sensing radius R_H. The low sensing radius is used by default, while the high sensing radius is activated only when required. The energy consumption associated with the low and high sensing radii is related as follows:

$$\frac{E_{lowbeam}}{E_{highbeam}} = \frac{r^2}{R^2} \qquad (1)$$

2. The most of the time, a sensor's correspondence and detecting direct remain in the hibernation phase, where they use very little energy. The communication channel will periodically awaken in order to receive any prospective messages from its group leader. The sensor will carry out detection in accordance with the needs of its bunch head.

To create exact sufficient data to find the moving objective, our calculation requires that at some random time there ought to be no less than 3 sensors to mutually detect the objective. We pick 3 sensors as the split the difference between expanding exactness and limiting the used up energy (note that this is definitely not a hard suspicion and contingent upon the sensor hub determinations the number might fluctuate). The sensor thickness, λ hubs/m2, of the detecting organization is automatically chosen when determining the number of required sensors per target. To lessen the likelihood of missing a goal, the likelihood p that an erratic point inside the sensor organization can be detected all the while by no less than 3 sensors with their ordinary bars ought to be near 1. Since the sensors are thought to be consistently disseminated over the detecting district and the quantity of sensors is huge, the circulation of the quantity of hubs in some random region An has a Poisson rate λ_A. The probability that at least three sensors are present within the low shaft detection scope of any erratic location is therefore determined by:

$$p = \sum_{i=3}^{\infty} \frac{e^{-\lambda\pi r^2}(\lambda\pi r^2)^i}{i!} \qquad (2)$$

The predicted node density is obtained from the above formulation by substituting an appropriate value for the probability parameter p, for example $p = 0.99$, from which the parameter λcan be readily derived. No specific assumptions are made regarding the motion model of the targets. However, it is assumed that targets initially originate outside the sensing region and subsequently enter it. In addition, the movement of each tracked target is assumed to be directed toward a focal point referred to as the **sink**. The sink may correspond to a dedicated sensor node or a terminal connected to a human operator.

B. Distributed Predictive Tracking Algorithm

The primary principle maintained throughout the design of the Distributed Predictive Tracking (DPT) algorithm is simplicity. A lightweight algorithm reduces both computational complexity and communication overhead among sensors and clusters, thereby lowering the energy consumption rate of sensor nodes and extending the overall network lifetime. Moreover, this simplicity minimizes the hardware and software requirements imposed on individual nodes.
Following sensor deployment and cluster formation, the DPT algorithm becomes the core operational component of the system. Based on their roles, sensors are classified into boundary sensors, sensors located within a predefined distance from the boundary, and non-boundary sensors. Boundary sensors are required to remain continuously active in order to detect all targets entering the sensing region. In contrast, non-boundary sensors keep their sensing modules inactive unless explicitly instructed by their corresponding cluster head.
Since targets are assumed to move from outside into the sensing region, boundary sensors are responsible for detecting targets as they cross the perimeter. Once a target is detected, a sequence of operations—**sense, predict, communicate, and sense**—is distributed among sensors positioned along the target's trajectory. This operational sequence constitutes the fundamental concept underlying the DPT algorithm. The main components of the algorithm are described below.

Target Descriptor: Initial Definition and Computation

Cluster heads employ a structure known as the **Target Descriptor (TD)** to uniquely identify each target and characterize its state. The TD consists of the following elements:

1. Target identifier
2. Current estimated position of the target
3. Predicted next position of the target
4. Time stamp

For each tracked target, the cluster head computes the corresponding TD using the target descriptor formulation process, which is described in detail below.

To clarify the computation of the TD, we introduce the concepts of **upstream cluster heads** and **downstream cluster heads**, distinguished by their relative locations along the target's movement trajectory. Let $CH_1, CH_2, CH_3, \ldots, CH_i, \ldots, CH_N$denote the sequence of cluster heads involved in tracking a target as it moves from its initial detection point to its final destination. Upon detecting the target, each cluster head generates a target descriptor TD_i. Whenever possible, each descriptor is forwarded to the sink—either directly or through aggregation—as well as to the downstream cluster head $CH_{i+1}$for further coordination.

The computation of TD_iat cluster head CH_iproceeds as follows. The **target identifier** is generated when the target is first detected. This identifier is unique and is consistently used by all cluster heads involved in tracking the same target, enabling unambiguous identification during inter-cluster communication. As discussed later in this section, cluster head CH_ipredicts the future position of the moving target and proactively informs the downstream cluster head $CH_{i+1}$to ensure smooth tracking continuity. The target identifier is included in all inter-cluster messages to clearly associate transmitted information with the corresponding target.

The **current target position** constitutes the second component of TD_i. As previously discussed, a trio of sensors is required at each sensing location to accurately localize the target. Each sensor in the trio independently estimates the coarse position of the target and transmits this information to the cluster head. The cluster head then aggregates these measurements—typically using triangulation techniques—to determine the current target position. Details regarding the selection of the sensor trio are provided in Section III-B.2.

The third component of $TD_i$is the **predicted next position** of the target, which represents the estimated location of the target after a predefined time interval. This prediction enables the cluster head to identify the most likely downstream cluster heads that the target may encounter and to notify them in advance of the target's expected arrival. Downstream cluster heads can then proactively activate appropriate sensors to prepare for detection. To maintain low computational and communication overhead, this prediction is based solely on estimates of the target's current velocity and direction of motion. Let the current position of the target in TD_{i-1}be assumed

Fig. 1.

Look for the sensor-trio with ordinary shaft.

(x_{i-1}, y_{i-1}), and (x_i, y_i) in TD_i. Then, at that point, we can estimate the target's speed as

$$v = \frac{\sqrt{(x_i - x_{i-1})^2 + (y_i - y_{i-1})^2}}{t_i - t_{i-1}} \qquad (3)$$

While the direction is given by

$$\theta = \cos^{-1} \frac{x_i - x_{i-1}}{\sqrt{(x_i - x_{i-1})^2 + (y_i - y_{i-1})^2}} \qquad (4)$$

This data allows for the prediction of the target's location.

$\theta = \cos(x_{i+1}, y_{i+1})$ after a given time t is given by

$$x_{i+1} = x_i + vt\cos(\theta) \qquad (5)$$

$$y_{i+1} = y_i + vt\sin(\theta) \qquad (6)$$

To be more exact, The objective's next region very well may be demonstrated to submit to a two-layered Gaussian conveyance with (x_{i+1}, y_{i+1}) as the mean. We intend to enhance the bunch head's estimation and reduce the number of messages sent between group heads and sensors by blatantly using (x_{i+1}, y_{i+1}) as the "expected future area".

The exactness of the "expectation" is vital on the off chance that downstream bunch goes to be recognized precisely and the general following component is to be successful While numerous forecast systems are

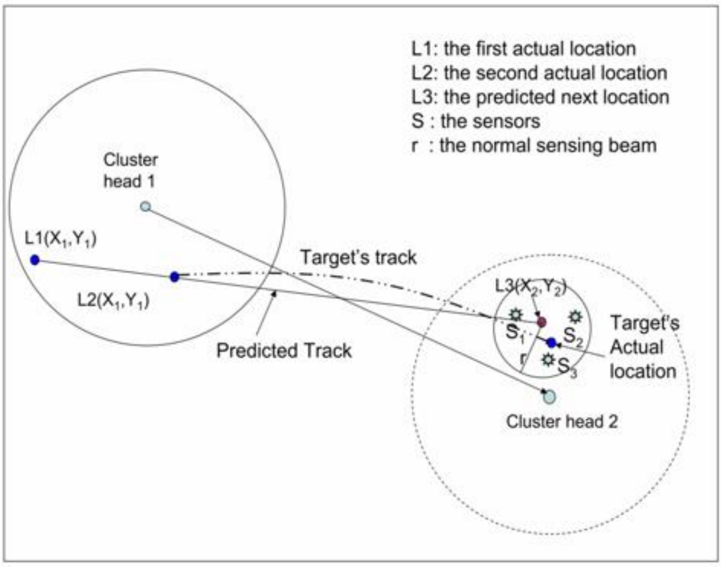

Fig. 1. Search for the sensor-triplet with normal beam.

conceivable, what we have picked is a direct indicator, which just purposes the past two areas to foresee the third area straightly. We can likewise embrace higher request forecast, which predicts the nth area data in light of past $n - 1$ genuine areas. However, request expectation brings about additional precise outcomes, however, at the expense of more prominent energy utilization. In Area IV we break down the exhibition of our expectation system. We highlight that under specific circumstances, specifically in the light of exceptionally irregular objective development, the objective miss likelihood (the probability that the objective drops out of the sensor-detecting trio's range) might be actually high even with larger request expectation. In order to handle such situations, the subsequent calculation should have a disappointment recovery system to re-catch the lost objective. We thoroughly examine this in Segment III-B.3.

1) The "Time Stamp," the last part of the TD_i, shows when this TD_i was created.

2) Sensor Choice Calculation: After group head CH_i predicts the location of the objective, CH_i sends a message to the downstream group head CH_{i+1}, in that direction, indicating the predicted location. The search calculation executing at CH_{i+1} can locally select the sensor-trio to identify the object since data from all sensors with a location with CH_{i+1} accessible in its data set is available. The selection rule chooses three sensors (if possible) such that their distances from the expected area are not only the smallest but also differ from the sensor's typical shaft r. The sensor-trio is chosen, and CH_{i+1} sends them a wake-up message so they can get ready to find the target. After detecting, each sensor will send CH_{i+1} an area message if the forecast and decision-making process is successful. CH_{i+1} will then form TD_{i+1} based on this information. This cycle can be seen in Figure 1.

CH_{i+1} will attempt to hunt for qualifying sensors inside a distance R, the higher detecting pillar, from the predicted area if it is unable to locate a enough number of sensors qualified for this detecting duty using the standard detecting bar. The chosen sensors will now be approached and trained to detect with their high shaft, while the other sensors in the trio use their standard bar, because their separation from the predicted area is greater than r and lower than R. the high-beam sensor search process

is represented in Figure 2. Assuming Even with strong detecting radiation, CH_{i+1} is unable to locate enough sensors, so it asks its neighboring group for assistance and heads in that direction. This can be seen in Figure 3.

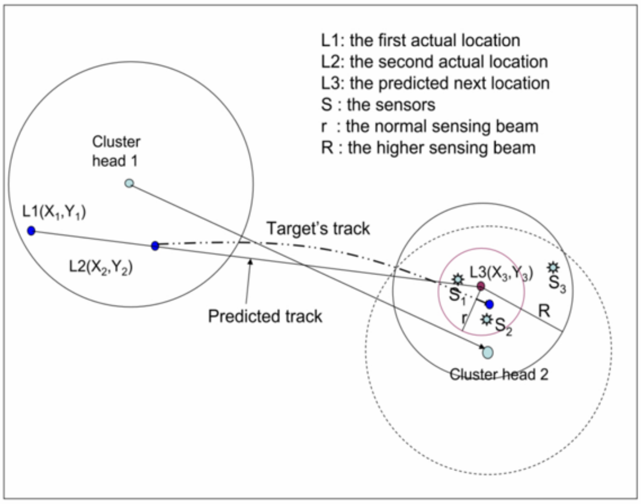
L1: the first actual location
L2: the second actual location
L3: the predicted next location
S : the sensors
r : the normal sensing beam
R : the higher sensing beam
Cluster head 1
L1(X_1,Y_1)
L2(X_2,Y_2)
Target's track
Predicted track
L3(X_3,Y_3)
S_1
S_2
S_3
r
R
Cluster head 2

Fig. 2. Search for the sensor-triplet with highbeam

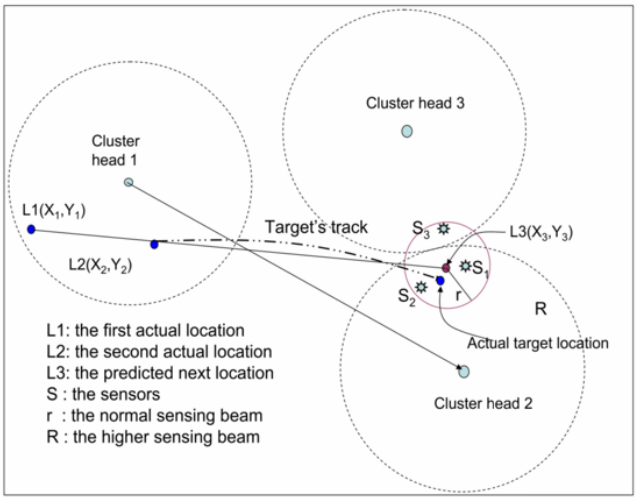

Fig. 3. Coordination between multi-cluster

3) Disappointment Recovery: In this section, we look at the recovery plot in light of connection/hub failures or incorrect forecasts. We first set apart the potential letdown scenarios. Each upstream bunch head plans an objective descriptor and transmits it to the typical downstream group head, as shown in the previous subsections. After a certain amount of time, if the upstream group leader has not heard from the downstream group head, it presumes that they are no longer reachable and that the goal has been missed.

Another case that leads to disappointment is when the object completely departs from the area that was predicted and disappears from the area that the sensor trio selected for the detecting task can perceive. This can happen when the object abruptly changes its trajectory or speed. This situation is depicted in Figure 4.

The simple solution in both of these disappointment scenarios is to activate all sensors within a specific area that is determined based on the objective's previous actual area. The "re-catch" span, a key barrier in this cycle, is established by the moving pace of the objective and the amount of time since it was last identified. Finding the minimal number of sensors necessary to cover this entire region is essentially the fitting decision of. In any event, given the cost and calculation power of the sensor, solving this problem isn't a viable option.

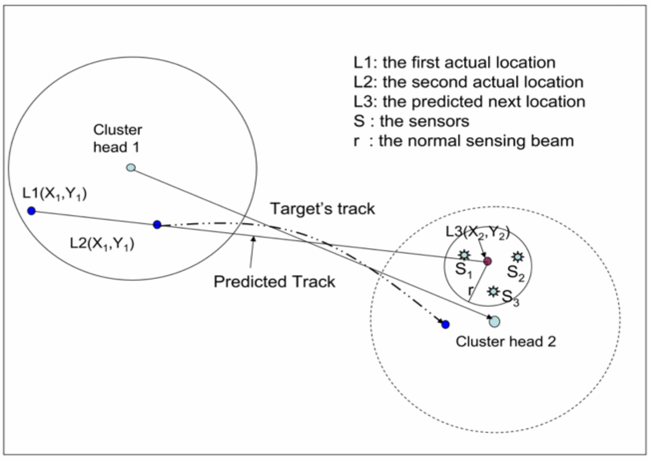
L1: the first actual location
L2: the second actual location
L3: the predicted next location
S : the sensors
r : the normal sensing beam
Cluster head 1
L1(X1,Y1)
L2(X1,Y1)
Target's track
Predicted Track
L3(X2,Y2)
S1
S2
S3
r
Cluster head 2

Fig. 4. Failure scenario where the target is out of range.

Our recovery plan is based on comparison criteria, but it is kept simple in execution to be acceptable to sensor companies. The recuperation interaction is broken into different levels:

1) First stage of recovery: If the currently selected sensor-trio was using the standard bar earlier, let them switch to high radiate now. If this is successful, proceed according to the standard "sense-anticipate impart sense" cycle.

2) Second Degree of Recovery: The primary activity of the second degree of recovery is depicted in Figure 5. A group of sensors that are situated about r meters away from Li are activated in case the initial level of recovery is insufficient. These sensors can effectively screen a span 2r circular area.

3) Nth degree of recovery: If the second degree of recovery is unsuccessful, a new group of sensors that are (2N 3)r meters from Li are started to search for the target.

It is apparent that higher levels of recovery consume far more energy than lower levels do. We have demonstrated via reenactments that the disappointment possibility of the primary level recovery is quite low. Thus, the energy lost as a result of missed targets isn't significant.

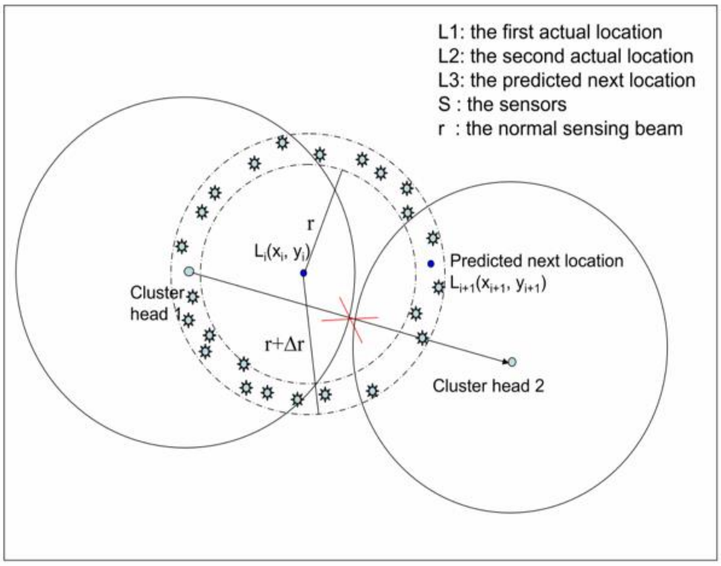
L1: the first actual location
L2: the second actual location
L3: the predicted next location
S : the sensors
r : the normal sensing beam
r
Li(xi, yi)
Cluster head 1
r+Δr
Predicted next location
Li+1(xi+1, yi+1)
Cluster head 2

Fig. 5. 2nd level of failure recovery

4) Energy Considerations: Improving the organization's energy proficiency is one of the main objectives of the DPT calculation. To do this right away, the DPT calculation incorporates the sensor-hibernation component to conserve energy and postpone the lifespan of the sensor organization.

Until they get an enactment message from their group head, a significant number of the sensors remain in the hibernation phase. Whenever, just those sensors that are decided to detect the objective should be dynamic, while all others can in any case rest. This is made conceivable by foreseeing the objective's "next area". In the event that there is no expectation by any stretch of the imagination, a lot of sensors need to remain dynamic to detect the objective, which will bring about quick energy exhaustion. Energy is conserved by "putting sensor into hibernation," but it likewise prompts a bigger data gathering delay, which is the greatest deterrent to continuous following. Luckily, The "prediction" tool, which needs the upstream group head to predict the objective's region regarding the data transmission season of the downstream group head, also overcomes this drawback. In this way, the postponement caused by slumber is inhibited and the downstream group head can be prepared considerably earlier.

Additionally, sensors use the standard shaft when the circumstances permit. Only when a group head is unable to locate adequate 3 sensors for the detection with an ordinary pillar will it determine whether switching to high radiate will satisfy the detection requirements.

Since the correspondence cost is the primary energy executor in sensor organizations, we prefer to let the sensor switch to high radiate rather than requesting the neighboring group to assist in the initial iteration [9]. When multiple group heads participate, there will be higher communication expense than when detecting is highly impacted by a single group leader. Although the group head must conduct a few more calculations to do this, the energy required is substantially lower than that required for planning with neighboring bunch heads.

Thirdly, although the transmission of TD_i by C Hey to the downstream group head seems to result in an additional communication cost, this cost is generally minimal. This is a direct outcome of the way that TD_i must be sent off the sink, despite everything. As a result of this message's omnidirectional propagation, CH_{i+1}, C Hey's one bounce neighbor, is also prepared to receive TD_i. T Di is thereafter successfully forwarded to CH_{i+1} without incurring additional correspondence costs. While receiving this message at CH_{i+1} requires some energy, the benefit provided by the prediction more than makes up for this correspondence cost. We can see that the DPT computation is planned to the point where energy is consumed as needed based on these energy-saving approaches. Currently, the expectation is that we must find N focuses on the moving track of the objective, and each point has a p_{miss} miss chance. We anticipate that a sensor will use units of energy each time it uses the standard bar to obtain the location of the target. The energy required to identify a single location with a high pillar is then provided by μR2/r2. The effort anticipated to obtain the Objective Descriptor for a specific location can be expressed as

$$E_{total} = (1 - p_{miss})E_{success} + p_{miss}E_{failure} \qquad (7)$$

As a result of a victory, three sensors use their standard bar to identify the target. Due to the inclusion of 3μ sensors, the energy consumption is 3.

$$E_{success} = 3\mu \qquad (8)$$

As per our disappointment recuperation technique, the energy consumed on account of a disappointment is:

$$\begin{aligned} E_{Failure} &= 3\mu + 3E_{HB}P_{HB} + (1 - P_{HB})(3E_{HB} + \mu \min_{n}\{n: \pi\sigma^2\}) \\ &= 3\mu\left(1 + \frac{R^2}{r^2}\right) + (1 - P_{HB})\mu \min_{n}\{n: \pi\sigma^2\} \end{aligned} \qquad (9)$$

As shown in the Section III-B.3, in the event that disappointment happens we originally let the dynamic sensor-trio change to high radiate and detect once more.

The energy used during this phase is represented by the second component in the scenario above. The third term deals with the energy used by the previous configuration: start the "base number" of sensors, n, which is expected to screen the area of 2 and once more find the lost object. The objective's speed and yet another catch outcome significantly alter. We find an articulation for PHB that makes use of the Chebyshev imbalance in IV-B.2 part.

From the aforementioned scenarios, it is clear that it is essential to maintain p_{miss} at a low enough level to prevent excessive energy use during recovery (since disappointments cause additional correspondence among bunches and sensors which emphatically increment the energy utilization). We comment on this possibility for our suggested computation in section IV.

5) Pseudo-code for Computation: The DPT calculation is split into two portions that execute at the sensor and the bunch head, respectively. Both of these calculations are message-driven, which implies that messages received from the outside trigger all activity. The pseudo code for the DPT calculation running at the sensors and bunch heads separately is presented in calculations 1 and 2. The convention makes use of a variety of message types, which are sent between the group heads and the sensors, and we list them below:

Message #1: [Message #1, target location, sensor ID] When an item is recognized, a sensor transmits this message to the bunch head.
Message #02: [Message #, TD] This communication is sent by the group leader to get its own group's reasonable sensors alert so they can find the designated goal.
Message #03: [Message #, TD] When the bunch head transmits this message, the sensor switches to high radiate detecting.
Message #12: [Message #, next awaken time] This message is sent by the sensor to the leader of its group to show that the sensor is entering hibernation mode and when it will next awaken.
Message #21: [Message #, target area, next awaken time] To report the following result, the sensor sends this message to its bunch head. Naturally, the sensor will shut off its correspondence channel and start to hibernate after sending this message.
Message #31: [Message #, CH ID, Outstanding Participation number, TD, Required number of sensors When a group head can't locate enough sensors to follow the item, it sends this message to its neighboring bunch heads.
Message #32: [Message #, CH ID, Novel Participation Number, Available Sensors Qualified group heads will respond with this message after receiving message #31, which will activate the co-detecting system. Finally, all detecting data will be sent to the group leader who needs to participate and who will also serve as the final TD.
Message #33: [Message #, CH ID, TD] The downstream CH will get this communication once the upstream CH has finished its detection.

IV. RESULTS OF REPLICATION

We give recreation findings in this section to evaluate the DPT calculation's exhibition and viability. The reproduction concentrate is mostly concerned with the calculation's supporting components:

Algorithm 1 Algorithm running at each sensor

```
while (1) do
  switch(event) {
    event 1: object detected
      send an "Object detected" message #01 to CH;
      stay awake;
      set Timer_awake;
    break
    event 2: sensing requested by CH
      start sensing;
      finish sensing and send message #21;
      shutdown communication and sensing channel;
    break
    event 3: high beam sensing requested by CH
      start sensing;
      finish sensing and send message #21;
      shutdown communication and sensing channel;
    break
    event 4: timeout
      send message #12 to CH and initiate hibernation;
      shutdown communication and sensing channel;
    break
  }
end while
```

1) The likelihood that the dynamic sensor trio will miss differentiating the objective is measured by the miss likelihood, or pmiss. This boundary can be used to evaluate the nature of the expectation in different scenarios (for instance unique following goals, t).
2) The adaptability of the calculation to different rates as a target.
3) normal energy usage for the next.

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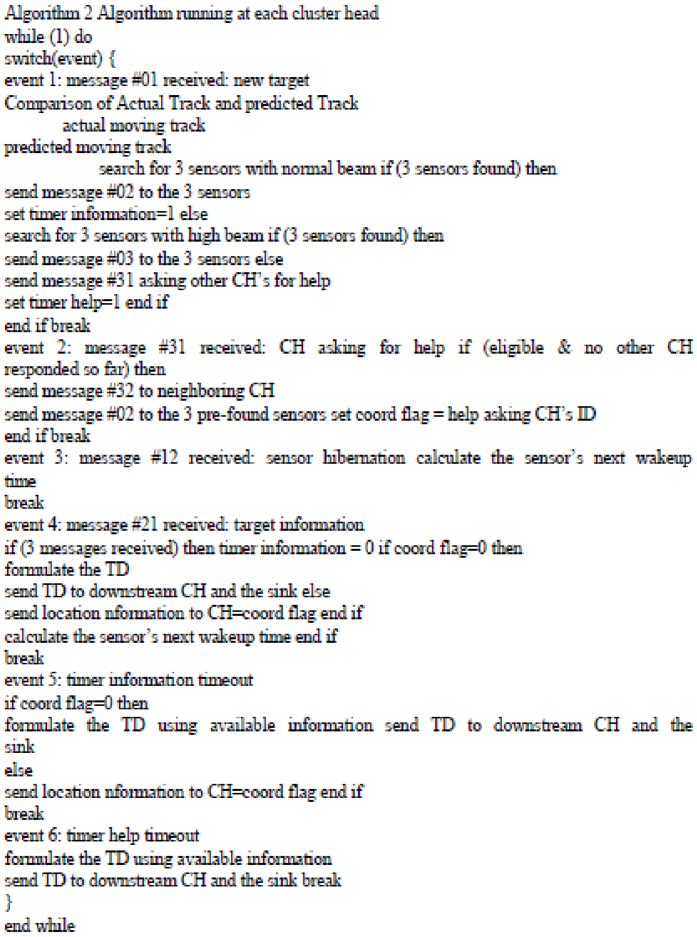
A. Reproduction Arrangement

We simulated a scenario in which an objective wander aimlessly through a two-layered detecting region. The test system was created to track this moving objective while also accurately observing the likelihood of a miss and the amount of energy used. The reenactment program was developed using ANSI C as a discrete-occasion test system.
We initially evenly distribute the sensors across a 600 m x 600 m field. As previously shown, the hub thickness should be sufficient for at least three sensors to be able to detect any irregular area within the detection area using their standard pillar. After performing the estimations with r = 35, we determine that the hub thickness is 0.01 and that there is a greater than 0.99 probability of successfully locating the sensor triple.
The objective's development example uses the irregular waypoint model, in which the heading of the objective is arbitrarily updated at predetermined intervals. We use the objective's speed as a variable boundary to determine how it affects the next quality.

B. Implications of Reproduction

1) Miss Likelihood vs. Following Goal: The DPT calculation allows for a little amount of separation between the objective's actual area and the anticipated area without missing the goal. The next region of the target is subject to a two-layered Gaussian dispersion with the expected area acting as the mean. The dynamic sensor trio will really want to screen a region in which the predicted area is covered and not just one spot, so even though there is no chance that it will fall exactly at the anticipated location, the DPT calculation is still feasible. However, in the event of utterly arbitrary development, the goal may undoubtedly shift outside of this covered area. We accurately depicted this miss likelihood under various "Following Goals" using replicas. With the assumption that when the goal improves, the miss probability will decrease, we define the Tracking Goal as the interval between two consecutive detecting focuses. We count the number of times an objective is missed out of 100 detecting focuses for each goal. Every one of these foci causes the objective to change course arbitrarily by 0 to 360 degrees.



```
Algorithm 2 Algorithm running at each cluster head
while (1) do
switch(event) {
event 1: message #01 received: new target
Comparison of Actual Track and predicted Track
          actual moving track
predicted moving track
                search for 3 sensors with normal beam if (3 sensors found) then
send message #02 to the 3 sensors
set timer information=1 else
search for 3 sensors with high beam if (3 sensors found) then
send message #03 to the 3 sensors else
send message #31 asking other CH's for help
set timer help=1 end if
end if break
event 2: message #31 received: CH asking for help if (eligible & no other CH
responded so far) then
send message #32 to neighboring CH
send message #02 to the 3 pre-found sensors set coord flag = help asking CH's ID
end if break
event 3: message #12 received: sensor hibernation calculate the sensor's next wakeup
time
break
event 4: message #21 received: target information
if (3 messages received) then timer information = 0 if coord flag=0 then
formulate the TD
send TD to downstream CH and the sink else
send location nformation to CH=coord flag end if
calculate the sensor's next wakeup time end if
break
event 5: timer information timeout
if coord flag=0 then
formulate the TD using available information send TD to downstream CH and the
sink
else
send location nformation to CH=coord flag end if
break
event 6: timer help timeout
formulate the TD using available information
send TD to downstream CH and the sink break
}
end while
```

In figure 6 we show how the objective anticipated area contrasts and the objective's real area. We observe that the predicted track closely mirrors the actual progression of the goal. The objective speed for the results in Figure 6 is 15 m/s, and the typical/high detecting bar is 35/55 m.

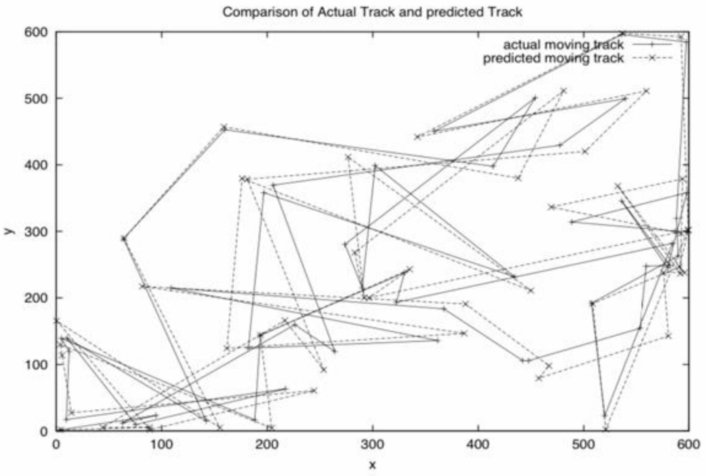


Fig. 6. Comparison of the actual and predicted track

Figure 7 shows the relationship between the next goal and the miss probability. As expected, the miss probability increases as the next goal's precision increases. A better goal reduces the extent of the error caused by the objective's speed and course variations, which improves the accuracy of the straight expectation used in the DPT calculation. It is also evident that the miss probability does not follow the speed of the target. This shows that in order to offset the rise in the miss likelihood for a faster moving aim, we need increase the next goal. This is also instantly obvious since, when pursuing a similar purpose, the faster moving item is harder to track. Figure 7 gives a numerical representation of the relationship

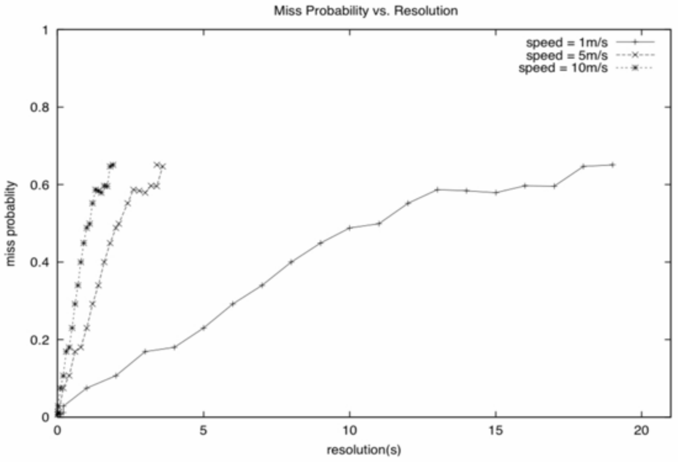


Fig. 7. Relationship between the miss probability and tracking resolution for various target speeds.

2) Miss Likelihood as opposed to detecting range/moving velocity:

Figure 8 demonstrates the relationship between the miss rate and the ratio of objective moving velocity to detecting sweep.

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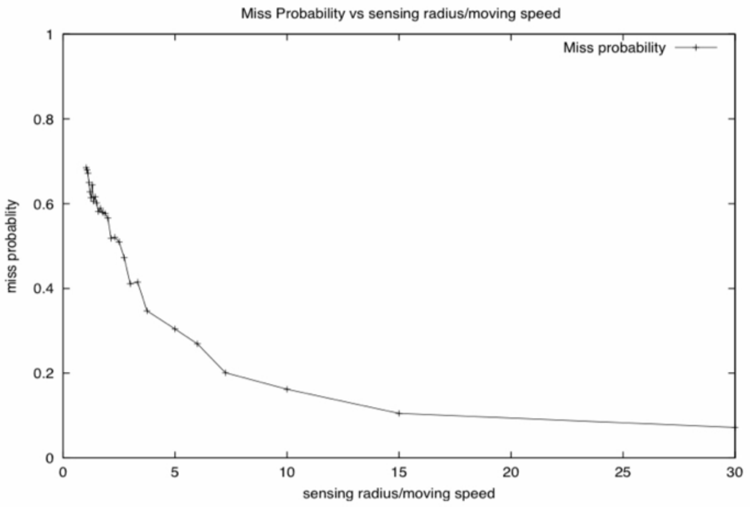

Fig. 8. Relationship between the miss probability, target's moving speed and the sensor's sensing radius

We see that the miss likelihood increases noticeably as the objective's greatness of removal in unit time becomes steadily more similar to the sensor's detecting range. This naturally makes sense given that, even while the detecting range is equivalent to the object moving in relation to time, it becomes more and more likely that the sensors won't be able to detect the object with their standard shafts. As a result, in order to locate the target, the bunch head will gradually need to rely on high shafts or help from nearby group heads. Planning the detecting organization should take this important factor into account.

We now give a more in-depth analysis of the factual characteristics of the missed locations and employ it to determine the amount of energy used by the firm. Despite the pre-mentioned default boundaries, for the case to be practical, the typical/high detecting range is maintained at 35/55m, the objective's speed is 15m/s, and the subsequent goal is 1 sec. 59 of the 2000 detecting targets were missed by the global positioning system.
We determine the greatest distance between the three dynamic sensors for each missing spot as

$$D_i = \max\{d_{1i}, d_{2i}, d_{3i}\} \qquad (10)$$

where, independently, d_{1i}, d_{2i}, and d_{3i} address the distances between the three dynamic sensors and the real area of the target.

We plot D_i in Figure 9 for each of the 59 missing places, and the mean and change of D_i are obtained for the following places. The Chebyshev imbalance is as follows:

$$P[|D_i - ED_i| \geqslant x] \leqslant \frac{VARD_i}{x^2} \qquad (11)$$

For instance, if we choose a high detecting shaft of the sensor of 55m, the possibility that the objective, i.e.

$$E(D_i) = 43.9359$$
$$VAR(D_i) = 35.4416$$

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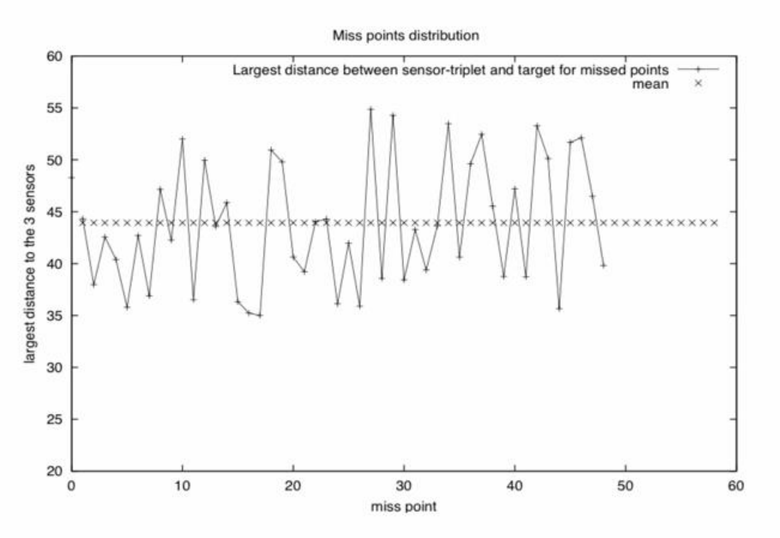

Fig. 9. Statistical characteristics of the missing points

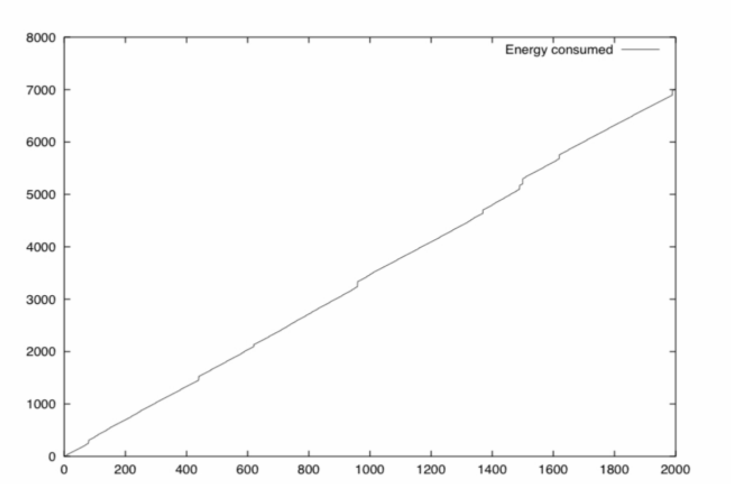

Fig. 10. Energy consumed for tracking 2000 points

The probability that the greatest distance to the sensor-trio is greater than 55m is constrained by

$$\begin{aligned}1 - P_{HB} &= P(D_i \geq 55)\\ &= \frac{1}{2} P[|D_i - E(D_i)| \geq (55 - 43.9359)]\\ &\leq \frac{1}{2}\frac{VAR(D_i)}{2(11.0641)^2}\end{aligned} \tag{12}$$

The calculation of the energy required to detect one point is given by Eqn. (7) and (9) as follows.

$$E_{total} = (1 - p_{miss})E_{success} + p_{miss}E_{failure}$$

With

$$E_{success} = 3\mu$$

$$E_{Failure} = 10.41\mu + +0.1448\mu \min_{n}\{n\colon \pi\sigma^2\}$$

Since it includes the cost of several communications between sensors and their group head or among bunch heads, min$_n${n: 2} in the scenario above is significantly larger than the other variables.

We display the amount of energy used by the organization to find these 2000 foci in Figure 10. The chart shows that the energy used is approximately 6900 units, although 6000 units of base energy are anticipated for the detecting. Our fictitious calculation shows that the overall amount of energy used should be

$$E_{total} = 200(3\mu) + 59(3\mu\frac{55^2}{35^2}) \approx 6437\mu$$

The difference between the two qualities refers to the amount of time wasted trying to recover by mistake using the second or higher levels of recovery (the term comparing to min$_n$ {n: πσ2}). We can observe that the amount of base energy required for succeeding is only slightly higher than the amount of energy spent on disappointment recovery.

Additionally, we observed throughout the reproduction that when the goal advances more quickly, the assumption and variation of D increased. The assumption and change of D, however, are reduced when we choose a more modest Following Goal. These findings imply that, with the sensors' normal/high detecting shafts fixed, we can adjust the Following Goal in accordance with the pace of the objective to achieve OK execution.

It should be noted that the energy used by the border sensors, which are awake all the time, was not included in this number. Large amounts of energy are consumed by the border sensors, so it is a challenge to come up with a useful planning strategy that would minimize energy consumption. An alternative strategy would be to keep the hub thickness higher close to the boundaries so that other line hubs in the area can be used when some of them fail without reducing the detectable area.

V. CONCLUSION AND FUTURE WORKS

In this paper, we introduced the Distributed Prescient Following computation as a workable solution for distributed following of portable targets using sensor networks. The main idea of DPT is to predict the target's future area based on known prior regions. It scaled well without any significant issue of letdown because it is entirely appropriated, and it may be easily extended to the following in 3-aspect. Our reproduction results demonstrate that, despite the use of a simple first request direct indicator for the expectation, the following exhibition is generally agreeable, with particularly strong execution at higher following objectives. Additionally, this estimate is specifically aimed at reducing the organization's energy consumption, an important consideration for sensor enterprises.

In order to achieve lower miss rates for a certain following goal, we are currently dealing with more complicated expectation computations. When a senior reports many objectives at once, further attention can also be focused on introduction mechanisms for group leaders. It's still unclear how energy use and expectation accuracy are related. The use of portable sensors is another another potential direction of exploration. With flexible sensors, the issue becomes quite complicated, and it may be necessary to handle the setup in a number of different ways.

REFERENCES

[1] S. Banerjee and S. Khuller, "A clustering scheme for hierarchical control in multi-hop wireless networks," *Proceedings of IEEE INFOCOM*, Anchorage, AK, USA, pp. 1028–1037, Apr. 2001.

[2] D. Estrin, L. Girod, G. Pottie, and M. Srivastava, "Instrumenting the world with wireless sensor networks," *Proceedings of the IEEE International Conference on Acoustics, Speech, and Signal Processing (ICASSP)*, Salt Lake City, UT, USA, pp. 2033–2036, May 2001.

[3] M. Ordouei and T. BaniRostam, Integrating data mining and knowledge management toimprove customer relationship management in banking industry (Case study of Caspian Credit Institution), Int. J. Comput. Sci. 3 (2018), 208–214.

[4] M. Ordouei and T. Banirostam, Diagnosis of liver fibrosis using RBF neural network and artificial bee colony algorithm, Int. J. Adv. Res. Comput. Commun. Engin. 11 (2022), no. 12, 45–50.

[5] M. Ordouei and M. Moeini, Identification of female infertility in people with thalassemia using neural network, Int. J. Mechatron. Electeric. Comput. Technol. 13 (2023), no. 48, 5371–5374.

[6] M Ordouei, A Broumandnia, T Banirostam,A Gilani, Efficient energy management in a smart city based on multi-agent systems over the Internet of Things platform,International Journal of Nonlinear Analysis and Applications,pp. 1-8, January, 2023.

[7]. Ordouei, I. Namdar."Web Robot Detection Based On Fuzzy System and PSO Algorithm", IJCSN International Journal of Computer Science and Network, Volume 7, Issue 4, August 2018.

DOI: 10.17148/IJIREEICE.2025.131209

[8] M Ordouei, A Broumandnia, T Banirostam, A Gilani, Providing A Novel Distributed Method For Energy Management In Wireless Sensor Networks Based On The Node Importance Criteria, Journal of Namibian Studies:History Politics Culture, 2023.

[9] C. R. Lin and M. Gerla, "Adaptive clustering for mobile wireless networks," *IEEE Journal on Selected Areas in Communications*, vol. 15, no. 7, pp. 1265–1275, Jul. 1997.

[10] A Moradi, M Ordouei, SMR Hashemi, Multi-period generation-transmission expansion planning with an allocation of phase shifter transformers, Int. J. Nonlinear Anal. Appl. In Press, (2023) 1–12.

[11] M. Ordouei, A. Broumandnia, T. Banirostam and A. Gilani, Optimization of energy consumption in mart city using reinforcement learning algorithm, Int. J. Nonlinear Anal. Appl. In Press, (2022) 1–15.

[12] M Ordouei, B Jalali, A Tolouee, Enhancing Diabetes Diagnosis: A Comparative Analysis of Machine Learning Algorithms and Evalution Metrics, Dandao Xuebao/Journal of Ballistics, Vol. 36 No. 1(2024).

[13] M Ordouei, B Jalali, New Design and Clustering of Sensors to Optimize Energy in the Internet of Things Network ", IARJSET International Advanced Research Journal in Science, Engineering and Technology, vol. 10, no. 11, pp. 76-82, 2023. Crossref https://doi.org/10.17148/IARJSET.2023.101111.

[14] A Nourbakhsh, M Ordouei, B Jalali, Proposing a New Framework for Optimizing Energy Consumption in Sensor Nodes Used in the Internet of Things, Power System Technology, Vol. 48 No. 1 (2024).

[15] M Ordouei, A. Tolouee, Comparative Analysis of Evolutionary Algorithms for Optimizing Vehicle Routing in Smart Cities, Power System Technology, Vol. 48 No. 1 (2024).

[16] W. Zhang and G. Cao, "DCTC: Dynamic convoy tree-based collaboration for target tracking in sensor networks," *IEEE Transactions on Wireless Communications*, vol. 3, no. 5, pp. 1689–1701, Sep. 2004.

[17] M Ordouei, M Moeini, Identification of hepatitis disease by combiningdecision tree algorithm and Harris HawksOptimization (HHO), International Journal of Advanced Research in Computer and Communication Engineering, Vol. 12, Issue 7, July 2023.

[18] Mohammad Ordouei, Azamossadat Nourbakhsh*, Ali Sahib Jebur, "Enhancing PV Inverter Performance Using ANN-Based Control Technique," International Journal of Advanced Research in Computer and Communication Engineering (IJARCCE), DOI: 10.17148/IJARCCE.2025.141029

[19] H. Yang and B. Sikdar, "A protocol for tracking mobile targets using sensor networks," *Proceedings of IEEE Sensor Network Protocols and Applications (SNPA)*, Anchorage, AK, USA, May 2003.