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A Human Abnormal Behavior Recognition and Collaborative Tracking Algorithm

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Abstract

In this paper we focus on the problem of human abnormal behavior recognition and collaborative tracking algorithm based on Wireless Sensor Networks (WSN), and presents a novel solution that combined single intelligent monitor with the advantage of optimized WSN to improve the tracking accuracy and energy consumption. At first, divide the monitors in WSN into two types: Behavior Recognition Monitor (BRM) and Collaborative Tracking Monitor (CTM), and settle all the monitors utilizing ROCK clustering algorithm into many groups. Then get best answer set though PSO algorithm and BRM in it recognize the behaviors of moving targets as to locate the abnormal one. Finally, CTM track the target collaboratively until it leaves the guard area. Each monitor in the system consists of three parts: camera sensor, intelligent module and wireless communication module. In addition, an energy consumption model is proposed for measuring the quality of the algorithm. We compare our algorithm with three existing solutions. The experiment results show that our solution has a better collaborative tracking accuracy and less energy consumption.

Keywords: *Collaborative Tracking; Behavior Recognition; Wireless Sensor Networks; PSO; Energy Consumption*

1. Introduction

With the development of wireless technology and multimedia technology, Wireless Sensor Networks (WSN) pays more and more attention for researchers in recent years, especially for surveillance. Moving target tracking is an important application of wireless sensor networks, although wireless monitors have the advantages of low cost and settle easily, the communication and compute ability is limited. So how to improve the detection accuracy, the tracking efficiency and reduce the energy consumption are the measurements of collaborative tracking performance [3].

Researchers proposed different solutions for various application scenes aim at collaborative tracking issue in recent years. The solutions can be divided into two types: sensor related solutions and communication related solutions [12]. WANG Xinbo [1] proposed a collaborative tracking solution that combined maximum likelihood estimation with kalman filtering. Diluka Moratuwage [2] put forward a method of collaborative tracking based on the multi movement tool that using random finite set to express map features. ZHU Guibo [4] combined short time tracker with long time target detector and proposed a dynamic collaborative tracking solution that is good for frame losing, mutation and long time interference problems. LIU Qin [5] utilized binary particle swarm optimization algorithm for tracking multi hiding targets in radar networks. X. Xing[7] depended on three status transport module and put forward a moving target tracking method based on drove, experiment results shown that the solution play a good performance in detection, awakening mechanism and logical networks architecture. The

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existing solutions have merit and demerit considering detection tracking accuracy and energy consumption roundly. Just like the solution that is proposed by WANG Xinbo get outstanding detection accuracy but poor performance in tracking precision. Diluka Moratuwage's algorithm can obtain better detection and tracking accuracy except high energy consumption.

In this paper, we divide monitors in function and utilize PSO algorithm to create groups for collaborative tracking, the behavior recognition monitor is obliged to judge the behaviors of moving target and wake up the corresponding collaborative tracking monitor using prediction and awakening mechanism aim at abnormal moving targets. The experiment results shown that the algorithm we proposed have better detection and tracking accuracy, less energy consumption than the solutions we mentioned.

The reminder of this paper is organized as follows: system constitutive and problem formulation is reviewed in Section 2 and in Section 3 we describe our solution process. We discuss the experiments and results in Section 4. Finally, the paper concludes with Section 5.

2. System Constitutive and Problem Formulation

2.1. The Deployment of Wireless Sensor Networks

WSN (wireless sensor networks) is wireless network that some collection messages are added to, such as videos, audios, images. In this paper, we refer to two kinds of monitor nodes: Behavior Recognition Monitor (BRM) that is expressed as circle in Figure 1 is used to recognize behaviors of moving targets and manage messages, Collaborative Tracking Monitor (CTM) that is expressed as triangle in Figure 1 is responsible to collaborative tracking aim at the targets that BRM locked. The hardware of each monitor node is composed of three parts: video collection module, intelligent message processing module and wireless communication module.

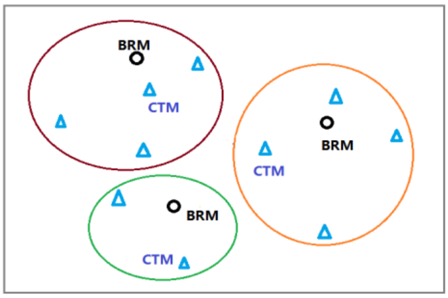


Figure 1. The Sketch Map of Groups' Partition

The PSO (Particle Swarm Optimization) is one of an evolutionary algorithms that growing up in recent years. It begins with random solution and works out the optimal solution through iteration process, search for the global optimal solution by following with the local solution it has got [6].

We presume the WSN consists of S BRM and D CTM, the aim of our work is to make WSN cover the whole area and save energy. First of all, we use ROCK cluster algorithm to make monitors become N groups, each group have at least one BRM and CTM. According to PSO algorithm, the answer $X_i[d]$, $i \in [1, N]$, $d \in [1, M]$,d is the dimension of the answer, it indicates that the answer could be a answer set. We define a speed vector V_i for each answer, the speed vector is equal to ΔX_i and the same as answer set in first generation, which is generated in the beginning. We assume the amount of dynamic monitors in a group as S_n, the status of the granule i in k generation could be show as:

$$X_i(k) = \left[x_{i.1}(k), y_{i.1}(k), \ldots, x_{i.s_N}(k), y_{i.s_N}(k) \right] \quad (1)$$

$$V_i(k) = \left[v_{i.x_1}(k), v_{i.y_1}(k), \ldots, v_{i.x_{s_N}}(k), v_{i.y_{s_N}}(k) \right] \quad (2)$$

In the formula, i=1, 2, …, Lj, Lj is the amount of grains; k=1,2， …， H, H is iteration degrees. As for the k generation of the whole evolution process, the answer vector in next generation could be getting from each answer vector as follow equation:

$$X_i(k+1) = X_i(k) + V_i(k) \quad (3)$$

We can definite pbest (personal best) and gbest（global best）[11] that represent the best value of answer set in k-1 and k generation as $X_{pbest,\ i}$ and $X_{gbest,\ i}$. The D-value $X_{pbest,\ i} - X_i$ and $X_{gbest,\ i} - X_i$ present the distance between answer vector of each generation with the best location and the distance of location related the best answer in every generation. The change of iteration formula can be obtained according to (2) and (3) as:

$$V_i(k+1) = \omega V_i(k) + C_1 \times \eta(X_{pbest,\ i} - X_i) + C_2 \times \eta(X_{gbest,\ i} - X_i) \quad (4)$$

So the update location equation of grains can be obtained:

$$X_i(k+1) = X_i(k) + V_i(k+1) \quad (5)$$

In the formula above, c_1 and c_2 are Hooke constant, η is random value in the area between 0 and 1, the value of ω depends on the speed of convergence and amount of panel points.

2.2. Recognition of Anomalous Targets

In order to save energy consumption and improve tracking efficiency, BRM and CTM divide the task. BRM is responsible for recognizing the behaviors of moving targets in some important place. We can set some legitimate behavior according to the need in fact, for example, we define walking and slow running as the normal behaviors, so other actions are anomalous behaviors. CTM in the same group only need to track the suspicious target related.

Our solution recognize behavior of motion target utilize the method couple template matching with feature points tracking [9]. Each monitor in the WSN share the same behavior library which some behavior template would be defined, such as walking, running, jumping, *etc*. Surveillance system can definite some regular behaviors in the beginning, so other behaviors are suspicious. For example, the jumping behavior could be shown as the behavior template below:

Figure 2. The Jumping Behavior Template

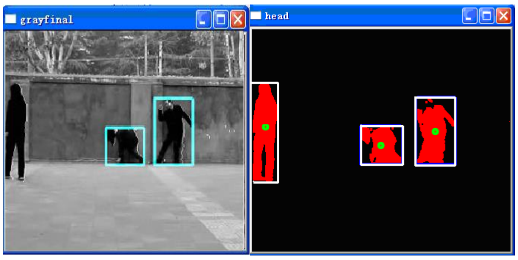
The similarity of the two images could be defined according to PMSD (Procrustes Mean Shape distance). The type of behavior would be conjecture through minimum standard variance algorithm aim at behavior sequence. The standard variance is used to describe the data that behalf the degree of deviation from average data, standard variance increase with the degree of deviation and vice versa. The similarity distance matrix between standard behavior sequences with the real-time video could be present with [8]:

$$S_j^k = \min_{i=1,2\cdots 8} (d_{(j)}^{(i)}(\hat{u}_1, \hat{u}_2)) \tag{6}$$

As for each video segment, the minimum standard variance of horizontal vector of the matrix can be show as:

$$\sigma_j = \sqrt{\frac{\sum_{k=1}^{N} (S_j - \overline{S}_j)^2}{N}} \tag{7}$$

We can get the related variable j from the $\min(\sigma_j)$, the variable j is the index that direct to the current behavior. So BRM could judge whether or not the current motion targets should be collaborative tracking. If we define walking is the normal behavior, the figure below shows the detection result that the middle and the right people should be collaborative tracked:



(a) BRM detection results (b) Motion targets extraction

Figure 3. The Result of Motion Targets Detection

In this solution CTM only need to collaborative the suspicious motion targets, so it decrease the burden of system enormously and avoid a large calculation for paralleling tracking and behavior recognition.

2.3. Prediction and Activation Mechanism

For further save energy consumption and take full advantage of the result utilizing PSO algorithm, we propose the prediction and activation mechanism in the system. BRM is the leader of dynamic subnet, so it always active, but CTM is on the default sleeping mode. CTM would be activated when the target need to be collaborative tracking according to the trajectory.

The method to predict trajectory of moving target and activate corresponding CTM is a dynamic process as the monitor subnets are dynamic clustered. BRM take charge of transmission the order ACTIVE to CTM expect recognize the behaviors of targets, so it should maintain a latest subnet member list and boundary messages for the subnet in the all directions. When a suspicious target move in a monitor subnet, the BRM would predict the trajectory of the target and send order ACTIVE to CTMs related. If the target moves to the boundary of the subnet, BRM will send COWORK order to the BRMs nearby that would active CTMs in the same subnet to relay tracking the target. The COWORK message includes the current subnet number and features of the moving target such as moving speed. When the tracking task completed or the target does not exist in the scope of CTM for a long time, it will change to sleep mode automatically for saving energy.

2.4. The Energy Consumption Module

The energy consumption for each monitor node consists of three parts: video sensor module, wireless communication module and intelligent computing module. The energy consumption for wireless communication is the key point that we considered, and it would be affected by the communication distance, the data amount and the work mode of each monitor node.

Suppose there are M BRM monitor nodes as $H_1, H_2, \ldots, H_m, \ldots, H_M$ [10], and the activated CTM can be described as $s_1^m, s_2^m, \ldots, s_n^m, \ldots, s_N^m$. For random H_m, the distance between BRM and the active node is d_{mn}. a_{mn} is the status factor, when $a_{mn} = 1$, the H_m select s_n^m as its subnet member and activate it, it would be contrary if $a_{mn} = 0$. We can set the energy consumption for wireless communication module send r bit data to the distance as d_{mn} is:

$$E_s = \sum_{m=1}^{M} \sum_{n=1}^{N} r \left[e_s + \eta_\alpha \left(a_{mn} d_{mn} \right)^2 \right] \tag{8}$$

In the formula above, e_s is the energy consumption for send circuit, and η_α is the energy consumption for power amplifier. The energy consumption for monitor node to receive r bit data could be calculated by this equation:

$$E_r = re_r \tag{9}$$

e_r is the energy consumption for receiving circuit. As a matter of experience, we can set $e_s = e_r$ =60 nJ/bit. The energy consumption for wireless communication affiliated with work mode and communication distance greatly. So dividing monitor nodes into several classes using dynamic fuzzy clustering algorithm and most message data delivered in the internal subnet that we mentioned in formal section, it can greatly shorten the distance for data communication. In addition, the prediction and activation mechanism can also benefit for energy consumption.

3. Methodology

The main step of the solution for motion recognition and collaborative tracking can be summarized as follow:

Step 1: Deploy the BRMs and CTMs according to ROCK cluster algorithm and make monitors become N groups, each group have at least one BRM and CTM;

Step 2: When a moving target exist in the guard area, the best answer group can be obtained though PSO algorithm and the group share a list that includes the serial number and locations of CTMs in the same clustering group, the serial number and location of BRMs nearby and boundary information of the group;

Step 3: BRMs detect the moving targets and recognize its behaviors real time. If the behavior is abnormal, the BRM would activate the CTMs related to tracking the target. The activation area would be enlarged if the selected CTM is busy;

Step 4: The CTM in a group boundary would activate the CTM border upon when the target move from the clustering group to another one and send message to the current BRM for plan as a whole;

Step 5: When the moving target leave the current guard group, the BRM in the group can judge and send DORMANCY order to the disengaged CTMs.

When a moving target arrived at the boundary CTM of the whole surveillance area, the BRM judge whether the target leave the whole guard area according to the moving direction. If it leaves, the BRM send message to the system management and terminate the collaborative tracking task.

4. Experimental Results

For demonstrating the veracity and efficiency of the solution, we design experiment in MATLAB simulation environment. Suppose 10 BRM for behavior recognition and 60 CTM for collaborative tracking random distribution in the region of interest, which is a 200m*100m with the coordinate from (0, 0) to (200, 100).

Consider a moving target uniform move from point A to B on the speed $v = 1.2m/s$ depicted in Figure 4. The energy consumption for receiving circuit and emission circuit in each monitor could be valued as $e_s = e_r$ =60 nJ/bit. The simulation lasted for 100 time steps and the trajectory of moving target is just like the curve in Figure 4 below.

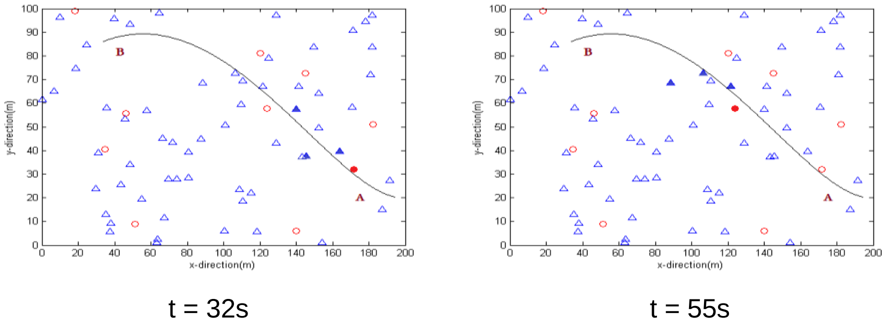


Figure 4. Moving target collaborative tracking by WSN

The result of PSO algorithm can be shown in Figure 4 using the solution we proposed. We cut out the performance in the two time points. When the moving target accesses the guard area from point A, it will be detected by the BRM in lower right corner and ascertained as collaborative target. The CTMs described with solid triangles would be activated by the BRM according to the result of PSO algorithm and relay track the target until it leaves the current subnet. A new period PSO calculation would process for the guard need and there are some monitors nearby moving target are busy. When the moving target leaves the region of interest from point B, simulation experiment is completed.

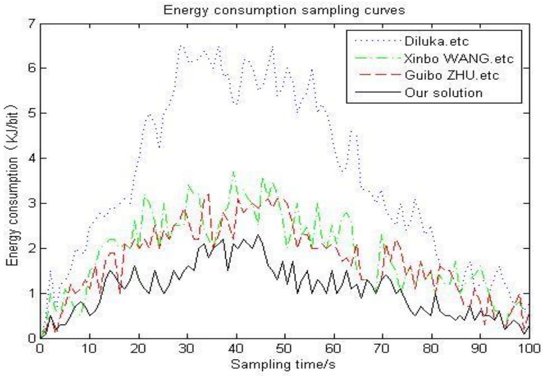


Figure 5. The Energy Consumption Sampling Curves using Different Methods

For testing the performance of energy consumption, we compare it with other three similarity algorithms in the same simulation environment. The sampling time is 100s and the energy consumption sampling period $T = 1s$, the energy consumption sampling curve using the four different methods can be shown as Figure 5.

We can see from Figure 5 the energy consumption is largest using the algorithm proposed by Diluka.ect, and using our solution can get the better result than other three solutions. At the same time, we make comparison from moving targets detection accuracy, tracking accuracy and energy wastage. The statistic data can be shown in table 1 below.

Table 1. The Result of Statistics Analysis for Different Algorithms

Solutions	Detection accuracy	Tracking accuracy	Energy wastage/J
Xinbo WANG [1]	84.6%	79.1%	0.631e8
Diluka Moratuwage [2]	78.5%	81.4%	2.135 e8
Guibo ZHU[4]	79.3%	83.5%	0.612 e8
Our solution	85.7%	86.9%	0.574 e8

From the data of Table 1, Xinbo WANG's algorithm can get better detection accuracy but the tracking accuracy needs to be improved. An ideal tracking accuracy would be made by Diluka's solution except the large energy wastage. Guibo ZHU combined the dynamically fusing short-term trackers with long-term detector to get a better performance in the all directions. But comprehensive consider the three factors we can draw a conclusion that our solution has a better performance than the similar solutions we mentioned.

5. Conclusion

In this paper, we proposed a collaborative tracking algorithm to improve the tracking accuracy and energy consumption of moving targets in wireless sensor networks. The wireless sensor monitors can be divided into two types: the behavior recognition monitors and the collaborative tracking monitors. Settle all the monitors utilizing ROCK clustering algorithm into many groups and get best answer set though PSO algorithm. BRM in it recognize the behaviors of moving targets as to locate the abnormal one. Finally, CTM track the target collaboratively until it leaves the guard area. In addition, an energy consumption model is proposed for measuring the quality of the algorithm. Comparing the solution with several existing methods, the results show that the algorithm we proposed has a better detection and tracking accuracy, reducing energy consumption simultaneously.

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