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A New Localization Technique for Target Tracking Using Binary Sensors

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ABSTRACT

Target tracking is one of the most important and complicated applications of Wireless Sensor Networks. In this application, temporal and spatial information of mobile object is continuously investigated at particular times. Object tracking sensor networks have been studied in this paper and a target tracking protocol has been proposed under the name of not sensed Sensors Information (NSI). The proposed NSI technique tries to obtain location of the moving object using information of all sensors of a cluster including those sensors that have not sensed the object in their duty cycle. The proposed protocol minimizes the margin of error in estimating the location of the target. We believe data aggregation is the important phase of target tracking and all of the field information must be analyzed. We compared the proposed protocols with PES protocol in the sense of network lifetime, number of target misses and tracking accuracy. Simulation results how that the proposed method has prolonged the network lifetime and increased tracking accuracy. Also, NSI has decreased number of target misses significantly in comparison to PES.
KEYWORDS: Target tracking, data aggregation, not sensed sensors, localization.

1. INTRODUCTION

Sensor networks are considered as a system of many small and simple devices deployed over an area in order to sense and monitor events. The emerging technologies in low-power micro-sensors, actuators, embedded processors, and RF radios have facilitated the deployment of large scale sensor networks. Due to their low cost and capabilities for pervasive surveillance, sensor networks and their applications have tremendous potential in both commercial and military environments. Among them, target tracking has attracted considerable attention in both literature and application domains. Aiming to detect the presence of an object and determine its path in an area of interest, target tracking thus requires effective coordination among sensor nodes. However, in addition to the inherited limitations of the sensor nodes such as scarce power resources, highly distributed co-operations and unstable wireless communication, the specific requirements of applications may bring additional research challenges and issues to the design of sensor networks. One of the most important demands is to design a reasonably accurate estimation whilst minimizing the overhead of network configuration. A lot of existing researches are focused on optimizing the tracking accuracy using sophisticated and computationally heavy algorithms that are almost impractical due to sensor limitations.

The realistic binary sensor network (BSN) suffers from problems of a noisy link and low estimation precision. Thus, in this paper we propose a localization technique which improves target estimation using information of both those sensors have sensed the target as well as those which have not sensed the target referred as not sensed sensors. We must exploit all information we acquire from the field. In this contribution, in order to reduce the estimation and tracking error in object tracking sensor networks (OTSN) and minimize the computation overhead, we develop a prediction based tracking protocol which is executed on a fully decentralized cluster scheme. At every instant, only one cluster is triggered according to the prediction of the target location and its tendency. The cluster head (CH) collects information from its members and determines the target position, then predicts the target location of the next instant as well. In order to have a good estimation of target position, we develop a new technique based on vectors.

In fact these vectors are made according to topology of sensors in a cluster. Based on the reliable estimation of the target location, we can have a more accurate tracking while cutting down dramatically the number of target misses. Thus more accurate estimation of target location is achieved. The proposed architecture is also robust to the rare events of abrupt changes either in the random way point or in the random direction point target motion model.

The rest of the paper is organized as follows: Section 2 provides a background about the previous works. The proposed algorithm is introduced in Section 3 and also the assumptions for this paper as well as the system factors that are contribute to the network design is discussed in this section. In section 4, we describe the proposed method under the name of target tracking using not sensed sensors information (NSI) and discuss the achieved accuracy improvement. Section 5 provides the simulation results; and finally, Section 6 gives the concluding remarks and points out the future work.

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A. Reviewing Related Works

There are many references have focused on the problem of target tracking [1, 2, 3]. Shrivastava et al. Using binary sensors and binary sensing models result in some constraints that have been discussed in [1]. By considering the physical network structure, tree has always been one of the favorite structures for many researchers as a reliable framework for efficient object tracking [4]. In order to be energy efficient a sensor can be activated only if there is an object in its coverage region, this is a network model proposed in [5]. The idea of using prediction in OTSN to predict mobile target behaviors including its velocity, position and movement direction has been discussed in many previous works, such as [5, 6, 7, and 8]. In [6], the observed data of a sensor node is sent to its cluster head. Using received data, the CH tries to predict the object movement. When a sensor recognizes that the target is leaving its coverage area, the sensor will send the target movement information to its CH for prediction computation. Since this algorithm exploits long range transmissions, it obviously leads to much energy consumption. Authors in [10] provide a cluster based Wireless Sensor Networks (WSN) composed of a static structure of CHs. The model focuses on collision issues during the clustering phase. The protocol loses its efficiency as the target speeds up. The authors of [2] utilize a linear approximation model to find the scale of target velocity and they also have some idealistic assumptions about being error-free in their simulations. The sensing model implemented in [3] is trying to compute direction of the desired target. However, without further proximity information, parallel trajectories cannot be recognized. A mobility estimation has been proposed in [11] for ad hoc wireless mobile networks. The authors utilize a Robust Extend Kalman Filter. Considering the users' location, heading and altitude for a variant of the GSM network, the model tries to reach an estimate of the mobile users' next mobile base station. The authors in [12, 13] exploit a computing approach to estimate accelerate parameter adaptively. The proposed method uses a fuzzy target detector in order to decide about resetting the covariance matrix. Although this method is attractive from several aspects, it does not improve tracking accuracy significantly. This deficiency is due to the weakness of its maneuver detector system. Beheshtipour and Khaloozadeh [14, 15], discuss using MIE method instead of the standard Kalman filter as a solution to the problem leading to overcome the need for a separated maneuver detector system. Also a fuzzy system is used to reset the covariance matrix intelligently. However, the designed fuzzy system is not properly setup. In order to reduce tracking error, in [9], authors implement a new fuzzy self-tuning method for the MIE. Using fuzzy logic, the proposed method can effectively determine the optimal values of forgetting factor in each iteration.

2. THE PROPOSED PROTOCOL

It has been tried in NSI protocol to use all gathered field information in tracking process. Normally in localizing a target using binary sensors, location of those sensors which have sensed the target in their vicinity, are contributed in a process called data aggregation to achieve the target location. There are number of methods for the aggregation phase. But in different methods the information that can be extracted from those sensors that have not sensed the target in their sensing range are overlooked. Here we show how important this information can be, also we propose a novel technique for extracting and utilizing this information.

A. NSI protocol assumptions

The assumptions about the sensors and sensor network for developing proposed target tracking algorithm are stated below:

It has been assumed that sensors are binary and immobile. Each sensor is aware of its own location and also location of its adjacent sensors.

Sensing range of all sensors is the same and communication range is twice the sensing range. In other words, if two sensors sense the target, those sensors are sure adjacent.

B. sensing model and localization

In this protocol, sensing radius of binary sensors is equal to RS and binary sense has been derived from [16]. When a target enters sensing range of sensor, sensors can detect it. Formally:

$$S_i(T) = \begin{cases} 1, & if \quad d(S_i, T) \le R_S(i) \\ 0, & otherwise \end{cases} \tag{1}$$

$S_i(T)$ is the sensed information of sensor S_i and $d(S_i, T)$ is the distance between sensor S_i and target T. Therefore, it can be stated that:

$$S_{ix} - R_s \le T_x \le S_{ix} + R_s \tag{2}$$

$$S_{iy} - R_s \leq T_y \leq S_{iy} + R_s \tag{3}$$

As it is seen in figure (1), sensor S_i with value of S (t) = 1 could bound the target in a box.

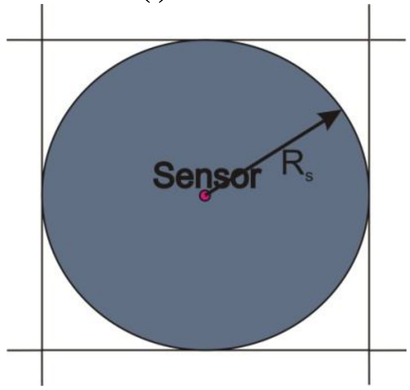

Figure 1. Bounding box around the sensor

The smaller are the dimensions of this box, the smaller will be estimation error. Now if more sensors sense the target, this bounding box becomes smaller as it is shown in figure (2). Bounding box algorithm is discussed below:

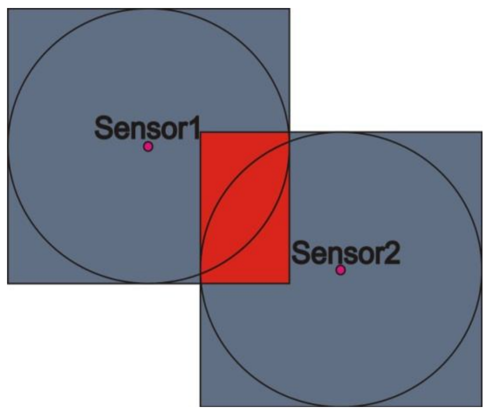

Figure 2. The more sensors detects the target, the smaller is the bounding box

When region of target was determined, the center of this box can be considered as target position estimation. However, there are various localization algorithms which try to estimate real position of the target by target sensing sensors. One common available method is using center of gravity of sensors detecting the target. Position of target can be calculated by dispersion (RSSI) method thereby, target position is calculated according to below equation:

$$\overline{X} = \frac{1}{n}\sum_{i=1}^{n} Xi \tag{4}$$

$$\overline{Y} = \frac{1}{n}\sum_{i=1}^{n} Yi \tag{5}$$

Where (Xi, Yi) and n_{sd} are coordinates and the number of sensors which detect the target, respectively. Target estimation coordinates is $[\overline{X}, \overline{Y}]$. But center of gravity method usually results in higher errors comparing to bounding box center method. In figure (3) this matter is shown. When the arrangement of sensors capable of recognizing the target is not symmetrical, one condition arises in which many sensors in one side and few sensors capable of recognizing the target locates in the other side. Thereby, averaging causes target estimation position to be more away from its real position. Therefore, as it is implied by figure (3), the use of bounding box is much better.

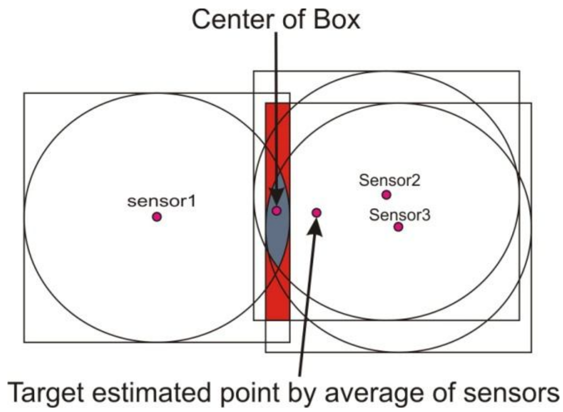

Figure 3. Bounding box VS Centroid method

There is still another problem in estimating the target position even using boxes. Considering the figure 4, we can see sensor 1 sense the target but sensor 2 doesn't sense the target. Nevertheless, using either centralizing or boxing techniques target estimated point will be centre of the box that belongs to sensor 1. To be exact the estimated target position is the location of sensor 1 which is in the sense range of sensor 2 that indeed it should not have.

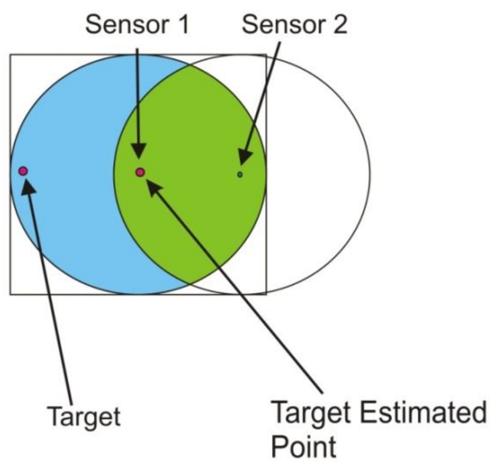

Figure 4. Estimation problem in both boxing and centralizing

One thing to be sure is the fact that target cannot be in the green area in figure 4, if sensor 2 doesn't sense the target. The very original information of sensor 2 is actually is the green area that is ignored in different localization methods including centralizing and boxing. In the follow we show how NSI exploit information of sensor 2 and other sensors which have not sensed the target but their sensing range intersect with those sensors which have sensed the target.

C. Vector Based Method

For better realization of NSI protocol the following points should be considered:

When a sensor doesn't sense the target in its active duty cycle, it means the target is not in the sense range of that sensor.

When there are some sensors that are not sensing the target but their sensing range has no intersection with sensing range of any sensor which senses the target, information of not sensing sensors in this case is useless for NSI.

Information of those sensors which were unable to sense the target but have intersection with those sensors were able to detect the target are exploited in NSI using a vector based method. The vector based method is as follow:

1. Compute a vector from the location of each not sensed sensor to the destination of the location of the sensor which has sensed the target. If multiple sensors have sensed the target then the destination of the vectors will be target estimated point. Target estimated point can be computed through either boxing or centralizing approach or localization approach. Length of the vector should be R_s i.e. sensing range of the sensor. These vectors are shown in figure 5. Vector 1 and vector 2 belong to sensor1 and sensor 2 respectively. Green area is the area that target has not been detected by sensors 1 and 2. Red area is the area that target must be there

since sensor 3 has detected the target. Normally, localization algorithms only rely on the information of sensor 3 and estimate target location as shown in figure 5. Using vectors 1 and 2, we propose an optimized location for the target that is as explained follow.

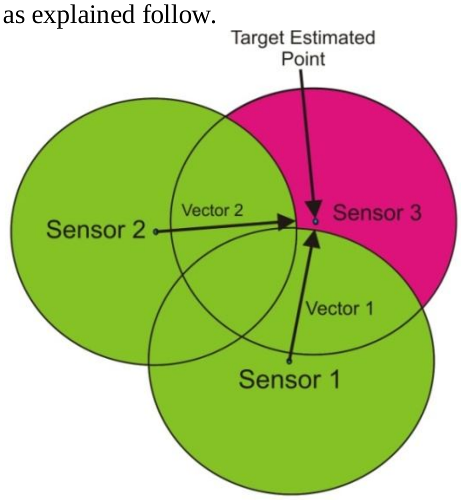

Figure 5. Vectors for sensors not sensed the target

2. Compute the resultant vector of all vectors. This vector indicates the amount and direction that we should move from target estimated point to reach to the optimized position proposed by NSI. The resultant vector is computed as follows:

$$R_x = (V1_x + V2_x)/2$$
$$R_y = (V1_y + V2_y)/2 \qquad (6)$$

R_x and R_y are the X and Y components of the resultant vector respectively. $V1_x$ is the X component of vector 1 and $V1_y$is the Y component of vector 1. For $V2_x$ and $V2_y$ everything is the same as vector 1 except they belong to vector 2.

3. Apply the resultant R on the target estimated point. The resultant vector we compute here is not the same resultant vector that is computed in physics. Actually this vector is averaged by the number of vectors contributed in the process. We should apply vector R as follow:

$$OTEP_x = TEP_x + R_x/2$$
$$OTEP_y = TEP_y + R_y/2 \qquad (7)$$

$OTEP_x$ and $OTEP_y$are the X and Y components of optimized target estimated point. Also TEP_x and TEP_y are X and Y components of target estimated point. As equation (7) indicates, resultant vector is applied with a constant of ½. We have obtained this constant through experiments on more than 100 different cases. Now that we have optimized target estimated point, we can continue the target tracking process.

General structure of this protocol is similar to PES protocol and actually it has been inspired from PES but with a different localization mechanism. In fact all prediction protocols have similar procedures. Prediction protocols initially analyze previous information and then compare them with present information and finally make a decision. NSI algorithm aims at reducing target location estimation error.

Presented protocol is simulated and then is compared with PES. The results reveal that presented protocol causes anacceptable increase in accuracy of tracking and hence a reduction in the number of target loss. Also it saves amount of energy and prolongs lifetime of wireless sensor network.

3. EVALUATING THE PROPOSED METHOD

In this section, we evaluate the proposed tracking and prediction strategies by measuring the tracking error, missing rate, network life time, consumed energy and transferred packets. All of the experiments were conducted on a

P4-2.4 GHz machine with 2 GB of main memory. The algorithms and the sensor network simulator were implemented in C#.

*A. **Experimental setup***

In order to evaluate the performance of the proposed methods, we implemented a simulator that generates the random scenarios of an OTSN.

*B. **Simulation model***

We first summarize the primary parameters used in the simulation model with the default setting. We simulate a wireless sensor network consisting of a set of sensor nodes randomly deployed in a field of 1000×500 m2. Each sensor node is able to detect the existence of nearby moving target communicate with other sensor nodes in the vicinity and do some simple computation. Sensing range RS is considered 30m and communication range RC is 60m. Sensor nodes are aware of their location. Target is moving with the maximum velocity of Vmax =10m/s and target motion model is random waypoint. We adopted the basis of energy consumption model from [16] which is as follows. Each sensor begins with an initial energy of 3 J. The transmission energy is 0.175 J and reception energy is 0.035 J, and the sensing energy is 1.75 µJ. We compared our proposed approach with PES protocol in the sense of network lifetime, tracking accuracy and number target losses during network lifetime that is first sensor battery drain out. In these comparisons, we vary the number of sensor nodes in the network from 2000 to 4000 sensors and also all scenarios have been simulated in three different cluster member numbers. In fact we changed cluster members from 4 to 8 to investigate impact of this variant on different network parameters like tracking accuracy and network lifetime.

*C. **Performance of prediction strategies***

In the following series of experiments, we take three metrics, the tracking error, missing rate, network life time. Tracking error represents the mean difference of target estimated position and target real position. Missing rate is the number of times that none of cluster members can detect the target and subsequently target losses and target retrieval procedure is invoked. Lifetime of sensor network is the time from node deployment to the time when the first node is out of function because of energy depletion. The goal of prediction strategies is to track the moving objects with low tracking error, low missing rate and low energy consumption.

*1) **Network Lifetime***

Network lifetime is one of the most important parameter in comparison of majority of WSNs applications. Actually, the idea is to increase this parameter using various methods. Figures 6,7 show the effect of increasing number of sensors and cluster members respectively on the network lifetime.

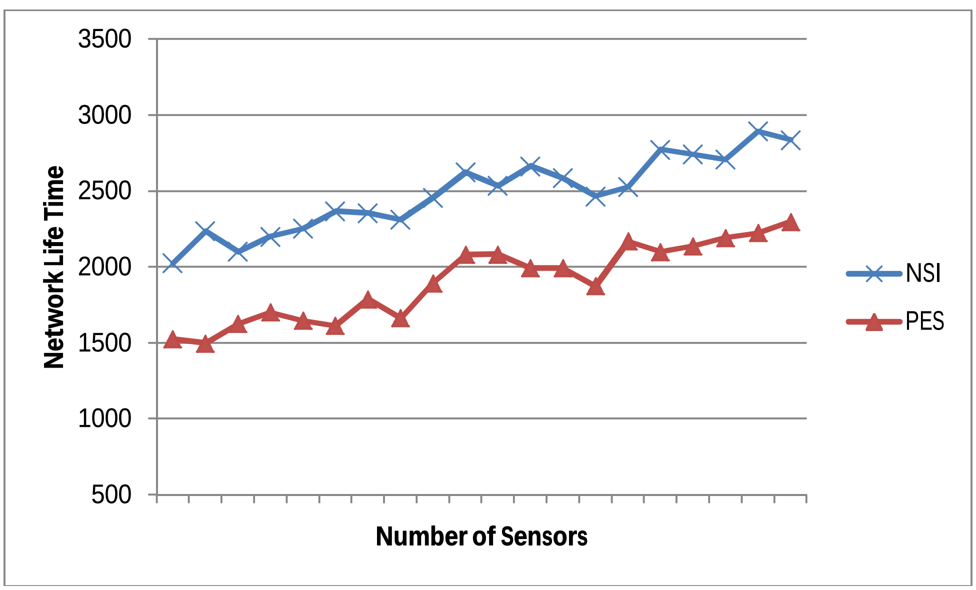

Figure 6. Effect of increasing number of sensors on network life time CM=4

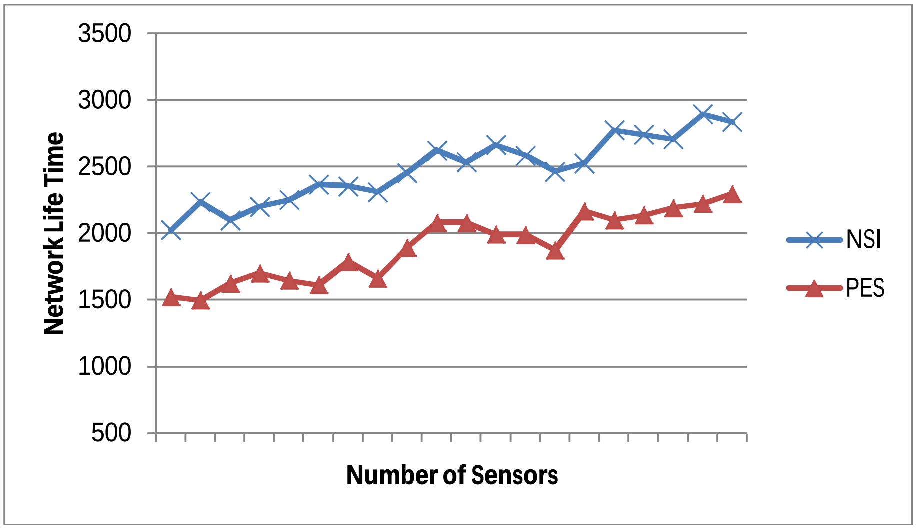

Figure 7. Effect of increasing number of sensors on network life time CM=8

Considering figure 6, it is obvious that increasing number of sensors enhances network lifetime in both methods. This can be explained by considering the fact that the more sensors in the field, the more energy and much covered area which in turn results in the less target miss. The difference between PES and NSI is a noticeable point. By increasing number of sensors PES does not grow as much as NSI approach, it is because there has been applied a more efficient localization algorithm causing fewer target misses. Therefore, figure 7 illustrates effect of cluster members on the network life time. Increasing cluster members again leads to growth of message transmission. Hence, CH battery drains mush faster and it shortens lifetime.

2) ***Tracking error***

Unlike to above parameters tracking error is target tracking specific parameter. And in particular applications like military application is highly important. By tracking error here, we mean the difference of target real and reported positions. As it can be inferred from figures8 and 9, tracking error of the NSI approach has a significant improvement comparing to PES different scenarios.

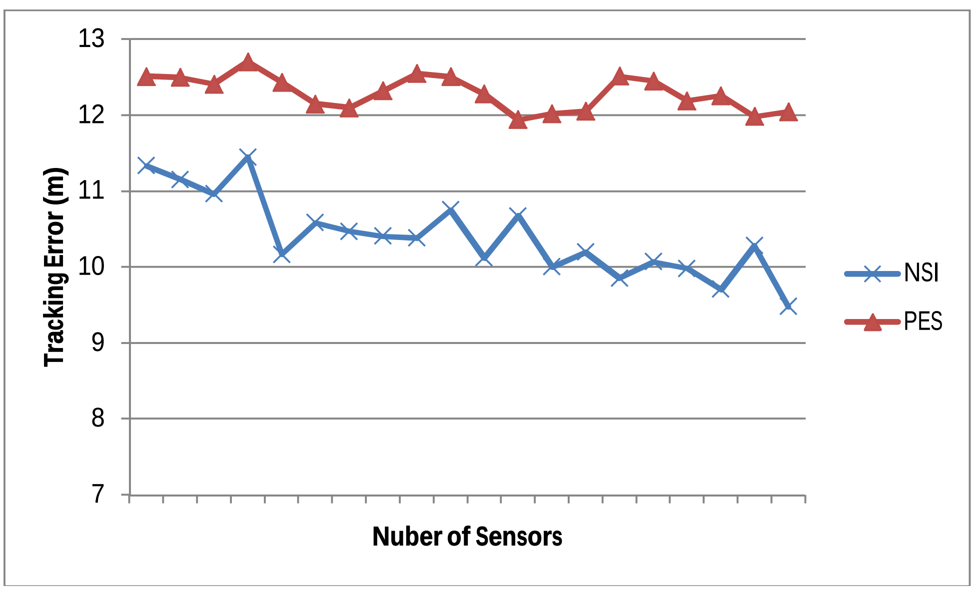

Figure 8. Effect of increasing number of sensors on tracking error CM=4

Figure 9 demonstrates an important fact that having more sensors activated and used in tracking process, reduces tracking error and increases accuracy.

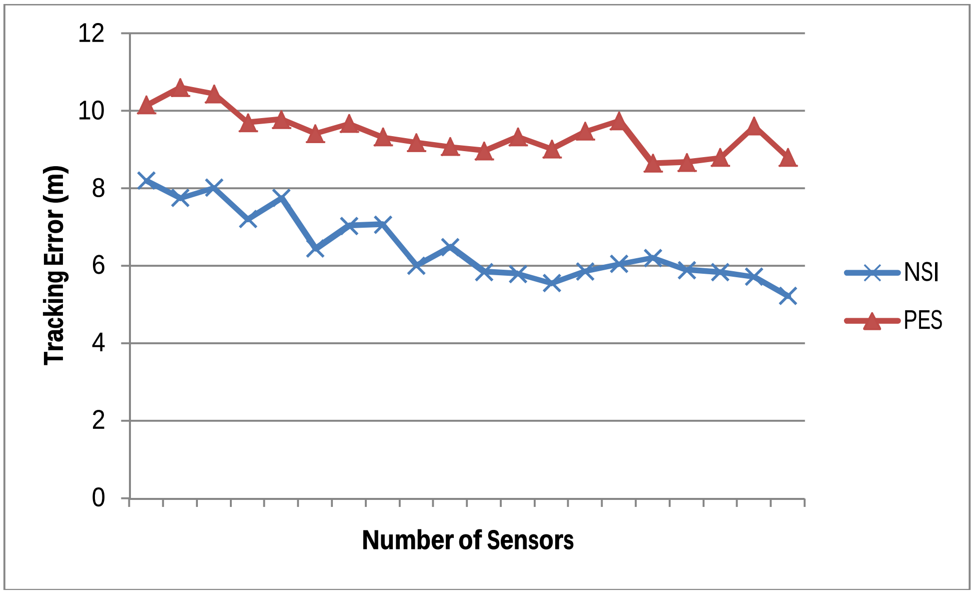

Figure 9. Effect of increasing number of sensors on tracking error CM=8

3) Target Loss

Target loss is again one of those usually tracking specific parameters and it must be kept low, particularly in surveillance and military applications. By target loss we mean a condition that nor CH, neither cluster members detect the target.

Since target change its location in each interval, then not having an accurate prediction of target next position leads to continual target loss which indeed it results in a severe growth of transmitted packets and consumed energy due to continual cluster formation. Simply saying, target loss is directly related to energy consumption. As it is obvious in Figures 10, NSIhas fewer target losses in comparison to PES.

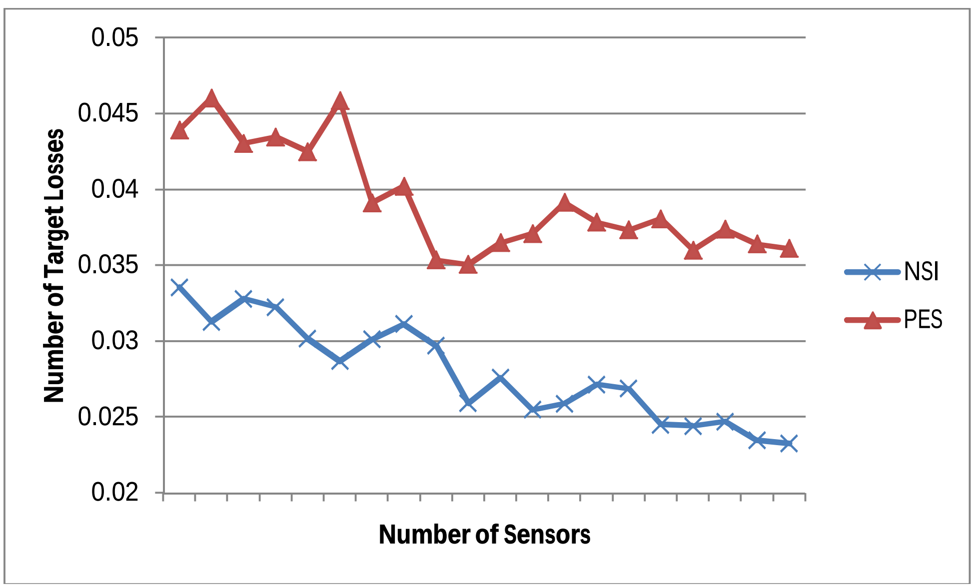

Figure 10. Effect of increasing number of sensors on target losses CM=4

By increasing number of sensors scattered in the field, on one hand, more area is under the coverage of sensor network, and tracking estimation on the other hand gets improved, since CH has more options (candidates) in the selecting of cluster members.

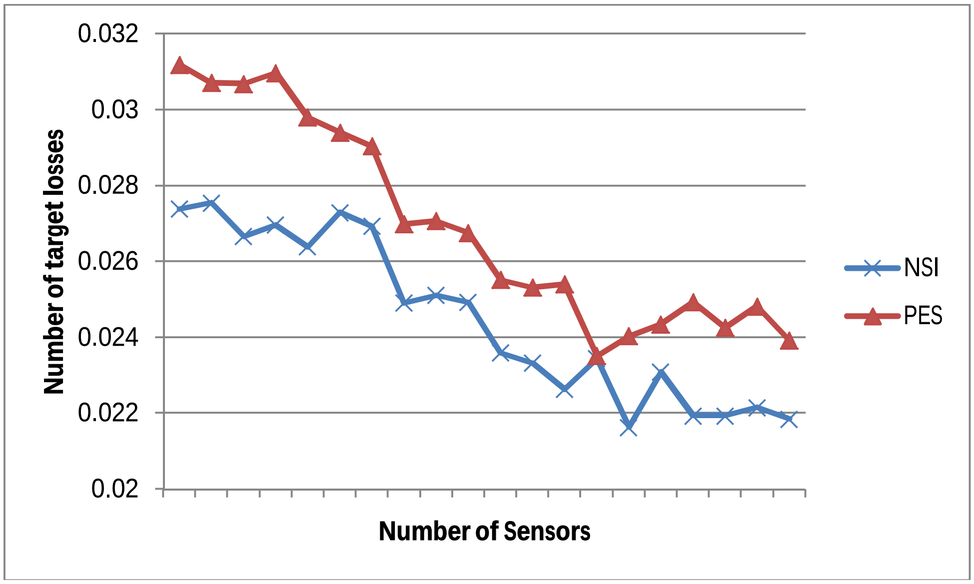

Figure 11. Effect of increasing number of sensors on target losses CM=8

It is clear that increasing number of cluster members results in reducing the target losses. The more area is covered, the less the probability of target loss. As figure 11 depicts, when number of cluster members is 8, there are less target losses comparing to the condition cluster member numbers is 4.

Also considering the fact that by increasing the covered area (increasing the number of cluster members) fades the effect of prediction. It is because even if there is an error in predicting target next position, target is not going to be lost in many cases since the adjacent areas are under cover owing to increasing number of cluster members.

4. CONCLUSION

In this paper we propose a new localization mechanism used in a target tracking protocol for WSNs. The proposed method firstly, tries to find those sensors which have not detected the target but has intersection with those sensors which have sensed the target. Using a vector based technique introduced in this paper, a resultant vector is computed. The vector then is used for exploiting the information of not sensed sensors in the process of data aggregation. The estimation of target position is then optimized by resultant vector R.Our evaluation results demonstrate the efficiency of the proposed method in terms of tracking accuracy, target losses and network lifetime.

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