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Intelligent Target Tracking in Wireless Visual Sensor Networks

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***Abstract*— In this paper, a new target tracking method is proposed in Wireless Visual Sensor Networks (WVSN) using target movement prediction. Two important criteria in this regard are accuracy of tracking and efficient energy consumption. Because there is a direct relationship between the amount of coverage and accuracy tracking, an Evolutionary Algorithm (EA) is used as pre-processing to increase the coverage percentage. Then, a neural network-based approach using history of target movements are presented to predict the path of the target. Computer simulations showed improvement in tracking accuracy, configuration of WVSN cost and energy conservation. The important advantage of this approach is the capability of tracking in an environment, which is not covered completely.**

Keywords-Target Tracking; Wireless Sensor Networks; Intelligent algorithm; Coverage; Energy consumption.

I. Introduction

One of the most important types of Wireless Sensor Networks (WSNs) is WVSN. In these networks, each node is equipped with a camera, embedded processor, a receiver and a sender for transferring information within the network [1]. To maximize the network lifetime, decreasing energy consumption is necessary because the energy source of each node is a battery and it does not usually have access to any external resources [1-2]. As the visual sensors, the data that should be processed or sent to the sink are very large; decreasing energy consumption is very important and vital. Target tracking is one of the most important applications of WVSN. Most applications of target tracking are in security and military contexts; so, the accuracy of tracking is critical.

The targets usually move with an unknown movement model. Therefore, at first, the network must predict this movement model and then activate the minimum number of sensors based on this model. On the other hand, one of the most important factors of a good tracking is its accuracy; thus, a tradeoff should be considered between energy consumption and the accuracy of the tracking. If the target is placed in the coverage area of the network, then tracking is possible. So, the important challenge is the selection of the deployment and the number of sensors. In this paper, a neural network-based method is proposed for target tracking with optimized coverage. The coverage optimization process is done using EA.

The remainder of this paper is organized as follows. The related works are presented in Section II. The proposed method is introduced in Section III. An EA for optimizing coverage of the environment is presented in Section IV and neural network based target tracking in Section V. And finally, Sections VI and VII are dedicated to implementation, simulation of results and conclusion.

II. Related works

Target tracking using WSN has recently attracted a lot of interest in the research community due to its wide range of applications. Target tracking methods can be divided to five categories: tree-based, prediction-based, cluster-based, mobicast and hybrid [10]. On the other hand, from topological point of view, tracking algorithms can be divided to three categories of centralized algorithms, hierarchical algorithms and distributed algorithms [18].

Authors in [3-4] proposed a tree based method. When the target is entered into the environment, then the tree is dynamically configured. In [5-11], a method-based clustering is introduced. In these methods, several sensors constructed a cluster and chose one node as the cluster head. The clusters are constructed in two static and dynamic forms. Implementation of static clustering is easy but of having some disadvantages like not being robust against errors and clusters did not sharing information among themselves. Several methods based on the predictions are proposed in [6-9]. In these methods, when the target entered into the area, the information of the target is sent to the sink node. Therefore, in each time instance, the sink had the history of target movements and this information is used to predict the next location of the target. In the Mobicast methods, when a message is received by a group of nodes, these nodes adjusted themselves to predict the speed and location of the target. In recent years, to achieve more efficiency, the traditional methods have been combined with intelligent methods. For example, in [7], a Kalman filter based method is suggested for target tracking in wireless acoustic and visual sensor networks. In [9, 12], prediction based methods are presented to save more energy. In [13], the target tracking is introduced and reviewed in WSN. In [14], an ant colony based method using two types of sensors, static and mobile nodes, is proposed. In this method, mobile sensors are moved to improve the quality of target tracking and static nodes are uniformly distributed in order to ensure continuous coverage of the

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network independent from the movement of the mobile ones. In this method, to improve the accuracy of tracking, each mobile node is assigned to a new location using an ant colony algorithm. A node task allocation based on a Particle Swarm Optimization (PSO) is introduced in WSN multi-target tracking application in [15] which aimed at task allocation in multi-target tracking of wireless sensor networks. The discrete PSO based on the nearest neighbor is presented to reduce the communication energy consumption between nodes. The use of a reinforcement learning approach for a target tracking sensor network application is introduced in [16]. Random behavior and unpredictable situations of sensor nodes in such an application required a self-tuning mechanism for the nodes to adapt their behaviors over time. The method is examined under high dynamic network conditions and is compared with a similar method, called self-organizing resource allocation, over different performance measures. The weak point of this method is the predefined path for target and is advantageous like its stationary environment. In [19], an evolutionary strategy is proposed as a method based on population gradual adjustment by environmental conditions to solve the heterogeneous coverage problem in WVSN in a dynamic environment using mobile targets with minimum energy consumption.

In most of the related works which have been introduced before, there is a high abstraction level and, in most of them, a simple target movement model is proposed. In this paper, it is attempted to introduce a method with the assumption of random target movement model. To achieve more accuracy and energy conservation, an EA algorithm is used.

III. The Proposed Method

To maximize the coverage area and minimize the sensors' overlap coverage, a pre-processing procedure is done at first; then, a Multi Layer Perception Neural Network (MLPNN) is used to predict next locations of the target and k nearest sensors to the predicted locations are activated while others are deactivated.

In this paper, it is supposed that a visual sensor can return the exact location of every object in its field of view and each of the sensors knows its coordinates using Global Positioning System (GPS) or other localization methods.

The assumptions of this paper are listed below:

(1) The target is mobile and moves with a random waypoint.
(2) Each camera has the same Field Of View (FOV) and focal distance.
(3) Cameras can rotate 360° (pan capability) to cover the target.
(4) Camera nodes are randomly distributed and static in the network.
(5) Sink nodes have great processing power.

To achieve good accuracy, the target movement domain should be covered completely or a non-overlapped coverage based method must be used. The aim of this paper is to achieve the maximum coverage percentage with the minimum number of sensors.

IV. EA Coverage Method

In this paper, a pre-processing method similar to that proposed in [17] is suggested to maximize coverage area of the network. To cover an area using WVSN, the sensors are deployed randomly. Figure I shows the angle of one sensor with x-axis and FOV.

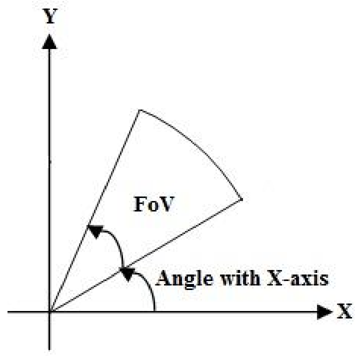

Figure I. FOV and angle with x-axis

As mentioned in previous sections, the aim of the EA algorithm is to achieve maximized coverage in WVSN. To achieve this aim, the angle of the sensors is tried to be adjusted with x-axis. So, the solution of this problem is an array of the angles of the sensors. These angles must be placed in chromosomes in some way. Figure II demonstrates the chromosome representation, in which s and α_i are the number of sensors and the angle of the i'th sensor with x-axis, respectively.

α_1	α_2								α_s

Figure II.Chromosome presentation

Fitness evaluation of each chromosome is calculated by (1):

Fitness (chromosome)=$\bigcup_{i=1}^{S} CA(Sensor_i)$(1)

where $CA(Sensor_i)$ is the coverage area of $Sensor_i$, The general problem solving procedure is as follows:

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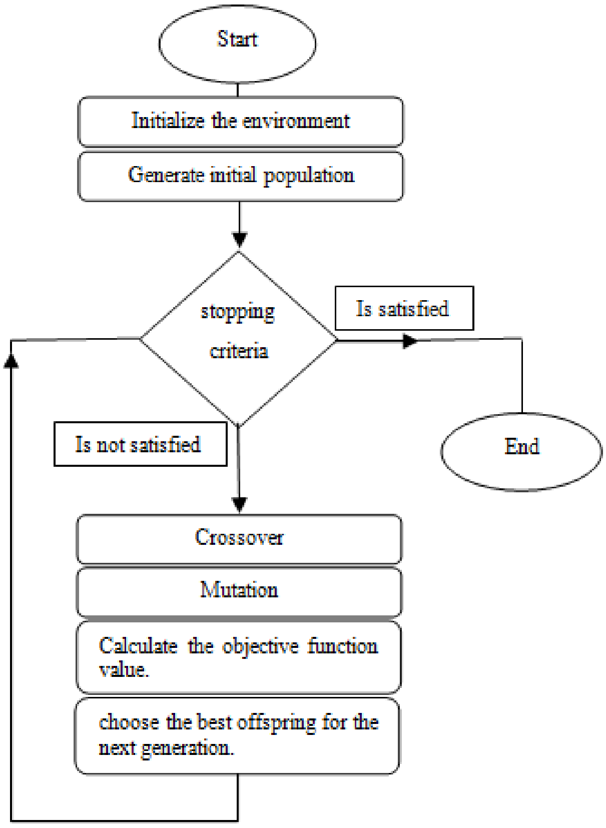

Initialization of the environment included determining the location of sensors and initializing the probability of mutation and crossover. To mutate the chromosome, two positions are chosen randomly and one unit is added to and subtracted from them, respectively. So, the overall shape of the chromosome remained valid.

Table I shows the effect of this algorithm on coverage percentage of an area with 200×200 dimension, Focal=15 and field of view=60.

Table I. Effect of EA on the improvement of coverage percentage

Number of Sensors	300	325	350	375	400
Normal Coverage	54%	56%	59%	62%	64%
Coverage after EA	56%	57%	62%	63.5%	66.3%

V. NNMLP Based Target Tracking in WSVN

As mentioned in previous sections, the path of target is a random walk. Each sensor that covers the target informed the exact location of the target to the sink nodes after T seconds. The sink had the history of target movements in *[0-T]* interval. This history is used to learn an NNMLP; therefore, the next Z movements of the target is predicted using NNMLP from *T+1* to *T+Z* seconds. Using this method, the sink knew the location of the target in (*T+Z*) th second in Tth second. So, the sink could activate the sensors near the predicted locations and deactivate others. This procedure is used repeatedly to track the target in each time. In this method, the area is supposed as a grid and the target could move to possible directions. Figure III shows a sample of target movements where *T* indicates the target and *1,2,3,4,5,6,7,8* show the number of each valid move. The stream of these numbers indicated a pattern of target movement. For example, this pattern is *[2-4-4-4-3-3]* and is related to Figure III.

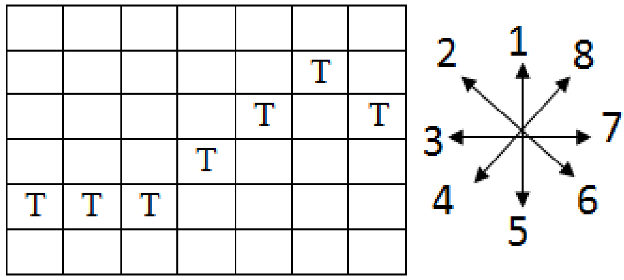

Figure III. An example of target movements

At each time, the history of target movements is divided to some patterns as learning data; each pattern is considered as [P,T] where P and T are input and desired output of NNMLP, respectively. For example, if the history of target movement in the [0-S] time interval is $[Mov_1, Mov_2, Mov_3, Mov_4, Mov_5, \ldots, Mov_L, Mov_{L+1}, Mov_{L+2}, Mov_{L+3}, \ldots, Mov_S]$, the extraction learning patterns would be as follows:

Pattern1: $(P=[Mov_1, Mov_2, Mov_3, Mov_4, Mov_5, \ldots, Mov_L], T= Mov_{L+1})$
Pattern2: $(P=Mov_2, Mov_3, Mov_4, Mov_5, \ldots, Mov_L, Mov_{L+1}], T= Mov_{L+2})$
……….. ……………………………………………….
$Pattern_{S-L}$: $(P=Mov_{S-L}, Mov_{S-L+1}, Mov_{S-L+2}, Mov_{S-L+3}, \ldots, Mov_{S-2}, Mov_{S-1}], T= Mov_S)$

After the NNMLP is learned, L recent movements in sth second is given to NNMLP to predict the movement in (S+ 1) th moment.
Therefore, this procedure is used as long as the target is in the environment. The pseudo code of the current algorithm is presented in Algorithm 1.

Algorithm 1:Prediction-based target Tracking using MLP

0: begin
1: **Let** *S* denote the visual sensor nodes and T the target.
2: **Let** S_w and S_s denote the awaking and sleeping visual sensor nodes.
3: Let S_c denote awaking sensors in which the Target is in their coverage //$S_c \subseteq S_w$.
4: Initialize the WVSN.
  Adjust the problem parameters including the parameters of evolutionary algorithm and neural network.
5: EA coverage(S) .
6: While T is not in the coverage area of WVSN:

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1: S_w={Borders Sensors} ,S_s=S– { Borders Sensors }

End while.

7: Report the location of Target by S_c.

8: S_w={S_c},S_s=S – { S_c}

9: For LT seconds, do //LT determined by the user and indicate the learning Time.

1: S_w={K nearest neighbor sensors of S_c}

2: S_s=S – { S_W }

3: Update(Sc)

4: S_c report the exact location of the target to the sink.

End for.

10: Sink produce the learning patterns using the movement history reported by S_c.

11: Learn MLP.

12: NM=Next movement that is predicated using MLP .

13: S_w={S_c},S_s=S – { S_c}, K=K/2 // the size of awaken sensors can be reduced at each time because , in this step, the location of target is known.

14: While T is in the coverage area of WVSN, do:

1: S_w={K nearest sensors to NM }

2: S_s=S – { K nearest sensors to NM }

3: Update(S_c)

4: If the NM is wrong, it should be correct using S_c information.

5: S_c reports the exact location of target to the sink and sink adds this new pattern to others.

6: Learn MLP.

7:NM=Next movement that is predicted using MLP.

End while.

15:End.

VI. Implementation and Experiment of Results

To evaluate the present solution, it is simulated using MATLAB programming language and its experimental results are presented. This method is executed in different conditions. All the results shown in this section are the mean of five different executions. Simulation parameters are depicted in Table II.

TABLE II. The simulation parameters

Network Area	200m*200m
Focal Distance	15
Field of View	90
Object Speed	5m/s
Number of Visual Sensor Nodes	300,350,400,450,500
Learning Times (LT in Algoritm1)	4 seconds
Number of active sensors per time unit	20 sensors

To show the accuracy of this algorithm, two criteria of tracking accuracy and Mean Square Error (MSE) are used between main and the estimated path of the target. Table III shows these criteria and the effect of efficient coverage as efficient tracking.

TABLE III. The result of Algorithm 1 tracking in 45 seconds, speed=5meter/second

Number of Sensors	Tracking Accuracy	MSE	Efficient Tracking Accuracy
300	0.72%	2.05	0.75%
350	0.79%	1.39	0.87%
400	%.80%	2.35	0.87%
450	0.81%	1.47	0.86%

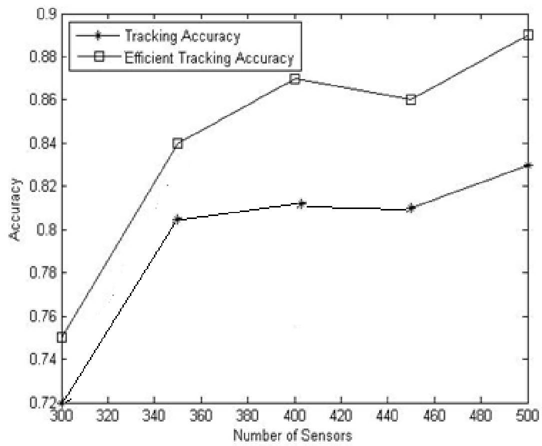

Figure IV Accuracy

The improvement accuracy after increasing the coverage using EA is shown in Figure IV.

Figure V demonstrates a sample of path and its estimation using Algorithm 1. The average of the activated sensor per time unit (second) is 10.88, which indicated the improvement in energy conservation.

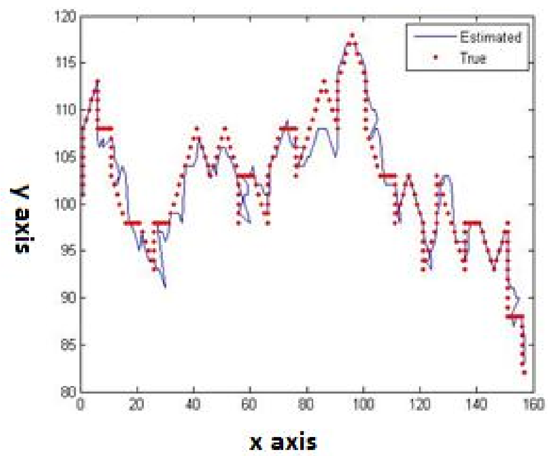

Figure V. Example of the estimated path

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VII. Conclusions

In this paper, a new method is proposed using NNMLP and EA as a pre-processing procedure. The capability of tracking in the areas that did not have complete coverage is the important advantage of the proposed method. However, this led to the low accuracy of tracking. The reason for this advantage is the learning and generalization power of NNMLP. In other word, the target movement model that is learned by NNMLP is used for tracking in the environment that is not covered completely. With respect to the coverage ratio of the target region, this algorithm could save the number of sensors and prolong the efficiency of network lifetime.

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