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Multi-Target Detection and Tracking (MTDT) Algorithm Based on Probabilistic Model for Smart Cities

**Khalid Jamal Jadaa^{1,2,3}, Latifah Munirah Kamarudin^{1,2}, Waleed Noori Hussein⁴,
Ammar Zakaria, Syed Muhammad Mamduh Syed Zakaria**

¹Centre of Excellence for Advanced Sensor Technology (CEASTech), Lot 16-21, Pusat Pengajian Jejawi 2, Jalan Jejawi Permatang, 026000 Jejawi Arau, Perlis, Malaysia

² School of Computer and Communication Engineering, Universiti Malaysia Perlis (UNIMAP), 02600 Arau, Perlis, Malaysia

³Computer Science Department, Al-Yarmouk University College, Diyala, Iraq

⁴Al-Zahraa college of medicine, University of Basrah, Basrah, Iraq

E-mail: khalid.jamal.jadaa@gmail.com

Abstract Wireless Sensor Network (WSNs) provides promising solutions for monitoring in several domains including industrial monitoring and control, home automation and smart cities, etc. There are numerous restrictions on the current development of target detection and tracking algorithms which makes them unsuitable or effective for indoor use. Such constraints include changes in the direction and changing target speeds, missing a target, and target dynamics. These issues come with difficulty in detection and tracking multiple targets. Moreover, the majority of the target tracking algorithms were presented on the conditions that the target is typically smooth with no unexpected changes that are difficult absolutely. Moreover, sensing coverage considers the crucial issue in a wireless sensor network. This paper implies an algorithm for detection and tracking of moving targets (intruders) for an indoor environment based on the probabilistic model utilizing WSN for safety and security. A mathematical model is presented to determine the optimum number of sensor nodes needed. The findings of the simulation showed that the MTD algorithm provides a low missing target rate of less than 0.7 % for worst-case and can be utilized for different kinds of environment scenarios.

1. Introduction

Wireless Sensor Networks (WSNs) are formed by a number of small sensing devices called sensor nodes that independently operate for performing sensing tasks and capturing data from a physical phenomenon. These nodes have a limited range of wireless communication that is used to report the detected phenomena via some data bits where they can be the generators and forwarders of the data. They also have the capability of processing and storing data [1-3]. WSN is widely used in numerous types of applications including building automation, transportation, environmental, indoor human detection localization, counting, tracking, and monitoring [4-11]. The design complexity of WSN depends on the specific application requirements. For indoor target detection and tracking need data instantly once the target emergence and accurate localization. The full analysis of the target tracking process helps to provide proper knowledge of the target's behavior. This is done by collecting and analyzing the related data throughout their evolution in space and time. Target detection covers the identification of the target in the monitoring area; whereas target tracking is the procedure of localizing and estimating the



development of the target over a specific time period. The design main idea of the proposed MTDT algorithm comprises two main elements used to detect targets and track targets. This paper focuses on detecting the emergence moving targets that appear in the monitoring area centered on the correct sensing accuracy function, localizing the targets, and tracking the moving targets that reflect various scenarios, examining the detection and tracking of targets by sensor nodes.

2. Background

This section discusses the well-known related research work on detection, localization, and tracking moving targets utilized wireless sensor network [4-6]. Target detection and tracking are vital for advanced applications such as classification and behavior learning. There are many studies in the literature that consider the detection and tracking targets utilized camera. Indeed, this kind of study is not suitable to use for indoor monitoring for most cases because of the violation of privacy. There are many techniques available that have been used for target detection: (i) Distributed Cooperative Target Detection many studies adopted this technique A distributed detection method based on the classifier was proposed. This concept was used in the probabilistic controlling event (PEMS) scheme suggested by [8-10]. A cooperative distributed platform for detection has been proposed [11-14] where (NPW) is combined with machine learning techniques identifying various raw-data occurrences. (SVM), (KNN) and (GMM) multi-dimensional function space was used. (ii) Active/Inactive Mode Scheduling in this context, [15] had proposed the (PDC-SMAC) protocol to minimize inefficient sensing (where the node is involved but nothing can be detected) that would, in turn, prolong the network lifetime. (iii) Activating/Deactivating Node Transceiver consequently [5] had proposed (GWR-MAC) protocol for short-range communication for WSNs. GWR-MAC includes source-initiated and sink-initiated wake-up procedures. (iv) Several Sensing Active Node [16] had proposed (ESCARGO) which assures well-timed delivery of event reports while maintaining network connectivity constantly. In terms of targets tracking many techniques presented such as (i) static clustering [17] had proposed three mechanisms for target tracking based on clustering. (ii) dynamic clustering [18-20] had proposed a clustering-based system for detecting unanticipated intrusions. (iii) utilizing prediction approach to improve target tracking such as Kalman filter, practical filter. However, these algorithms and techniques provide good results in terms of detection and tracking but still suffer from serious issues. Therefore, this paper aims to propose a new algorithm for detection and tracking continue moving targets utilize the ordinary sensors for reliable tracking.

3. Design Requirements and Objectives of the Proposed MTDT Algorithm

In the proposed algorithm, the data from distributed nodes are collected and combined to detect and track a real occurring physical phenomenon (such as intruder) and compute information to provide the anticipated useful information. The algorithm must take an action whenever an unauthorized object is detected in the smart home and apply cooperative centralized control roles, such as continuous dissemination of data statistics (when intruder event is triggered) to the BS where useful information such as direction, velocity, and/or position is obtained. The algorithm requirements include utilizing the resources optimally to sustain continuous coverage which increases the detection probability, covering the entire boundary of the physical event in a place completely (in case of multiple targets), and maintaining all-time accurate and complete information about the location of the target. Regarding the design objectives, the algorithm should initially have the ability to:

- Monitor a particular space/area.
- Sense and detect the presence of an object in the monitoring area.
- Propagating the detection information/data instantly.
- Localizing the detected object.
- Estimating the rate of the object's movement.
- Tracking the object as it moves.

4. Components of the MTDT Algorithm

The development of the proposed MTDT algorithm depends on the design structure which includes two key components that form the proposed target detection and tracking algorithm. These components are target detection and target tracking.

4.1. Target Detection Model

The goal of this process is to accurately and timely detect an unauthorized object in a smart home and immediately report the detection information. It means that to achieve the maximum detection probability, a proper sensing coverage of the monitoring area should be provided. Thus, a dynamic detection model is needed for precise observation. The proposed algorithm will be used for real-time detection and tracking of a moving target in a smart home, where the target is considered as transient and persistent due to its nature. Furthermore, the energy consumption is not of concern as the considered network is an indoor accessible and event-triggered WSN; therefore, always-active, ordinary, and stationary sensor nodes are used in the proposed algorithm. These sensor nodes are uniformly distributed to ensure proper sensing coverage. To eliminate the complexity of multi-hop which contributes to undesirable delay overhead in forwarding the notification reports across the network from the sensing node to reach the corresponding BS, the transmission of the sensed data is done directly. Based on the detection sensing accuracy probability publish on [7]. The probability of detection accuracy P can be defined is:

$$P(i, p) = 1 + \beta * d^{-k} \quad (1)$$

Also, the probability of detection can be defined by:

$$P(i, p) = e^{-(\beta*d)} \quad (2)$$

Moreover, the detection probability defines:

$$P(i, p) = \begin{cases} 1, & d < \min \\ 0, & d > \max \\ \beta e^{-(k*d)}, & \min < d < \max \end{cases} \quad (3)$$

The detection model is used to detect targets in this study, therefore several parameters, including the maximum probability of the target detected certainly, vertical and horizontal location, and the pattern of the detection probability is considered. Consequently, the probability detection model is as follows:

$$P(i, p) = \beta \gamma^{-(k*d)^m} \quad (4)$$

β is the parameter for detection accuracy which shows the maximum probability with which the sensing node i is detected, such that $0 < \beta \leq 1$; that is, when $d = 0$, then $\beta = 1$.

γ and k : Indicate the parameters of vertical and horizontal position where $\gamma > 1$ and $k > 0$ are respectively. Based on a reference point a probability distribution can be defined (d', P') . It means that the probability of the target being detected P' If a target is seen at d' distance from a sensor node i . Therefore, making $kd' = 1$, would lead to $P' = \beta \gamma - 1$, that helps to select a point of reference, (d', P') . When defining the position of the equation (5) and (6) parameters:

$$\gamma = \beta * (P')^{-1} \quad (5)$$

$$k = d'^{-1} \quad (6)$$

m is a positive parameter ($m > 0$) representing a drastic (or smooth) reduction in the probability of detection, from β to 0, concerning the d . If this is needed at a defined distance d_i , the detection accuracy of probability is P_i . Thus, m defined as:

$$m = \log d_{k*di} \log_{\gamma} \left(\frac{\beta}{P_i} \right) \quad (7)$$

where $d_i > d'$ and $d' < P'$, and vice versa.

4.2. Effective Detection Measure

The Effective Detection Measures (EDM) the sensory intensity from all nodes within the area (A) at point p when a target has been found represents the intensity of the sensor at that point. It can be determined by the combination of each sensing node's probability prediction function that helps to detect the target as follows:

$$EDM(A, p) = \sum_1^n P(n_i, p) \quad (8)$$

Where (A) is the field of object detection in an indoor environment, p is the point of detection of the target by n nodes; and $P(n_i, p)$ is the detection of probability in points p of the monitoring region of each sensing node. Also, EDM of the sensing node closest (EDM_{min}) for the object, the following calculated:

$$n_{min} = n_j \in P | d(n_j, p) \leq d(n_i, p) \forall n_i \in P \quad (9)$$

where n_{min} is the node with the shortest distance from the target in comparison with other nodes.

$$EDM_{min} = P(n_{min}, p) \quad (10)$$

The object detection takes place over dual successive stages; monitoring and detection. The sensor nodes are often involved to track their sensor ranges in a certain region or area. The sensors notice the surroundings and report the sensing data during the monitoring stage. The data is used to determine whether an object is in the tracked region at any point during the detection process. Once an object is detected, it returns a value for every sensor in any location of the monitoring area to detect an object and enables event-driven data transmission. Then a message (report) is generated that includes the value and the sensor ID of the object, and immediately sends a message to BS. Following that, it switches to monitoring, etc. Although the detection process is still waiting for the data. Figure 1 displays the target detection flow chart.

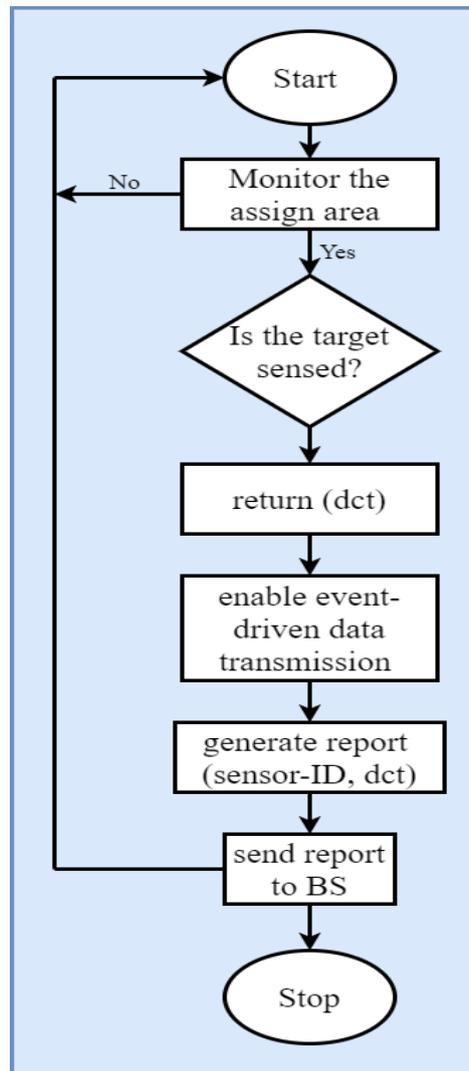


Fig. 1. Detection Procedure

4.3. Target Tracking Model

This process aims at providing an efficient tracking of the event in terms of accuracy and reaction by detecting and localizing the object as it moves in the smart home, considering the velocity and direction of the object. The main roles of the tracking process are collecting the data of the target; analyzing the collected sensed data and reacting in a proper form. When nodes report their readings about the object, the location(s) of the target can be abstracted precisely. In the proposed algorithm, tracking of the object is done at the BS where a more accurate and comprehensive global view of the object mobility can be observed, and proper reaction can be made. Statistical approaches are used to analyse the detection data and extract feature vectors from raw data to locate the target and to predict the path that it would take in near future and its potential behavior. With these statistical approaches, the tracking process provides the correct estimation of the current and potential future position of the target. Concerning target tracking, some of the preliminary information needed is given below. The ability to locate a target that moves from point to point in the smart home $p_i(t_i)$ to point $p_i(t_{i+1})$ On arbitrary route $r(t)$ the following may be defined:

$$D_0(r(t), p_i(t_i), p_{i+1}(t_{i+1})) = \int_{t_i}^{t_{i+1}} EDM(A, r(t)) \left| \frac{dr(t)}{dt} \right| dt \quad (11)$$

where D_0 is to detect a target inside the indoor environment at an interval of time $[t_i, t_{i+1}]$ within the monitoring area (A) along with the route $r(t)$ where the points $p_i(t_i)$ and $p_{i+1}(t_{i+1})$ fall in; and $\left| \frac{dr(t)}{dt} \right|$ is the element of route length and can be specified in Equation 12.

$$\left| \frac{dr(t)}{dt} \right| = \sqrt{\left(\frac{dx(t)}{dt}\right)^2 + \left(\frac{dy(t)}{dt}\right)^2 + \left(\frac{dz(t)}{dt}\right)^2} \quad (12)$$

This implies that the target detection is defined as the integral function of detecting nodes from a path from $p_i(t_i)$ to point $p_{i+1}(t_{i+1})$ over some time $[t_i, t_{i+1}]$. The detection function at any point $p(x,y,z)$ for each sensing node deployed in the smart home at a location (x,y,z) can be expressed as:

$$P(i(x, y, z), p(x, y, z)) = \frac{1}{d} = \frac{1}{\sqrt{(x)^2+(y)^2+(z)^2}} \quad (13)$$

where d is the distance from the sensing node i to the point p .

To define the minimum detection of the target, regarding the closest sensing node, that moves from point $p_i(x_i, y_i, z_i)$ to point $p_{i+1}(x_{i+1}, y_{i+1}, z_{i+1})$, we need to find the continuous functions $x(t)$, $y(t)$, and $z(t)$, such that, $x(0) = x_i$, $y(0) = y_i$, $z(0) = z_i$; $x(1) = x_{i+1}$, $y(1) = y_{i+1}$, $z(1) = z_{i+1}$; and

$$D_0 = \int_0^1 \frac{1}{\sqrt{(x)^2+(y)^2+(z)^2}} * \sqrt{\left(\frac{dx(t)}{dt}\right)^2 + \left(\frac{dy(t)}{dt}\right)^2 + \left(\frac{dz(t)}{dt}\right)^2} dt \quad (14)$$

As stated previously, the base station monitors the object detected as it has a global view of the sensing nodes' location. The monitoring of the object detected depends on its location. Therefore, the instant position of the detected object is determined by an internal mechanism. The method for the determination of the internal object position is defined in the following paragraph. In the BS, the identification and position coordinates of the receiving node were reported when the detection report was sent (message), in addition to the moment the report arrived. Then, if subsequent reports arrive at the BS, this case confirms that the appearance of the object is true. Therefore, the BS will define the region where an object was going. The BS would then return the identity sensing node, its location, and the moment when a notification is received for all sensor nodes detecting a moving target. If not, the internal method of assessing the location of the object must wait until the detection process informs. Figure 2 presents the flow chart of the process for determining the location of the object in the BS when the sensing report is obtained once the object has been identified.

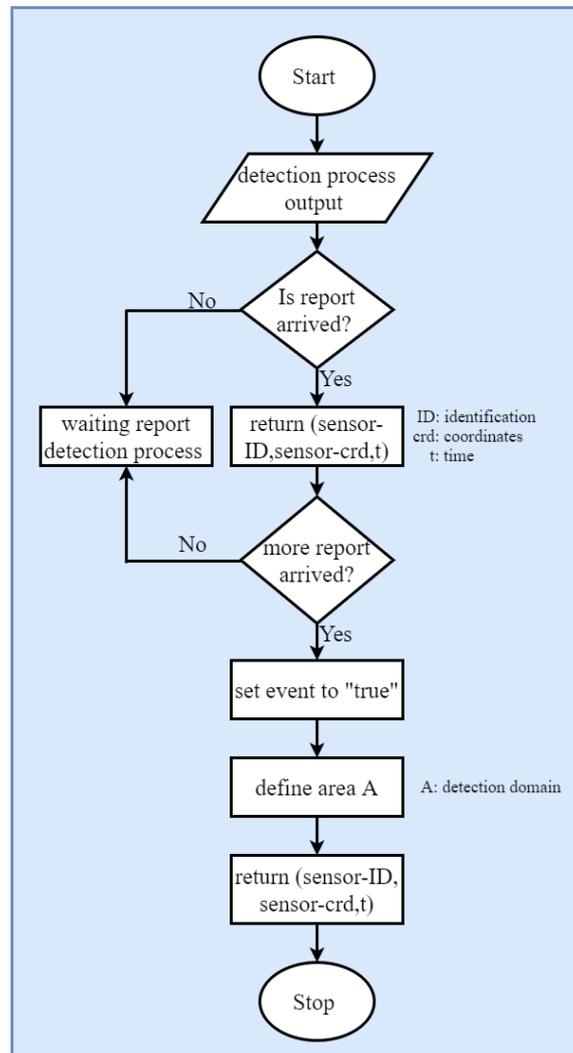


Fig. 2. Location Determination Procedure

In the following paragraph, the object tracking method is defined as a mobile target along with its corresponding procedure. When the identification of the object has been confirmed and the position of the object has been determined, the tracking process is triggered following the path of the moving object is taken. The following sequence of instructions will be followed by the BS:

- Record the reporting node location coordinates for the quarters of the circle and the sensor location radius.
- Calculate the distance between sensors that detect the moving object according to the position.
- Calculate the time span for the reports received, that reflects time change (Δt).
- Calculate the moving object direction by estimating the object's movement during the time interval $[t_i; t_{i+1}]$ together with the projective line $p(t)$.
- Compute the vector quantity that represents the moving object's direction.
- Compute the movement speed of the target in terms of time, which shows the rate of change in its position as a function of time in a specific direction.

Figure 3 illustrates the flow chart of the target tracking phase conducted by the BS after deciding the position of the moving target.

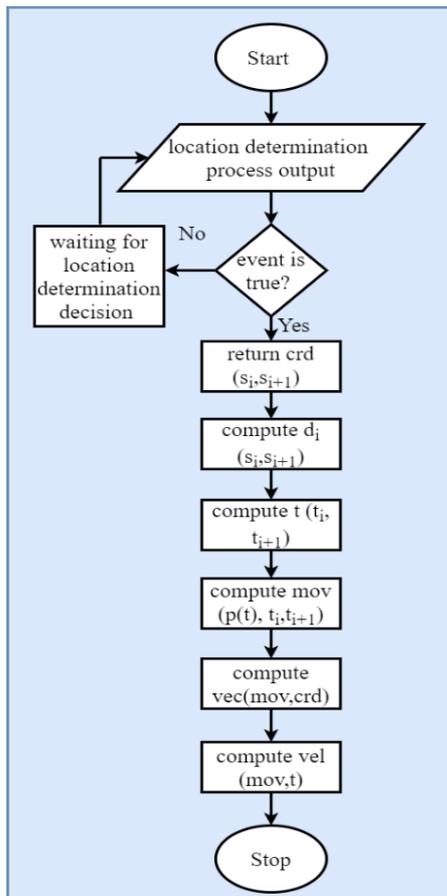


Fig. 3. Target Tracking Procedure

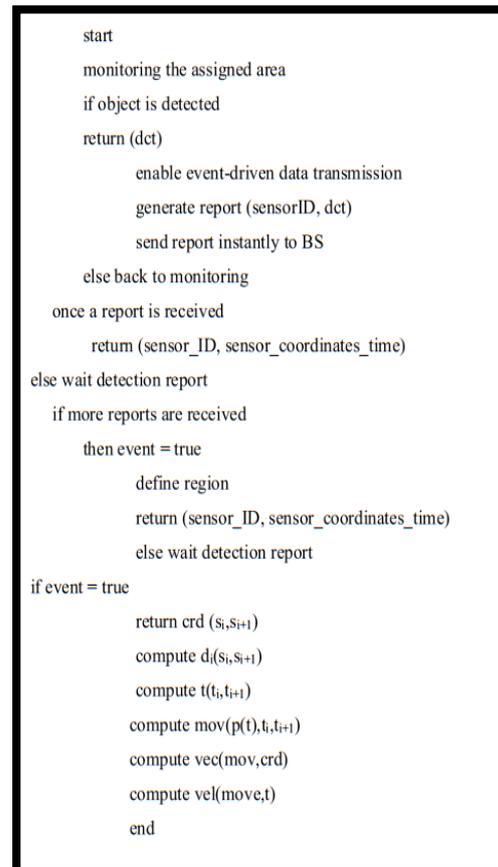


Fig. 4. MTD T Pseudocode in Term of Function

5. Location of Sensors

An optimal sensing coverage can be defined concerning the position of the sensor within the SF sensing field so that the maximum sensing coverage and the maximum detection probability are received. Let a sensor's position be at a distance d_i from the angle θ of a reference point p_r , then for SF coverage model (n, P_0, \dots, P_{n-1}) with r_i representing the sensing range of s_i positioned within d_r , and that $\frac{1}{2}(P_i + r_i) \leq r_i \leq \sqrt{(2) (\sum_{j=0}^i P_j)}$, the desired sensing coverage would be achieved concerning the location l_i of s_i for the reference point distance $d_i (s_i, p_r)$, for all $i = 0, 1, \dots, n - 1$, comply with the following conditions:

let s_i be positioned at point $(0, d_i)$, where $d_i \geq 0$. Considering the trajectory P_i depicted in Figure 5 proving can be done by determining the position of a sensor s_i that can maximize the sensing coverage.

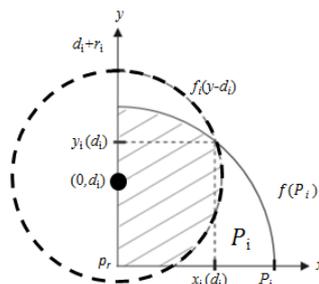


Fig. 5. Sensor Position on the Route

Assume that the equations (15) and (16) describe two circles as follows:

$$x^2 + y^2 = p_i^2 \quad (15)$$

$$x^2 + (y - d_i)^2 = r_i^2 \quad (16)$$

Where the first one that includes p_i , and the second one includes the semicircle of the sensing coverage. Solving for x in 17 gives:

$$x^2 = P_i^2 - y^2 \quad (17)$$

By substituting (16) in (17) it will give:

$$y_i(d_i) = ((P_i)^2 + (d_i)^2 - (r_i)^2) / 2d_i \quad (18)$$

Solving for P_i , $y_i(d_i)$ axis would have resulted in the intersection point $(x_i(d_i), y_i(d_i))$ of the two circles. $y_i(d_i)$ could also be derived by subtracting the equations of the two circles thus extending to achieve a linear equation for $x_i(d_i)$ and $y_{i0}(d_i)$. The linear equation is the line equation that moves via the points of intersection when the two circles intersect. Let $f(d_i)$ is the shaded area shown in Figure 3.8, as follows:

$$f(d_i) = \int_{y_i(d_i)}^{y_i(d_i)} f_i(y - d_i)dy + \int_{y_i(d_i)}^{P_i} f_{P_i}(y)dy \quad (19)$$

$$f(d_i) = \int_{-d_i}^{y_i(d_i)-d_i} f_i(y)dy + \int_{y_i(d_i)}^{P_i} f_{P_i}(y)dy \quad (20)$$

While $f_i(y)$ and $f_{P_i}(y)$ are both continuous functions, their antiderivatives can be $F_i(y)$ and $F_{P_i}(y)$ respectively; therefore, $f(d_i)$ can be written as:

$$l_i = \begin{cases} \sqrt{\frac{(P_i)^2 - (r_i)^2}{3}} & , \left(\frac{P_i}{2}\right) \leq r_i \leq P_i \\ \sqrt{(P_i)^2 - (r_i)^2} & , (P_i) < r_i \leq \sqrt{2} (P_i) \end{cases} \quad (21)$$

$f(d_i)$ can be written as:

$$f(d_i) = F_i(y_i(d_i) - d_i) - F_i(-d_i) + F_{P_i}(P) - F_{P_i}(y_i(d_i)) \quad (22)$$

6. Sensing Field Model

In regards to sensing field model (n, P_0, \dots, P_{n-1}) , the sensing coverage of a sensor (s_i) with a sensing range (r_i) (such that $\frac{1}{2} P_i \leq r_i \leq \sqrt{2} (\sum_{j=0}^i P_j)$, for $i=0, 1, \dots, n-1$), that is beyond the width P_i where target O moves can be minimized if the optimal placement of s_i at distance d_i away from the reference point p_r meets the following condition:

$$d_i = \sqrt{((\sum_{j=0}^{i-1} P_j)^2 + (\sum_{j=0}^i P_j)^2 - 2(r_i)^2) / 2} \quad (23)$$

For a sensing field model (n, P_0, \dots, P_{n-1}) , with a fixed trajectory width (P_i) and a fixed distance (d_i) of sensor (S_i) position from the reference point (p_r) , having the sensor sensing range (r_i) , the number of sensors m' that efficiently sense the object O in (P_i) is:

$$m' = \left\lceil \frac{\pi/4}{2 \cos^{-1} \left(\frac{(d_i)^2 + (\sum_{j=0}^i P_j)^2 - (r)^2}{2d_i (\sum_{j=0}^i P_j)^2} \right)} \right\rceil \tag{24}$$

$i = 0, 1, \dots, n-i$

Suppose there are two adjacent sensors in the route (P_i) Figure 6 indicates that. The maximum path sensor coverage (P_i) can be reached if no gap exists between these sensors' coverage areas. The maximum angle θ allowed of the two adjacent sensor nodes, Using the Cosine law the following can be extracted to optimize the sensing coverage:

$$(r_i)^2 = (d_i)^2 + (\sum_{j=0}^i P_j)^2 - 2d_i (\sum_{j=0}^i P_j) \cos(\theta) \tag{25}$$

Thus,

$$\theta_i = \frac{(d_i)^2 + (\sum_{j=0}^i P_j)^2 - (r)^2}{2d_i (\sum_{j=0}^i P_j)} \tag{26}$$

By taking the unit circle's first quadrant, the angel at $p_r (x_0, y_0)$ is 45° . Therefore, the number of sensors needed in the P_i trajectory to optimize the sensing coverage is

$$m' P_i = \left\lceil \frac{(\pi/4)}{\left(2 \cos^{-1} \left(\frac{(d_i)^2 + (\sum_{j=0}^i P_j)^2 - (r_i)^2}{2d_i (\sum_{j=0}^i P_j)} \right) \right)} \right\rceil \tag{27}$$

all $i = 0, 1, \dots, n-1$

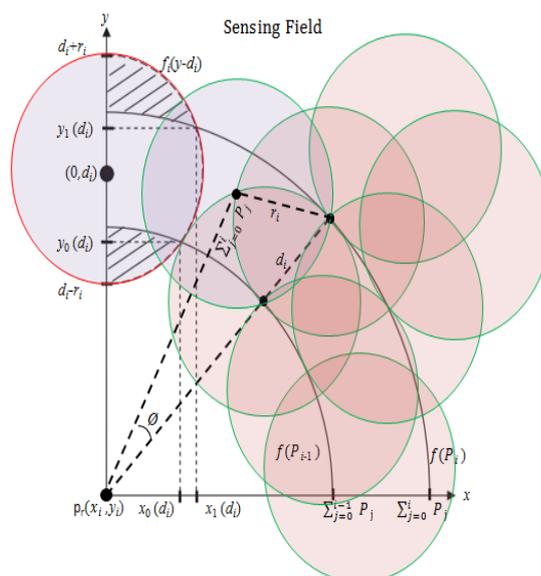


Fig. 6. Angle θ Between Two Sensors Nodes

7. MTDT Algorithm Validation

The validation of the proposed MTDT algorithm for detection, localization, and tracking is done through an experimental evaluation using simulation. This section presents the scenario and settings that have been utilized in the experimental evaluation after that the discussion on the results obtained from the simulation experiments.

7.1. Evaluation and Setting

A wireless sensor network of 128 sensor nodes was simulated using Network Simulator 2 (NS-2) carried out on Ubuntu 16.04 Lts environment and NS-2 2.35+dfsg-2 ubuntu. The sensor nodes are uniformly deployed on the monitoring area 30*30 m². The experimental evaluation explores the impact of the targets' velocity and node density on the missing target rate of the MTDT algorithm performance.

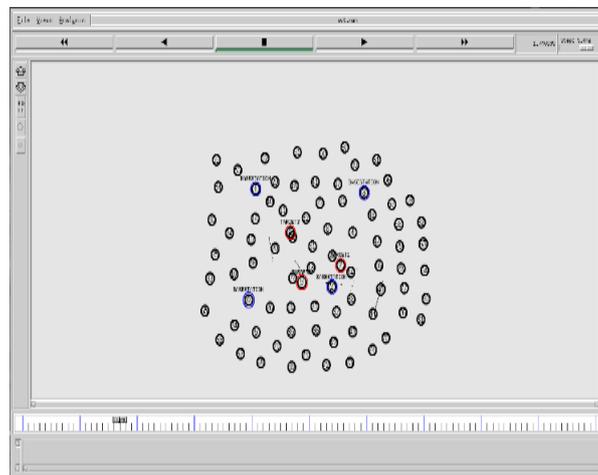


Fig. 7. Scenario Test

7.2. Simulation Environment

This paper used simulation data generated to evaluate the MTDT algorithm. The following are the descriptions. First, the sensor density "Di" is described this way:

$$D_i = \frac{S * \pi * R^2}{A} \quad (29)$$

S: sensor nodes number, R: sensing range, R = 3 meters, and A=900 m²: monitoring area. It is presumed that the minimum number of sensors will cover the entire region A by taking into consideration the best optimum number of nodes to get the best results. The research, therefore, fixes the density Di proximity 2, 3, 4,5 using equation (29) to calculate sensor nodes' number (S). The corresponding value of S for the first area is 65, 96,128, and 160 nodes as clarified in Table 1.

Table 1: Sensor Number

Density	Sensor
2	65
3	96
4	128
5	160

For each case, the target movement data is generated. The scenario goal is as follows: The targets would enter an area in the monitoring area across a door, windows, or any speed, then walk or run unexpectedly in the monitoring area. The target uses the shortest path to determine a destination location and walk towards it. Then either the target stops at the destination or moves to a new random destination. The

speed of each target is changed randomly from 1 m/s to 10 m/s. Table 2 should have listed the other parameters for the simulation.

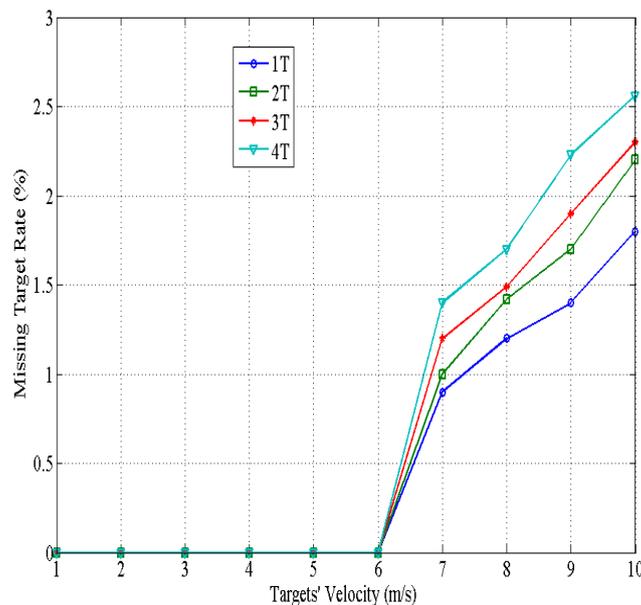
Table 2: Simulation Parameters

Parameters	Values
Simulation Area	900 m ²
No. Sensor Nodes	65, 96, 128, and 160
Speed of the Targets	1 – 10 m/s
Number of Targets	1-4
Antenna Type	OmniAntenna
MAC	802.11
Propagation Model	TowRayground
Channel	WirelessChannel
Protocol	AOVD

8. Results and Discussion

8.1. Missing Target Rate $D=2$

In this case, the proposed algorithm has been implemented with and 65 sensor nodes for single and multi-targets with a varying velocity of targets to check the missing target rate when $D = 2$. The simulation results show the missing target rate for this case is 0 % that means there is no missing target if the velocity of the target is below than 6 m/s for single and multi-target as shown in Figure 8 The reason behind these good results is the sensor nodes are always active and the nodes send their sensed data directly to their corresponding base stations (BS). Because of, using this kind of architecture, that means there is only one hop between the nodes and BS, which leads to a low missing target rate. The performance of the MTDT algorithm affected negatively when there are single or multi targets in the monitoring area after increased velocity to more than 6 m/s.

Fig. 8. Effect of Targets' Velocity on Missing Target Rate $D=2$

8.2. Missing Target Rate $D=3$

In this case, MTDT algorithm was implemented to check the simulation's results of the missing target rate by increasing the number of nodes to 96. Figure 9 illustrated the missing target rate for single and multi-targets with varying velocity and directions in the sensing field. The simulation results of MTDT algorithm show the missing target rate is 0 % if the velocity of the targets is below 6 m/s. By increasing the targets' velocity to 7 – 10 m/s the missing target rate increased gradually. Based on the two cases of simulation results that have been implemented when $D = 2$ and $D = 3$, the MTDT algorithm with $D = 3$ reduced the average missing target rate around 61 % compared with $D = 2$. This percentage of enhancement is because of increasing the sensor nodes removed the blind spots. Besides that, by increasing the sensor nodes enable MTDT algorithm to recapture the targets easily when missed.

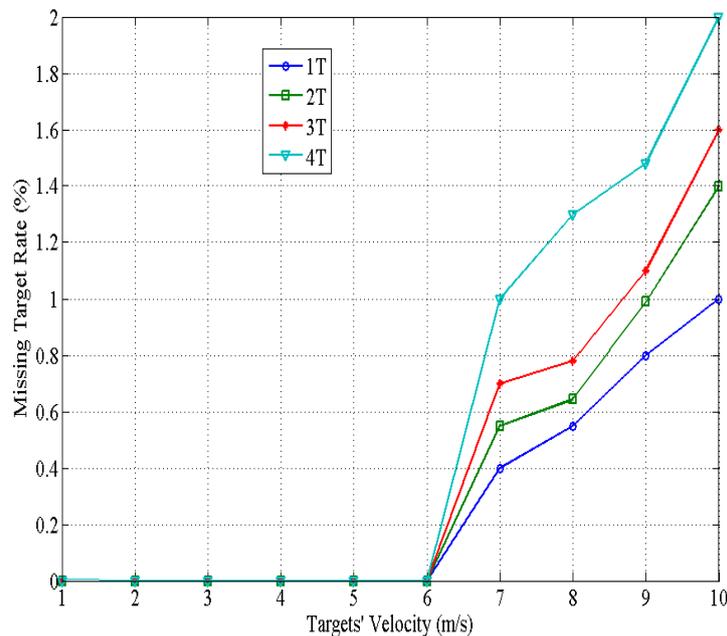


Fig. 9. Effect of Targets' Velocity on Missing Target Rate $D=3$

8.3. Missing Target Rate $D=4$

This case presents the simulation results of missing target rate after increasing the number of sensor nodes to 96. Figure 4.10 illustrates the missing target rate for single and multi-targets. The simulation results of case C show there is no missing target rate if the velocity of the targets below that 6 m/s. When the velocity of the targets increased to be 10 m/s, that leads the missing targets increased but much less than case A and case B as shown in Figures 4.10. The number of sensor nodes, in this case, is recommended because this density is optimum in terms of the number of sensor nodes and the position of these nodes based on the Equation (26). Because the number of sensor nodes and the position of these nodes is optimum that leads to significant enhancement on the performance of MTDT algorithm in terms of missing target rate more than 130% comparing with case B when $D = 3$. These results prove that the method used to deploy the sensor nodes and method to determine the optimum number of sensors nodes efficient besides an effective way that is used to detect the moving targets that have been described in section 3. The improvement increased a considerable amount because of the detection model that is used with the optimum number of sensor nodes and optimum positions. The proposed MTDT algorithm with $D = 4$ outperforms MTDT algorithm with $D = 4$ because it reduces the missing target rate due to less complexity.

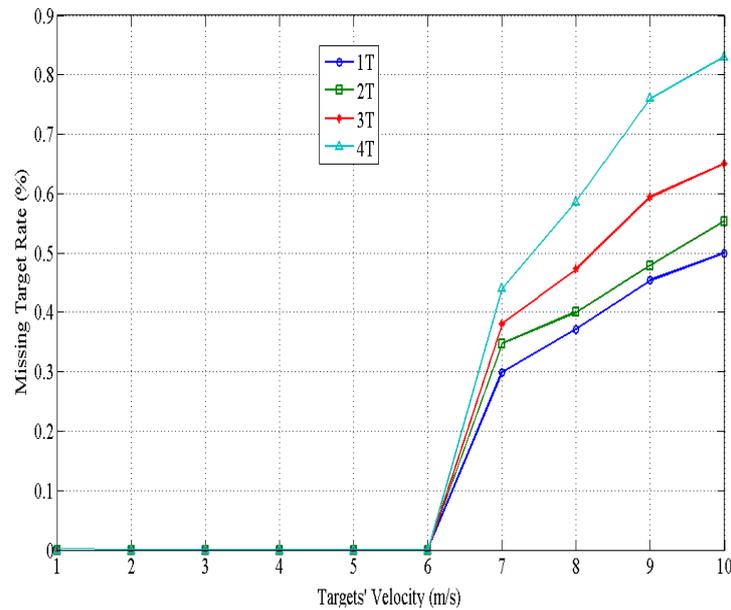


Fig. 10. Effect of Targets' Velocity on Missing Target Rate D=4

8.4. Missing Target Rate D=5

This case presents the simulation results of the missing target rate after increasing the number of sensor nodes to 160. Figure 11 illustrated the simulation results for single and multi-targets when D=5. The simulation results show keeping an increase in the number of sensor nodes will not minimize the missing target rate. Increasing the number of sensors nodes will lead to an increase in the complexity and network overhead. Therefore, in this case, increase the D = 5 backed a negative effect on the performance of the MTDT algorithm in terms of the missing target rate. Based on the comparison between D = 4 which is optimized and recommended to area1 and area 2 as mentioned earlier and D = 5 which more sensor nodes, the simulation results show when D = 5 increases the missing target rate around 14.35%. In conclusion, based on the simulation results from all the densities that have been implemented, D = 4 has the lowest missing target rate compared with the rest of the densities.

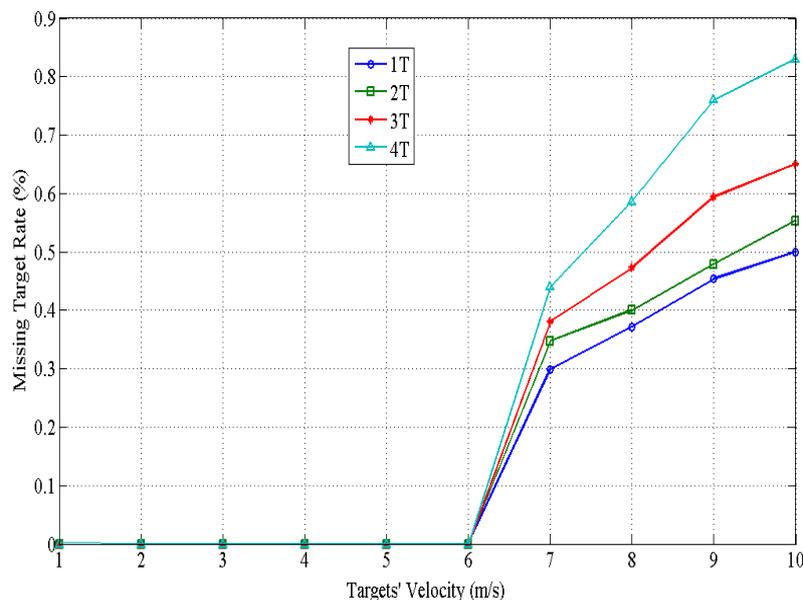


Fig. 11. Effect of Targets' Velocity on Missing Target Rate D=5

9. Conclusion

This paper presented a new algorithm based on a probabilistic model. It is provided with the use of wireless sensor networks to identify, locate, and track targets in a given monitoring area. The findings showed that for a wide variety of applications and situations the proposed MTDT algorithm could be used and this can help to monitor sensing coverage and to accurately track multi-targets. Future work can concentrate on the detection and tracking of continuous moving targets such as leaking gas and fire spreading to name a few.

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