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Multi Objects Detection and Tracking System for Smart Home using Wireless Sensor Network

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ABSTRACT

The current developed event detection and tracking systems have several limitations that make them not suitable or efficient to be utilized in smart homes. These limitations include dealing with direction changes and varying speeds of an evolving events, node fault tolerance, energy consumption, missing of target, tracking precision, dynamicity of the target, and prediction accuracy. The situation become more difficult in term of multi-targets. Efficient tracking after the detection of an event based on robust data control and management would definitely help in making reliable distributed control decisions, therefore a reliable system is highly needed. In this paper we proposed a system for monitoring and detecting of continuous moving objects according to certain requirements and specifications that are related to smart home concept. The system can be detecting and tracking multi objects in the monitoring area that are moving randomly with varying speed by using ordinary sensors. The proposed system able to collect and analysis the data during their development in time and space. In this paper have been used a dynamic sensing model for accurate observation and delectability of the event. The simulation results of the proposed system show high detection and tracking accuracy for detection and tracking multi continues moving objects. The proposed system shows high tracking accuracy in term of single reach to 97 % and multi-targets (up to 5) reach to more than 94 %.

Key words : Accuracy, Detection, Multi-targets, NS-2, Tracking, Wireless Sensor Network

1. INTRODUCTION

As sensors are capable of accurately sensing temperature, light, air pollution, and moving objects, WSN's technology become the promising solutions for in smart and efficient monitoring [1], [2]), [3] [4], [5], [6], [7]. With the use of WSNs, smart, safer, and secure environment for residents can be ensured. For instant, WSNs can be of great benefits to save lives where they can be smartly used to timely detect intruder and other events interior atmospheric such gas leak, explosions, smoke, fire and many more that would have catastrophic consequences [3]. Since the occurrence of such events is naturally random and unexpected, it would enforce serious challenges on the network smart home system in regards to dependency and data diversity [8], [9]), [10], [11]. Normally, when an event such as intrusion occur, it presents itself arbitrarily, and there might be noticeable physical evidence is witnessed of their occurrence when completed or they pass without notice based on the purpose of the intruder. Such target may occur for short time period where the consideration must be on maximizing the detection probability wherever the target moves; or for long time where minimizing the detection delay must be prioritized. In The following, the related research works on target detection and tracking are reviewed together with techniques, algorithms and analysis applicable for WSNs that are used to detect and track an intrusion event [12]. In multi-hop WSNs, the cost of propagating the reports of the event detection from the detecting nodes to the sink can be significant. Collaboration of neighboring nodes on deciding whether or not there is sufficient evidence exists to trigger the propagation of target detection notification would be of benefits regarding energy saving and accurate detection of the target as well as the detection delay [13],[14]. Accordingly, a classifier based distributed detection system was proposed by [15]. They stated that if parts of events are cooperatively composed by nodes, a comprehensive assessment of an event with low energy consumption is possible. The experimental evaluation results of their proposed system, with WSN of 49 nodes integrated in construction site fence elements, showed that the energy consumption is reduced beyond a two-hop distance communication while achieving high event detection accuracy. Based on probabilistic significance of the observations, sensing nodes can be collaboratively designated for monitoring an event, and the network topology can then be adjusted to enhance energy efficiency, where the CH is responsible of forwarding the sensed data. This concept has been utilized in the probabilistic event monitoring scheme (PEMS) proposed by [16]. Cooperative distributed detection framework was proposed by [17] where negative pressure wave (NPW) is integrated with intelligent machine learning technique to define specific events based on data raw sensed data. Support vector machine (SVM), K-nearest neighbor (KNN) and Gaussian mixture model (GMM) were applied in multi-dimensional feature space. The proposed system was validated on a field deployed test-bed aiming at detecting the leakages in pipelines. [18] they were proposed algorithm for tracking based on a probabilistic model with take in the consideration energy consumption and tracking accuracy (DC-AIPT). The work adopted the dynamic clustering technique and notion percolation theory to develop and evaluate their algorithm. [19] proposed several algorithms to track human movement paths for indoor environment (room 1) by using infrared sensors (IR) fond of to the ceiling of monitoring area randomly with known location coordinates. In their algorithms used binary sensor to reduce the energy consumption, the finical cost, to make the instillation easy to configure. Aiming at reducing the ratio of missing the target, [20] had proposed a system with five algorithms for tracking targets with fast movement. Among them, Dynamic Lookahead Spanning Tree Algorithm (DLSTA) is responsible for dynamically forming trees along the predicted path of the target prior to its arrival. The root of the tree is the node that has the shortest distance to the target. In DLSTA, the node closest to the target is elected as a root node. By estimating the speed, direction, and location of the target, the root node builds its clustered tree. The rest of the paper organized as follow: 2. Design process of the proposed system, 3. Theoretical preliminaries for detection and tracking, 4. Object detection, object tracking, 5. Simulation set up and parameters, 6. Results and discussion, 7. Conclusion and future work.

2. DESIGN PROCESS OF THE SYSTEM

The design structure of the proposed system composed of two key components used for target detection and target tracking. These components are designed based on some fundamental theoretical concepts including communication theory and statistics related to the position, speed, and directing of the target. The design process of the proposed object detection and target tracking system is illustrated in Figure 1 in terms of Finite-State Machine (FSM).

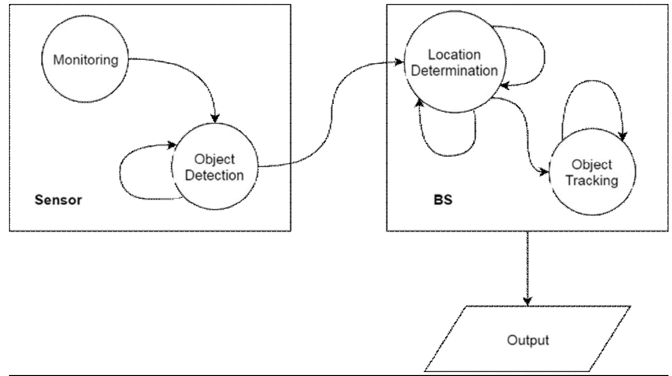

Figure 1: System design process

As illustrated in the figure, the deployed sensors are responsible of continuous monitoring of the monitoring area of interest and detecting any object once it emerges and updating the corresponding base station (BS). On the other hand, the rule of the BS is to determine the location of the appearing object based on the data received from the detecting sensors and tracks its movement accordingly. Then, the BS would generate the proper warning outputs. The procedures of the corresponding rules in accordance with system components are explained in the following sections.

3. THEORETICAL PRELIMINARIES FOR DETECTION AND TRACKING

This section presents the theoretical preliminaries used for modelling and designing of the components of the system proposed in this paper. In the following, the technical preliminaries for target detection are defined. A dynamic detection model can be used where the distance between a sensing node and the target at a specific location can be presented as a linear function which is inversely proportional to the detection accuracy such that the probability of the detection accuracy P of sensing node i at arbitrary point p is:

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

where d is the Euclidean distance between sensor i and the target at a specific point P, and β and k are specific sensing technology parameters where β is an adjustment parameter and that k varies from 1 to 4 (depending whether it is indoor or outdoor monitoring). The detection probability can also be inversely proportional to an exponential function of the distance specified by:

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

Moreover, the detection probability can be an integrated model of linear and exponential functions with minimum and maximum limiting thresholds (min, max), such that:

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

Even though the detection probability model presented in Equation (3) is more rational compared to the previous ones; however, it has limited applicability. Hence, the dynamic detection model that will be used in this research to detect a target considers several parameters such as the maximum probability with which the target is certainly detected, the vertical and the horizontal location of the target, and the tendency of the detection probability. Therefore, the detection probability model will be as follows:

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

where:

• β is the detection accuracy parameter that indicates the maximum probability with which the target is certainly detected by the sensing node *i*, such that $0 < \beta \leq 1$; that is, when $d = 0$, then $\beta = 1$.

• γ and k indicates the vertical and the horizontal location parameters respectively, where $\gamma > 1$ and $k > 0$. A probability distribution can be formed based on a reference location point that is can be defined by (d', P').

It means that when an object appears at d' distance away from a sensing node *i*, the probability with which the object is detected is P'. Thus, making $kd' = 1$, would result in $P' = b\,\gamma^{-1}$, which help in selecting a reference point $(d'; P')$. By determining the location parameters according to Equations (5) and (6):

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

$$k = d'^{-1} \tag{6}$$

• m is a positive parameter (m > 0) that indicates the sharp (or smooth) decrease of the detection probability, from *b* to 0, with respect to d. If it is required to designate that at specified distance di, the accuracy of the detection probability is Pi, then m should be set as follows:

$$m = \log d_{k*di} \log\gamma \left(\frac{\beta}{Pi}\right) \tag{7}$$

where di must be greater than d', and Pi must be less than P', and vice versa.

For a detection model that is based on a fixed radius, a sensing node would definitely detect any object appears within its sensing radius, such that:

$$P(i,P) = \begin{cases} 1, & d < r \\ 0, & otherwise \end{cases} \tag{8}$$

The effective detection measures (EDM) at the point p where a target is discovered (sensed) reflects the sensing intensity at that point from all the nodes in the area A where the target presences. It can be computed by combining the probability detection function of each sensing node ni that contributes with the detection of the target, as follows:

$$EMD(A,p) = \sum_1^n P(n_i,p) \tag{9}$$

where A is the area where the target is detected in the smart home, p is the point at which the target is detected by n sensing nodes, and P(ni; p)) is the probability detection of each sensing node at point p of the monitoring area.

Also, EDM of the closest sensing node (EDMmin) to the target can be computed as follows:

$$n_{min} = n_j \in P \backslash d(n_j,p) \leq d(n_i,p) \forall n_i \in P \tag{10}$$

$$EMD_{min} = P(n_{min},p) \tag{11}$$

where n min is the node that has the minimum distance to the target compared to the reset of nodes detecting the target.

In regard to target tracking, some of the required related preliminaries are presented in the following. The ability of detecting an object that is moving in the smart home from point pi(ti) to point pi+1(ti+1) along arbitrary route r(t) can be defined as follows:

$$D_0(r(t), p_i(t_i), p_{i+1}(t_{i+1})) = \int_{t_i}^{t_{i+1}} EMD(A, r(t)) \left|\frac{dr(t)}{dt}\right| dt$$
(12)

where Do is the detection of an object in the monitoring area A inside the smart home over an interval time of [ti,ti+1] along the route r(t) where the points pi(ti) and pi+1(ti+1) fall in; and *j* dr dt (t)*j* is the route length element and can be defined as in Equation 13.

$$\left|\frac{dr(t)}{dr}\right| = \sqrt{\left(\frac{dx(t)}{dt}\right)^2 + \left(\frac{dy(t)}{dt}\right)^2 + \left(\frac{dz(t)}{dt}\right)^2} \tag{13}$$

That is to say, the detection of the target is defined as the integral of the detection function of nodes on a route from pi(ti) to point pi+1(ti+1) during a period of time [ti,ti+1]. The detection function at any point p(x;y;z) for each sensing node deployed in the smart home at location (x;y;z) can be expressed as:

$$P(i(x,y,z), p(x,y,z)) = \frac{1}{d} = \frac{1}{\sqrt{(x)^2+(y)^2+(z)^2}} \tag{14}$$

where d is the distance from the sensing node i to the point p. Considering closest sensing node to the target, to define the minimum detection of the target that moves from point pi(xi;yi;zi) to point pi+1(xi+1;yi+1;zi+1), we need to find the continuous functions x(t), y(t); and z(t), such that, x(0) = xi, y(0) = yi, z(0) = zi; x(1) = xi+1, y(1) = yi+1, z(1) = zi+1; and

$$D_0 = \int_0^1 \frac{1}{\sqrt{(x)^2+(y)^2+(z)^2}} * \sqrt{\left(\frac{dx(t)}{dt}\right)^2 + \left(\frac{dy(t)}{dt}\right)^2 + \left(\frac{dz(t)}{dt}\right)^2}\, dt$$
(15)

4. OBJECT DETECTION

The detection of the object is done through two consecutive stages; monitoring and detection. The sensing nodes are always active to monitor a specific area or zone according to their sensing ranges. During the monitoring stage, the sensors sense the surroundings and record the sensing data. These data are used in the detection stage to confirm on whether there is an object in the assigned monitoring area at any given time. For every sensor at any position in the monitoring area, if object is detected; then it returns a value that identifies the detection of an emerging object; and it enables the data transmission that is event-driven. Then, it creates message (report) that would include the value and the identification of the sensor detecting the object, and send message immediately to the BS. After that, it moves to the monitoring stage and so on; while the detection process is continuously waiting for the monitoring information.

5. OBJECT TRACKING

As mentioned earlier, the tracking of the detected object is performed by the base station as it has a global view of the position of the sensing nodes. The tracking on the detected object depend on the determination of its location. Thus, there is an internal process for determining the instant location of the detected object. In the following subsection, the internal object location determination process is described along with its corresponding procedure.

5.1 Object Location Determination

In the BS, upon the receiving of the detection report (message), it would record the identification and the location coordinates of the sending node in addition to the time when the report has been arrived. Then, if the successive reports arrive at the BS, then this case confirms that the event of the object appearance is true. Thus, the BS would define the area where object has been moving. The BS then would return the sensing node identification, its location, and the time when its notification received for all sensor nodes detecting the moving object. Otherwise, the internal process of the object location determination would wait for report(s) from the detection process.
In the following subsection, the tracking process of the object as a mobile target is described along with its corresponding procedure.

5.2 Target Tracking

Once the detection of the object emergence is confirmed and the location of the object is determined, tracking process is trigerred follow the path the moving object is taken.
The BS would perform the following sequence of instructions:
• record the location coordinates of the reporting nodes with respect to the circle quarters and the radius of the sensor location
• compute the distance between the sensors detecting the moving object based on their locations.
• compute the time interval for the received reports, which reflects the change in time Δt.
• compute the path of the moving object by estimating the movement of the object during time interval $[ti;ti+1]$ along the projective line $p(t)$.
• compute the vector quantity that reflects the direction of the moving object
• compute the velocity of the object movement with respect to time, which reflects the rate of change of its location towards specific direction as a function of time. Figure 2 shows the flowchart of the procedure of the target tracking process performed by the BS after determining the location of the moving object.

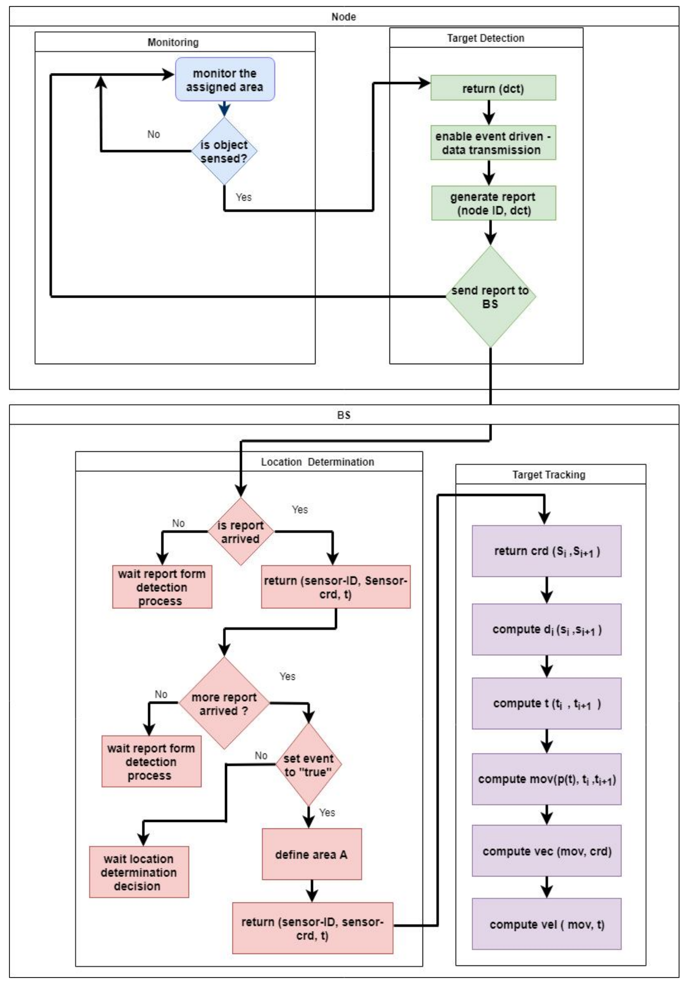

Figure 2: Flowchart of the proposed system

The simulation of this research carried out on Intel ® Core ™ i5 4200U CPU @ 1.60 GHz 2.30 GHz and 4 GB Memory on Ubuntu 16.04 Lts environment. The performance evaluation for the proposed system has been carried out using NS-2 2.35+dfsg-2 ubuntu1. The research experiments, (25-50-75) nodes are uniformly deployed on the area over a 900 m^2. To evaluates the proposed system, in this research used generated simulation data. The details are as follows. First, the density of sensors "D" is defined by:

$$D = \frac{S*\pi*R^2}{A} \tag{16}$$

where "S" is the number of sensors; "R" is the radius of the sensor detection range, R = 5 m; and "A" is the entire area of the home monitored, A = 900 m2 (30 m × 30 m). In this research assume that the entire area A should be covered with the minimum number of sensors. Thus, the research fixes the density D proximity 2, 4, 6.5 the number of sensors S that should be deployed is calculated using equation (16). The corresponding value of S is actually 25, 50, 75 as shown in Table 1. Here, "S" sensors should be uniformly deployed in the area.

Table 1: Sensors Number For 20m*20m

Density	Sensors
2	11
4	20
6.5	33

Table 2: Sensors Numbers For 30m*30m

Density	Sensors
2	25
4	50
6	75

The network is configured to run based on employ a centralized approach, in which the sensor nodes that detect the target send their data toward the base station. In this case, the base station is responsible for fusing the data received and estimating the target position. The other simulation parameters would have summarized in the table 3.

Table 3: Simulation Parameters

Parameters	Values
Area	30 m * 30 m, 20 m * 20m
Number of Nodes	50
Speed of the Targets	(25,50, 75)(11,20,33)
Number of targets	0 – 10 m/s
Antenna Type	1,2,3,4,5
Simulation Time	10 minutes
Mac Protocol	802.11
Propagation Model	TowRayground
Channel	WirelessChannel
AdhocRouting	AOVD
Queue	DropTail/PriQueue

The number of targets is changed from 1 to 5, and the targets movement data are created for each case. The human movement scenario is, the targets should enter the area from any side and move randomly. The movement of the targets decide the destination position or move randomly to the new destination by using shortest paths. The targets keep moving during the simulation time randomly with varying speeds and directions. The simulation repeated ten times and find out the average values of the simulations to add more reliability and creditability to the proposed system. In this paper will discuss the proposed system in term of tracking accuracy for single and multi-targets. The tracking accuracy of the proposed system measure according to the speed, direction, location of the target with respect to the number of detecting nodes. The figure (3) shows the tracking accuracy of proposed system for single target with different number of nodes (11, 20, 33,25,50,75) with varying speeds during simulation time. The figure 3 illustrated the tracking accuracy for single target with varying speeds and different densities for two different areas 400 m^2 and 900 m^2. The figure shows the proposed system basically afford good results and stable especially after increased the density to 4 and 6.

Figure 3: Tracking Accuracy For Single Target

The figure 4 shows the tracking accuracy of proposed system for two targets with different number of nodes (11, 20, 33,25,50,75) with varying speeds during simulation time. The figure (4) shows the tracking accuracy for two targets moving randomly with varying speeds and different densities is stable and almost similar with the two different areas (400 m^2 and 900 m^2).

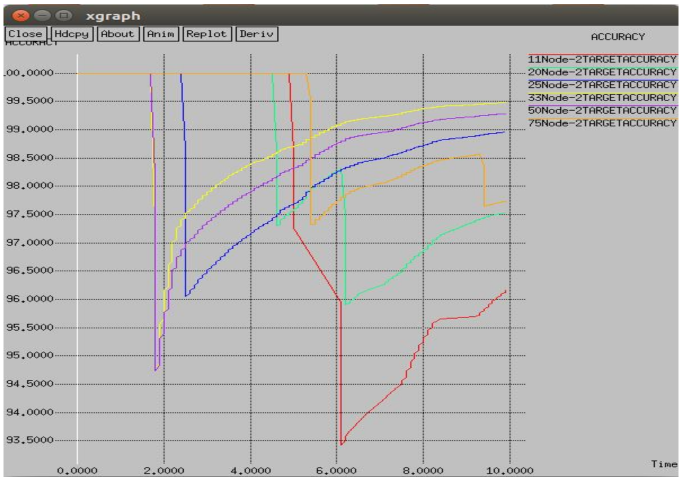

Figure 4: Tracking Accuracy For Two Targets

The figure 5 shows the tracking accuracy of proposed system for three targets with different number of nodes (11, 20, 33,25,50,75) with varying speeds during simulation time. The figure 5 shows the tracking accuracy for three targets moving randomly with varying speeds and different densities is stable and almost similar with the two different areas (400 m^2 and 900 m^2).

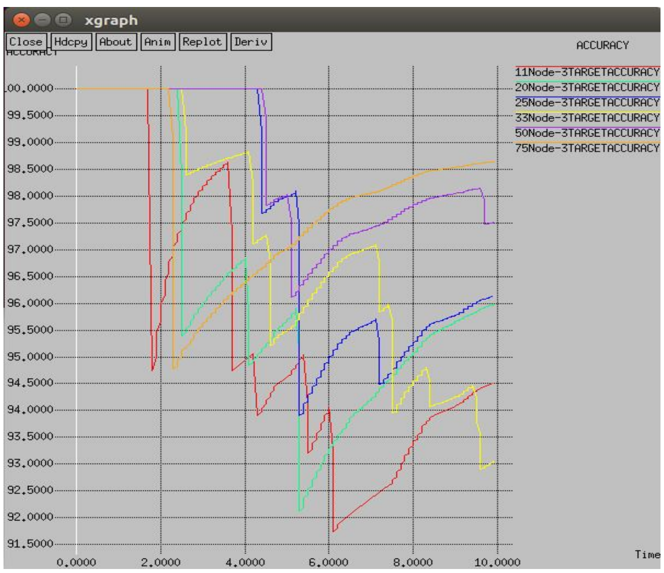

Figure 5: Tracking Accuracy For Three Targets

The figure 6 illustrated the tracking accuracy of proposed system for four targets with different number of nodes (11, 20, 33,25,50,75) with varying speeds during simulation time. The simulation results show the tracking accuracy for four targets that are moving randomly with varying speeds and different densities is stable and almost similar with the two different areas (400 m^2 and 900 m^2).

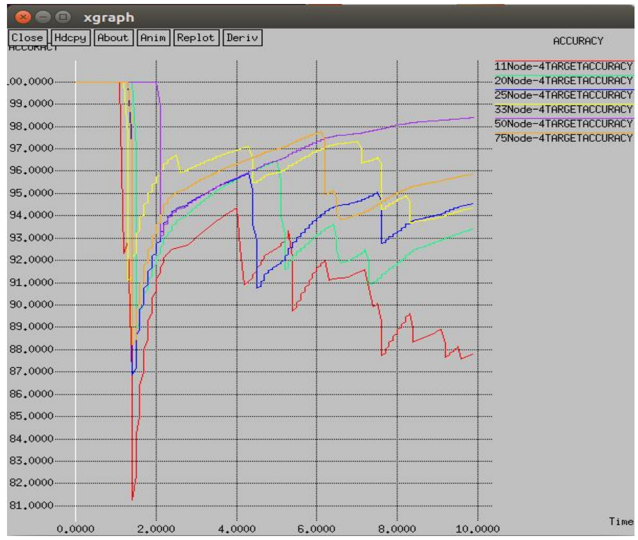

Figure 6: Tracking Accuracy For Four Targets

The figure 7 illustrated the tracking accuracy of proposed system for five targets with different number of nodes (11, 20, 33,25,50,75) with varying speeds during simulation time. The simulation results show the tracking accuracy for five targets that are moving randomly with varying speeds and different densities is stable and almost similar with the two different areas (400 m^2 and 900 m^2).

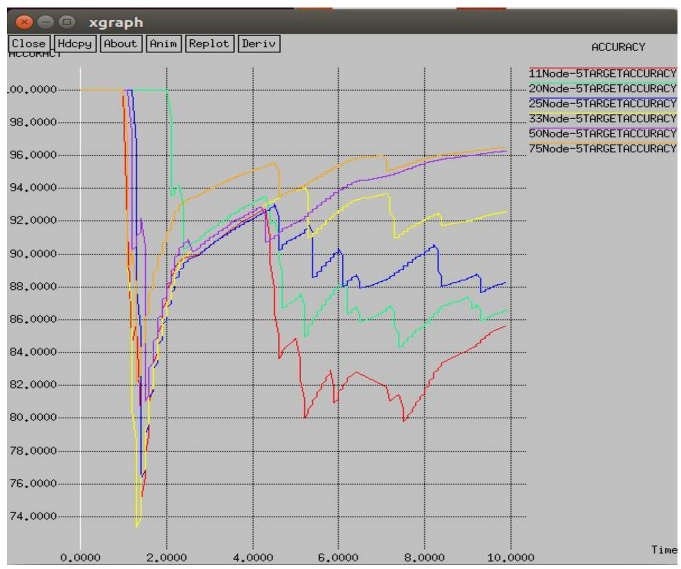

Figure 7: Tracking Accuracy For Five Targets

As mentioned before, the simulation repeated ten times for each case (number of targets) and find out the average value to consider it as a result of accuracy of the proposed system to strengthen and support the results. The table 4 shows the results of the average values comparted with multiple human tracking using binary infrared sensors (MHT).

Table 4: Results and Comparative

Density	Single Target			Two Targets			Three Targets			Four Targets			Five Targets		
	PS		MHT	PS		MHT	PS		MHT	PS		MHT	PS		MHT
	1	2	-	1	2	-	1	2	-	1	2	-	1	2	-
2	95.38	97.79	97.98	94.28	96.70	57.22	95.09	96.34	35.40	94.25	93.16	33.56	91.26	93.91	-
4	95.55	97.09	99.78	96.19	97.25	75.39	96.21	97.06	58.46	94.38	95.08	48.46	94.45	91.72	-
6	96.87	95.57	99.78	97.23	97.83	83.20	96.55	96.70	64.51	95.89	96.15	51.57	92.627	94.77	-

- PS mean Proposed System
- MHT mean multiple human tracking using binary sensors
- The density for the MHT for last density id 5
- 1 mean 400 m^2
- 2 mean 900 m^2
- Unit %

The table (3) shows the outcome results of the proposed system in two different areas are almost similar to each other that is indicate the proposed system ca apply it in different area size. Besides that, the average simulation results of the proposed system for different number of targets fixed and high even while there are multi-targets in the monitoring area. Moreover, by compared the results of our proposed system with the results of MHT in case of multi-targets (2,3,4,5) in the monitoring area. The comparison showed that the difference between our system and MHT is very large.

8. CONCLUSION AND FUTURE WORK

In this paper we have shown the modelling and development of the proposed object detection and tracking system. The function stages of the design process of the proposed system was explained and illustrated as Finite State Machine that represents the corresponding mathematical model of computation. In addition, theoretical modelling and mathematical arguments required to design the components of the proposed system have been presented thoroughly in this chapter. Moreover, it was explained how the object is detected and its location is determined, and then how it is tracked using statistical theories and mathematical methods, considering the coordinates of the detecting nodes and the time of the reports arrivals. The proposed system has been experimentally evaluated the performance by utilizing NS-2 simulator in term of tracking accuracy. The simulation results show the proposed system outcome very high in term of single and multi-targets. For future research, the proposed system can be enhanced in term of energy consumption.

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