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# Object Monitoring By Prediction And Localisation Of Nodes By Using Ant Colony Optimization In Sensor Networks

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**Abstract** — Wireless sensor network (WSN) consists of tiny sensor nodes with sensing, computation and wireless communication capabilities. Now days, it is finding wide applicability and increasing deployment, as it enables reliable monitoring and analysis of environment. The design of routing protocols for WSN is influenced by many challenging factors like fault tolerance, energy efficiency, scalability, latency, power consumption and network topology. Mobile Sensor Networks (MSN) is networks composed of a large number of wireless devices having sensing, processing, communication, and movement capabilities. In WSN, the coverage of the large area can be improved by the moving the sensor nodes.Coverage in a wireless sensor network can be thought of as how well the wireless sensor network is able to monitor a particular field of interest. In this paper the problem of object monitoring in Mobile Sensor Networks can be identified. The proposed system consists of estimating the position of nodes and then the estimated positions are used to predict the location of nodes. Once the object is determined, the mobile node moves to cover the particular object. If the Target cannot be defined then the set of new nodes are located and each node is assigned a position to minimize the total travelled distance. The estimation and prediction of nodes are done by Interval Theory and the Relocation of Nodes is done by using Ant Colony Optimization.ACO is the Localization of Sensor Nodes which Tracks the Targets. In this proposed paper the simulation results are compared to object monitoring methods considered for networks with static nodes.

**Index Terms** — Ant colony, Controlled mobility, Interval analysis, Interval-Based Method, Prediction, State estimation, Target tracking,

## 1 Introduction

The main constraint of sensor nodes is their limited energy resources since their batteries are non renewable. One important factor is thus to reduce the energy consumption of the sensors in order to increase the lifetime of the network. One can distinguish between two types of mobility in MSN: the uncontrolled (also called passive) mobility, where sensors are moved in an uncontrollable manner, and the controlled mobility, where sensors are moved in response to internal or external commands. MSN have a variety of applications in different fields, such as military and environment monitoring [1], [2], [3].One interesting application of MSN is target tracking. It consists of estimating instantly the position of a moving target. It is of great importance in surveillance and security especially in military applications. This problem has been mainly considered for networks having static nodes [4], [5], [6]. For instance, in [7], authors present particle filtering methods for target tracking using binary sensors, whereas in [8], a clustering algorithm using the variational filter is proposed. Different techniques have been proposed to manage the mobility of the nodes [9], [10].

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These techniques have mainly focused on upgrading the topology of the network, improving the area coverage or increasing the lifetime of the network a mobility management scheme based on the Bayesian estimation theory. In this paper, we propose a novel strategy for managing sensors mobility, aiming at improving the tracking of a single target. The method consists of four consecutive phases that iterate at each time step as follows:

1. Estimating the position of the target,
2. Predicting the next-step position of the target using Current and previous position estimates,
3. Computing a set of new locations to be taken by the mobile nodes in the way to improve the estimation process,
4. Assigning each mobile node one new location within the computed set using the algorithm (ACO)

The whole monitoring area should be covered by sensors in order to be robust to any other intruders. For this reason, we use two types of sensors: static and mobile nodes. While mobile sensors are moved to improve the quality of target tracking, static nodes are uniformly distributed in order to ensure a continuous coverage of the network independently of the movement of the mobile ones.

## 2 Estimation Of The Target Position

### 2.1 Interval-Based Estimation

A real interval, denoted [x], is a closed subset of IR given as follows

$$[x]=[x,y]=\{x \sum IR \mid x<=x<= y\},$$

where x and y are the lower and upper scalar endpoints of the interval, respectively. [x] could also be defined by its

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center and its width given by C([x])=(x+y)/2 and W([x])=(y-x) respectively.A multidimensional interval of Iran, also called box, is given by the Cartesian product of n real intervals as follows:

$$[x]=[x1] \text{ X } \ldots\ldots \text{ X } [xn],$$

An interval has a dual nature as sets and real numbers. The interval theory takes advantage of this duality to extend all arithmetic and set operations to intervals [11].For Localization and Prediction of nodes Interval-based Estimation is used.

### 2.2 Localization Algorithm

The key idea of the method consists of considering the target position as a two-dimensional box [12], [13]. In other words, the proposed method aims at computing the minimal box that includes all possible solutions of the problem. In this way, the target position is a rectangular area including the unknown location of the target and all Incertitude over its value. The algorithm used to perform the contraction is called the Waltz contractor [14], [15]. It is a forward- backward algorithm that iterates all constraints without any prior order until no contraction is possible.

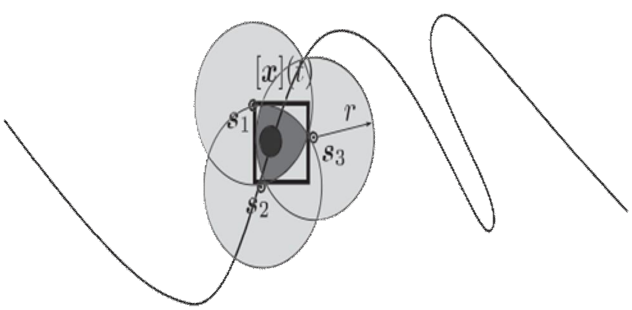
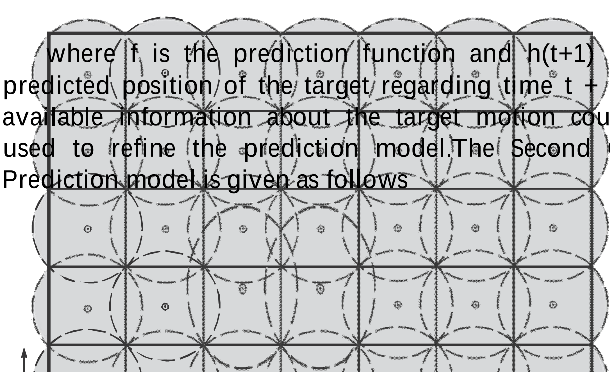



Fig.1.An Illustration of Estmation Phase

## 3 Prediction Of The Target Next-Step Position

Let x(1); . . . ; x(t) be all available estimated positions of the target. Then, a kth order prediction model is given as Follows

$$h(t+1)=f(x(t),\ldots,x(t-k)),$$



where f is the prediction function and h(t+1) is the predicted position of the target regarding time t + 1. All available information about the target motion could be used to refine the prediction model.The Second Order Prediction model is given as follows

$$h(t+1)=x(t)+\Delta t.v(t)+\Delta t^2/2.Y(t),$$

Where Δt is the time period falling between the following time-steps and v(t) is the estimate vector.

## 4 Relocation Of The Mobile Sensors

The goal of the method consists of moving the sensors in an energy-aware manner in order to better cover the area of interest.In the following, we first address the coverage problem. We then set the new locations that should be taken by the nodes. We finally introduce the positioning of the nodes using the ant colony optimization algorithm.

### 4.1 Coverage Problem

One main constraint of sensors relocation is to maintain Network coverage. Let r be the sensing range of the sensors. Then, each sensor covers an r-disk of the deployment area. Moving the nodes may yield uncovered regions, which makes the network exposed to intruders. We propose to use hybrid sensor nodes to address this problem: mobile and static nodes. While mobile nodes are moved to improve the tracking, static nodes are used to ensure continuous coverage. In order to have total coverage, the whole deployment area should be filled with the minimal number of sensing disks without leaving any uncovered region. Many algorithms, based on the disk packing theory, have been proposed for solving such problems [16]. These algorithms aim at packing equal disks, in an optimal manner, into a square area. In this paper, we propose a simple technique, using the squares inscribed in the sensing disks having √2 as side. The total number of static nodes required to cover the whole area is equal to K=K1.K2. Fig. 2 shows an illustration of the proposed distribution of the static nodes.

Note that, while only mobile nodes are used in the relocation phase, both static and mobile nodes are used in the estimation phase.

### 4.2 Definition Of Sensors New Locations

In this section, we propose a strategy to define a set of locations to be taken by the mobile nodes. The goal of this strategy is to cover an area of interest in the best way.

Fig.2.An Arrangement of Fixed Nodes

We propose thus to use all mobile nodes closer than a certain distance around the area of interest. Only close nodes are thus considered in order to limit the traveled distance and so to reduce the energy consumption. Let Km be the number of the considered mobile nodes. Then, the number of positions to be defined is equal to Km.

The proposed method is based on the triangulation principle. Consider only three nodes and a single point to be localized. The triangulation-based idea consists of constructing an equilateral triangle with the sensors. The barycenter of the triangle should fall at the point of interest. Let r be the sensing range of the sensors. Using these sensors in the estimation phase leads to the overlapping area of the sensing r-disks. Note that the overlapping region gets smaller as the triangle sides become larger.In Triangulation Principle, While the number of mobile sensors is limited, enlarging the target triangles induces a loss in the accuracy of the estimation.

As a consequence, we propose to use structures of $\Delta S$ where mobile sensors are rigidly linked. All target triangles generated by a given structure are thus fixed one to the other. This approach needs less sensors than the one above for the same number of target triangles.

An example of a structure of ten sensors is illustrated in Fig. 3. Such a structure leads to 10 target triangles which would need 30 independent sensors. Note that we show in dark gray the areas covered by at least three sensors, whereas the whole coverage zone of the structure is shown in light gray. Using triangle structures, one is able to cover every single point of the box of interest with at least three sensors.

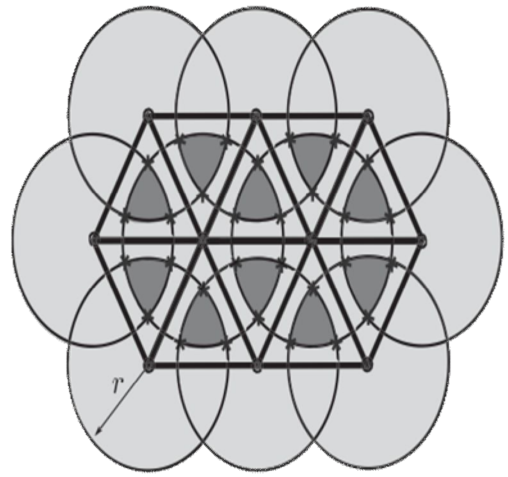



Fig.3.An Example of structure of 10 mobile sensors

### 4.3 Positioning Of Nodes Using Ant Colony Optimization

Having the set of positions that must be taken by the sensors, one should assign each sensor one position within the set while minimizing the traveled distance of the nodes. The problem is thus defined as an optimization algorithm that is solved using the ACO. In the following, we first introduce the ACO. We then apply it to the relocation problem.

#### 4.3.1 Ant Colony Optimization Algorithm

The ACO is a probabilistic method for solving complex computational problems. This algorithm was first developed to solve the Travelling Salesman Problem. It has been applied efficiently afterwards in different fields such as quadratic assignment problems [14], vehicle routing [15]. The main idea of ACO consists of imitating the behavior of real ants in their way to find the shortest path to get food sources. A path is thus generated according to two elements: a chemical substance called pheromone and the visibility of the ant which in turn determines the path to find the Target[18]. Let f(x1, . , xn) be a function of n variables whose values are taken from a specific set S. Optimizing f consists of finding the n-permutation of (x1, . . . , xn) over all possible permutations that optimizes the function f. In such problems, the function f is called objective function or fitness function, whereas x1, . . ., xn are called the decision variables. Let m be the cardinal of S, then the number of all possible n-permutations is equal to m!/(m-n)! with m! being the factorial of m. Evaluating all solutions requires too much computational time especially for large-size problems. In such cases, using optimization algorithms such as ACO becomes crucial to reduce the time of computation.

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Starting with an initial solution, ACO moves toward optimal solutions using an efficient memory-based search technique. The generation of solutions basically employs two parameters: visibility and pheromone. These parameters correspond to a priori and a posteriori information about the solutions, respectively. While visibility remains unchanged, pheromone is modified during the optimization process according to solutions evaluation. Technically, the ACO algorithm considers a fixed number of ants Ka, each of which generating one solution at every iteration. Solutions are thus encoded by assigning each decision variable, one after the other, a specific value of S.

### 4.3.2 Relocation Of The Sensor Nodes

The relocation problem consists of minimizing the total distance traveled by the nodes while moving to their new positions. The fitness function is thus equal to the sum of the distances traveled by the moving nodes, whereas the decision variables are the sensors coordinates. These variables take their values within the set of the positions. The relocation method for a given timestep t is illustrated.

## 5 Simulations

In order to evaluate the effectiveness of the proposed method, we suppose a target moving in a [0,100]x[0,100] deployment area. The sensing range of sensors is set to 10 m. The number of required static nodes is thus equal to K1.K2 where K1=K2=into$\{100/10\sqrt{2}\}=8$.A 100-steps target trajectory is illustrated in Fig.4. It shows static nodes as well. It is obvious that every single point of the area is covered by at least one static node. Note that static nodes are not required to have the same sensing range as for mobile nodes. The plot shows as well the initial positions of the mobile sensors. In the following, we first compare the proposed method to an interval-based method developed for static sensor networks. We then compare the guaranteed relocation-based approach of our method to the accuracy-based one.

We evaluate afterwards the sensitivity of the proposed method to the sensing range of the mobile sensors. We then compare the estimation technique based on intervals to a Monte-Carlo-based technique. We evaluate afterwards the second-order prediction model. We finally illustrate the effectiveness of the ant colony optimization algorithm.

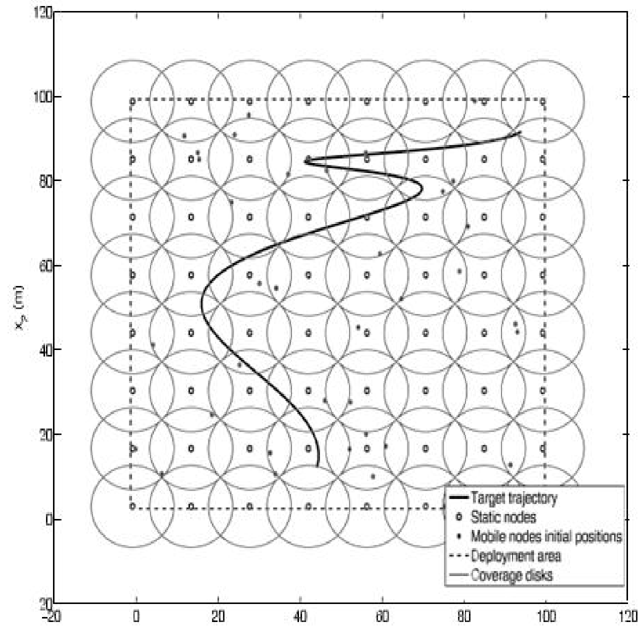


Fig.4. An illustration of the target trajectory with uniformly deployed static nodes and initial positions of mobile sensors.

### 5.1 Comparison Of An Interval-Based Method For Static Nodes To The Proposed Method

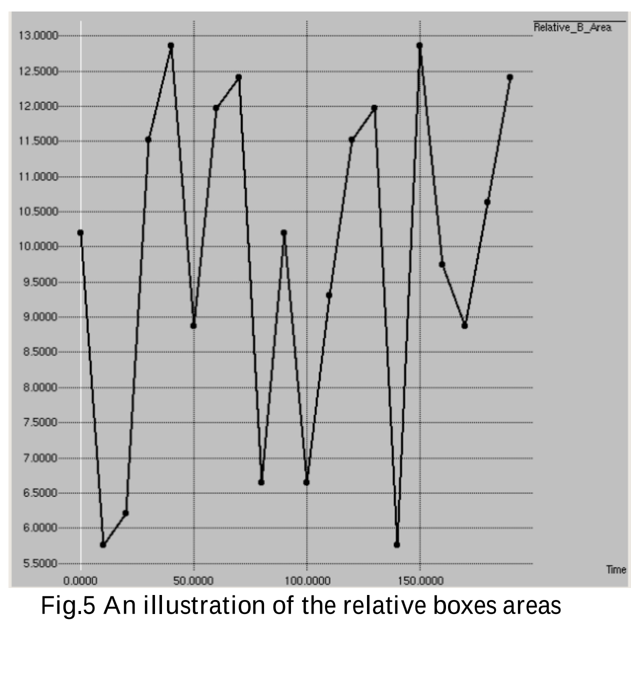


Fig.5 An illustration of the relative boxes areas

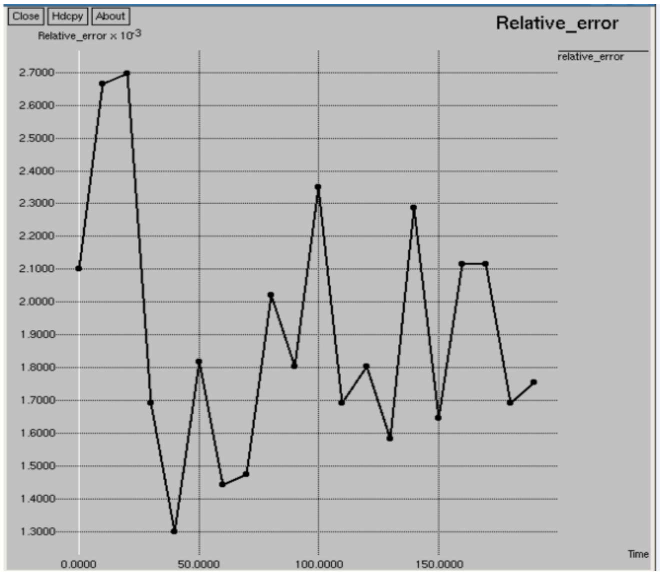


Fig.6 An illustration of the relative errors

In this section, we compare our method to a target tracking method developed for Static sensor networks. The sensors are deployed uniformly for the static method whereas for our method, the mobile nodes are initially deployed in a random manner. Hundred sensors are used for both methods.

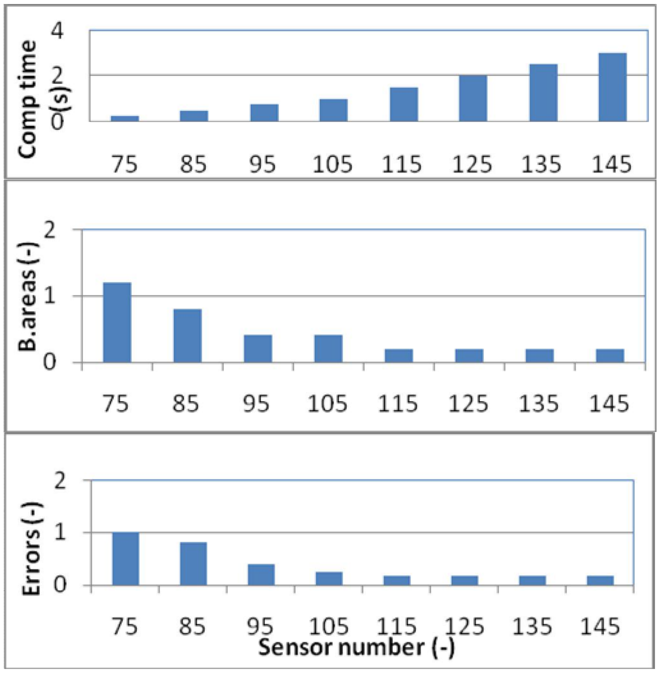


Fig. 7. An illustration of the variation of the computation time, the relative boxes areas, and the relative errors with respect to the total number of sensors.

Fig. 7 shows the variation of the computation time per time step with respect to the total number of sensors. Note that 64 of all sensors are static for our method.

Compared to the static method, the performance of our method increases with the increase of the number of mobile nodes at the cost of the computational time.

### 5.2 Comparison Of The Guarantee-Based Approach To The Accuracy-Based For Sensors Relocation

In this section, we show the impact of the distances between the sensors on the accuracy of estimation. For this reason,we consider 80 sensors, 64 of them being static.Accuracy based Controlled Mobility (ACM) and Guarantee based Controlled Mobility (GCM) is defined by the sensor nodes describing the localization[16],[17]. Figs. 6 illustrate the relocated mobile sensors The predicted and estimated boxes are also given. The plot shows that the real position falls within a target triangle covered by at least three sensors using ACM, whereas it falls within a larger target triangle with GCM. This leads to a smaller box with ACM yielding more accuracy than GCM.

In a different manner, Figs. 6 illustrate the relocated sensors corresponding to t =53tu obtained with ACM and GCM, respectively. In this example, the exact position falls outside the accurate target triangles with ACM leading to a larger estimation box.

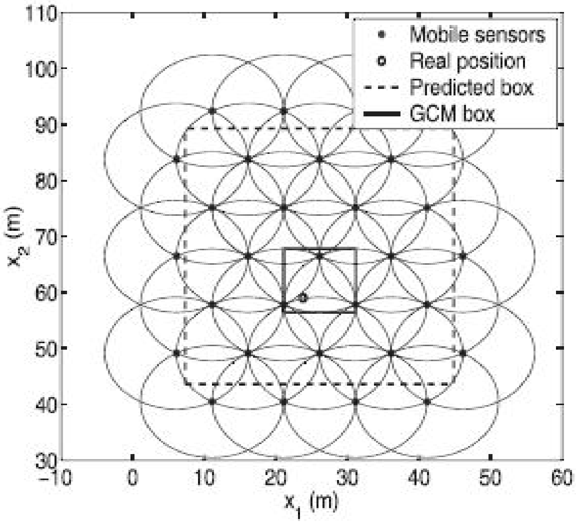


Fig. 6. An illustration of the relocated sensors obtained with Guaranteed Controlled Mobility

Note that only mobile nodes are involved in the estimation phase in this paragraph in order to illustrate in a better way the impact of sensors triangles size. Adding static sensors may lead to smaller estimation boxes than the one obtained with only mobile nodes. The average ratios of areas and errors with ACM over GCM are equal to 3.5765 and 1.5132, respectively. It is thus obvious that GCM works better than ACM for this example. In fact, with few mobile sensors, the guaranteed method with $\boldsymbol{\sigma}$s=r (GCM) covers in a better way the prediction box since with ACM, the area covered by less than three sensors is too large. Having a large number of mobile sensors, one is able to use the ACM version with larger sensor triangles. The target triangles which refines the mesh leading to more accuracy in the estimation. The method consists thus of covering the whole area with small.

### 5.3 Evaluation Of The Prediction Model

In this section, we study the sensitivity of the method to the prediction model performances. Being a second-order model, the prediction model combines three consecutive estimated positions in order to define a prediction box. Compared to the estimated boxes, the prediction box is large since it accumulates all incertitude given by the previous estimates. The proposed model assumes that the acceleration of the target is constant. When the target has abrupt changes in direction, the prediction box may not cover the real position. In order to illustrate such a case, we suppose a target moving using a random walk mobility model. The target is thus having an non predictable movement having at each time period a random velocity varying between 0 and 10 m:tu-1 and a random direction varying between 0 and 2.

### 5.4 Effectiveness of the Ant Colony Optimization

In this section, we illustrate the effectiveness of the ant colony optimization algorithm. For this reason, we compare it to the exact method where all possible permutations are evaluated. We thus consider a network composed of 64 static sensors and 10 mobile nodes. All mobile nodes are relocated at each time step. The total number of possible solutions is thus equal to 10!= 3,628,800. Having a set of 10 positions, the exact method consists of generating all 10-permutations of solutions where each mobile sensor is assigned one position of the set. It then computes the total traveled distance of the nodes. The permutation yielding the minimal movement is finally chosen. We consider a target moving over 100 time steps.

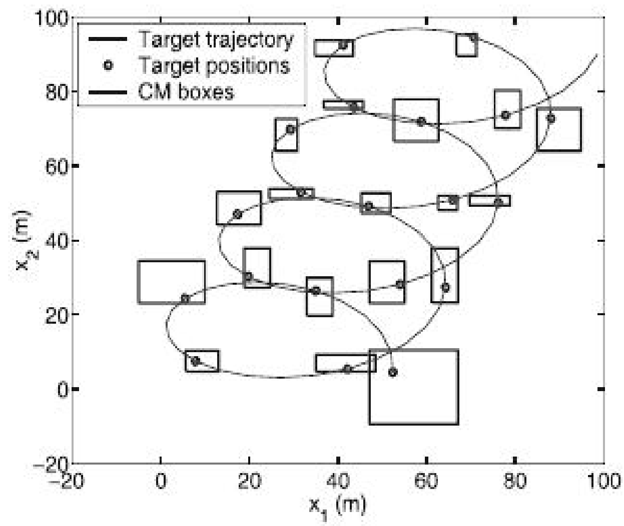


Fig. 7. An illustration of the target trajectory and the estimated boxes obtained with ACO-based Algorithm obtained with 10 relocated mobile nodes.

## 6 Conclusion

In this paper, we proposed an original method for target tracking in controlled mobility sensor networks. Having a moving target at each time step, the method consists of estimating the current position of the target and then predicting its following position using a second-order prediction model. A relocation of sensors is then performed in order to optimize the target localization for the following time step. A set of positions is thus defined using a triangulation-based method. Each sensor is then assigned one position of the set using an ant colony optimization algorithm. While the relocation phase uses a metaheuristic-based approach, estimation and prediction phases employ interval analysis where target positions are boxes including the real value. The proposed approach uses a hybrid sensor network composed of both static and mobile nodes. While mobile nodes are used for optimizing the target tracking, static nodes ensure the total coverage of the network. Simulation results illustrate the efficiency of the proposed method compared to algorithms developed for static sensor networks. Future works will handle the problem in a distributed manner where decisions are locally made. One is also able to extend the method to a multitarget tracking problem.

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