Fast Moving Object Tracking Algorithm based on Hybrid Quantum PSO

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Abstract: - Standard particle swarm optimization(PSO) has capacity of local search exploitation and global search exploratio. The population diversity gets easily lost during the latter period of evolution, which means most particles are convergenced into near positions which is the local optimia. In this paper, a Euclid distance based hybird quantum particle swarm optimization (HQPSO) is brought up. Based on the calculation of population diversity, when the diversity is less than thereshold, population division is proposed for seperating population into two sub-populations based on Euclid distance. One sub-population near Euclid center is defined as P_N will evolve according to traditional QPSO, while the other sub-population far away from center named P_F will fly to boundery which is far away from center. In this way, population diversity would promined to get particles convergence into global optima. Benchmark functions are adopted to testify the efficiency of HQPSO. And based on HQPSO Mean shift algorithm is designed for fast moving object tracking to improve tracking efficiency and decrease detection time cost, which will overcome the "tracking lost" problem of Mean Shift algorithm.

Key-Words: - Quantum particle Swarm optimization, Euclid distance, Fast moving, Population diversity, Object tracking

1 Introduction

With the popularization and application of intelligent transportation and intelligent community concept, high efficient tracking of moving object as the basis for its development has become increasingly important. Object tracking technology is used in the successive image frames of the shape, speed, texture, colour and other relevant characteristics for specific useful information (i.e. the object) problem. Traditional Mean Shift algorithm is a simple and efficient non-parametric density estimation method, which has a wide range of applications in practical application system. Ma etc.[1] combine Mean Shift and particle filter to complete the multi-target tracking, Lie etc.[2] complete infrared target tracking basing on the adaptive Mean Shift nuclear window width. The target based on Mean Shift algorithm can track object tracking in real time mainly existing three problems: (1) Mean Shift algorithm cannot track fast moving object[3];(2) Mean Shift template without the renewal ability[4];(3) the nuclear window is fixed and cannot achieve the accurate tracking of target scaling[5]. Fast moving object tracking is challenging in the process of practical application, Changjiang et al[6] improve the multi-dimensional image of Mean Shift method and the tracking speed, But the improved algorithm cannot guarantee the real-time performance. Yasir Salih[12] has proposed 3D tracking method for traffic applications which obtained satisfying performances. Saeed Malik, Collins[7] realize object tracking of the nuclear window dynamic transformation by combining the Mean Shift and scale space, realizing corresponding change window according to the moving object size changing, but the tracking window center position cannot be accurately determined. This paper design a Mean Shift algorithm based on hybrid quantum particle swarm to achieve accurate tracking of fast moving objects. Section II analyzes the basic principle of Mean Shift algorithm, adopting Bhattacharyya description similarity coefficient to determine the nuclear window center, nuclear window center position optimization is crucial to fast moving objects. Section III design a hybrid quantum particle swarm optimization, With more advanced particle swarm optimization test function to demonstrate that their rapid convergence and optimization of accuracy, so it can be used to optimize the Mean Shift similarity function, Thus can acquire nuclear window center position quickly ,achieve fast and accurate tracking. Finally, realizing the Mean Shift algorithm based on quantum-behaved particle swarm optimization algorithm and fast moving target tracking, demonstrating the validity of this method this paper proposing.

2 Mean Shift tracking algorithm

Mean Shift algorithm is a kind of pattern matching algorithm. we can create the target template before tracking, In the image, the object is generally expressed by a certain shape area, such as ellipse, rectangle, etc, After normalized coordinate the values is $\{x_i^*\}_{i=1\ldots n}$, The center of the object is x_0. $b: R^2 \to \{1\ldots m\}$ is the index value acquired by the image pixels x_i^* corresponding to the histogram. Thereby the histogram probability density corresponding to the feature value can be expressed as

$$\hat{q}_u = C_q \sum_{i=1}^{n} k\left(\left\|\frac{x_i^* - x_0}{h}\right\|^2\right) \delta\left[b\left(x_j^* - u\right)\right], u = 1,2,\ldots,m \quad (1)$$

where $\hat{q} = \{\hat{q}_u\}_{u=1,2,\ldots,u}$ is the histogram value of the object model, $\delta(x)$ is the Kronecker delta function. $k(x)$ is the Kernel function. Its role is to assign weights for pixel in the object template regions. $\left\|\frac{x_i^* - x_0}{h}\right\|$ in kernel function is to eliminate the impact that different sizes targets brings. h is the kernel function width, C_q is the normalization constant. Then we have

$$C_q = \frac{1}{\sum_{i=1}^{n} k\left(\left\|\frac{x_i^* - x_0}{h}\right\|^2\right)} \quad (2)$$

With the target template, In each frame image, We may let the region containing the target become the candidate region. Similar to the target template, model histogram probability density candidate distribution corresponding to the feature of the can be expressed as

$$\hat{p}_u(y) = C_p \sum_{i=1}^{n} k\left(\left\|\frac{x_i - y}{h}\right\|^2\right) \delta\left[b\left(x_i - u\right)\right], u = 1,2,\ldots,m \quad (3)$$

$\{x_i\}_{i=1,2,\ldots,n}$ is the pixel position in a candidate target area after normalization, The center coordinates of the candidate target is y. $\hat{p} = \{\hat{p}_u\}_{u=1,2,\ldots,m}$ is a candidate target histogram value, Similar to (2) the normalization constant C_p is

$$C_p = \frac{1}{\sum_{i=1}^{n} k\left(\left\|\frac{x_i - y}{h}\right\|^2\right)} \quad (4)$$

where C_p can be calculated by the kernel function and kernel width, h is the candidate target size.

Knowing the target template and also defining the candidate templates, how we should get the template from the candidate target template, Mean Shift algorithm adopts similarity detection method. Using the similarity measure to describe the degree similarity between the target model and the candidate model, here we take the Bhattacharyya coefficients, it is defined as follows

$$\hat{\rho}(y) = \rho\left[\hat{p}(y), \hat{q}\right] = \sum_{u=1}^{m} \sqrt{\hat{p}_u \hat{q}_u} \quad (5)$$

The value is between [0, 1], and the smaller of the value $\hat{\rho}(y)$, the smaller of the similarity degree between target model and the candidate models.

The task of the target tracking is to find the object location in the current frame image, Mean Shift algorithm uses the formula (5) to measure the similarity, and the bigger value shows that the closer the target template to the candidate template, that is to say, the candidate template is more likely to be the target. Thus obtain the mean shift vector of the target:

$$y_l = \frac{\sum_{i=1}^{n} x_i w_i g\left(\left\|\frac{y_0 - x_i}{h}\right\|^2\right)}{\sum_{i=1}^{n} w_i g\left(\left\|\frac{y_0 - x_i}{h}\right\|^2\right)} \quad (6)$$

We can get a maximum candidate templates Bhattacharyya coefficient, i.e., the object, by continuing iteration of this formula.

3 Hybrid quantum particle swarm optimization

3.1 The standard particle swarm algorithm

Eberhart proposed the basic PSO algorithm[8], Particle swarm particles randomly distributed in the solution space when the search is initialized, at the same time provide the random initialization velocity for each particle; Particle swarm is searched in the N-dimensional space, $x_i = (x_{i1}, x_{i2}, ..., x_{iN})$ denotes the particle's position, which represents a solution to the problem. $v_i = (v_{i1}, v_{i2}, ..., v_{iN})$ denotes the particle's velocity, which search for the new solutions by constantly adjusting its position. Each particle will record the optimal solution in the search process, it is represented as $P_i = (P_{i1}, P_{i2}, ..., P_{iN})$, it is also referred to as $pbest$. And particle swarm current optimal solution is recorded as $P_g = (P_{g1}, P_{g2}, ...P_{gN})$, it is referred to as $pbest$. In continuing iteration of the particle, the velocity and position updating equations as the following formulas:

$$V_{id}(k+1) = \omega \cdot V_{id}(k) + c_1 \cdot r_1 \cdot (P_{id} - x_{id}(k)) + c_2 \cdot r_2 \cdot (P_{gd} - x_{id}(k)) \quad (7)$$

$$X_{id}(k+1) = X_{id}(k) + V_{id}(k+1) \quad (8)$$

where $i = 1, 2, ..., M$, M is the size of particle swarm. c_1, c_2 is the learning factor, typically the values are two. r_1, r_2 are two random numbers in the interval [0, 1], they are independent of each other, ω is the inertia weight function.

In the PSO algorithm, the convergence of particles is in the form of track, the search space of the particle is a limited area in the search process because of the limited velocity, which could not cover the entire feasible space, so the standard PSO algorithm cannot guarantee convergence to global optimal solution with probability 1[9].

3.2 Quantum particle swarm algorithm

Based on the study of particle convergence behaviour by Clerc, Sun put forward a new PSO algorithm model from the view of quantum mechanics, thus proves the quantum behaviour of particle and proposes the quantum particle swarm algorithm (QPSO). In quantum space, the particles nature of the state of aggregation is totally different. It can search in the feasible solution space, so the global searching performance of QPSO algorithm is much better than the standard PSO algorithm. Finally the position equation of particle is obtained through Monte Carlo simulation method. In QPSO algorithm, the particle only has the location information, and the updating location decided by the following three equations:

$$mbest = \frac{1}{M} \sum_{i=1}^{M} pbest_i \quad (9)$$

$$p_{id} = \phi \cdot pbest_{id} + (1 - \phi) \cdot gbest_d \quad (10)$$

$$x_{id} = p_{id} \pm \beta \,|\, mbest_d - x_{id} \,|\, \cdot \ln(1/u) \quad (11)$$

In formula (9), $mbest$ represents the current center of the all individuals optimal location; in formula (10), ϕ is a random number in the interval [0,1], p_{id} represents the random location between $pbest$ and $gbest$, M is the size of particle swarm; In formula (11), parameter β is expansion - contraction factor which is used to control the convergent speed of the algorithm, this is the only QPSO parameter required to control , The way to get the value of β is a linear function of the number of algorithm iterations, as followings:

$$\beta = (\beta_{\max} - \beta_{\min}) \cdot (iteration - iter)/iteration + \beta_{\min} \quad (12)$$

where $iter$ is the current number of iterations, $iteration$ is the total number of iterations, $\beta_{\max}$ and $\beta_{\min}$ are two positive numbers, the value is 1.0 and 0.5, respectively.

From the above motion equation, we can see that the obvious difference between QPSO and PSO is that QPSO introduces the stochastic distribution of particle position, this paper also propose the concept of $mbest$ and p_{id}. The particle position of the exponential distribution makes the search space of each iterative step the real space, it can cover the whole solution space, thus increasing the ability of searching global optimal solution. Besides, the introduction of $mbest$ enhance the convergence properties of QPSO.

The QPSO algorithm can be described as: (a) Initialize the particle swarm; (b) Calculate the value of $mbest$ according to equation (9); (c) Find the fitness value of each particle, and calculate the value of p_{id} ; (d) obtain p_{gd} with comparing to p_{id} for each particle; (e) update p_{gd} ; (f) for each dimension of the particles, obtain a random point between p_{id} and p_{gd} according to equation (10); (g) obtain a new position according to equation (11); (h) repeat (b)~(g) until the condition is not satisfied, then the iterative process will end.

3.3 Hybrid quantum particle swarm optimization

Quantum particle swarm algorithm can overcome the defects of general particle swarm algorithm in convergence performance: Firstly, quantum system is a complex nonlinear system and in line with the state superposition principle, thus the quantum system linear system has more states than a linear system; Secondly, a particle in the quantum system can occur at any location in the search space with a certain probability , because there is no certain p article trajectory; Finally, in traditional PSO algorithm, the finite search scope limit the particle in a fixed area, in the QPSO algorithm, the particle can appear at any position in the whole feasible search space with certain probability, even the position is far from intermediate point. This position may have a better fitness value than $gbest$ in the current population. In the QPSO algorithm, in the later process of search, the particle diversity decrease rapidly, groups lost the ability to further expand the search space in the stagnation of local extreme points, which makes the whole group is likely to be trapped in local optimal solution. For analysis of particles in the late evolution of population diversity, species diversity model are introduced to analyse the convergence property of particles.

3.3.1The particle population diversity

The quantum particle swarm (QPSO) population model proposed according to the paper [11], we use d_n to evaluate the QPSO population diversity quantitatively, d_n denotes the current location and population gravity center position of Euclidean distance,

$$d_n = [1/(M \cdot |A|)] \cdot \sum_{i=1}^{M} \sqrt{\sum_{j=1}^{D} [X_{i,n}^{j} - \overline{X}_{n}^{j}]^2} \qquad (13)$$

where $\overline{X}_n^{j} = (1/M)\sum_{i=1}^{M} X_{i,n}^{j}$, $|A|$ represents the length of the longest diagonal search space, D represents the dimensions of the problem, M represents the population size. As D and $|A|$ are fixed value parameters, Population diversity is determined by $\sum_{i=1}^{M} \sqrt{\sum_{j=1}^{D} [X_{i,n}^{j} - \overline{X}_{n}^{j}]^2}$ .we can obtain the optimal distribution of X by getting the extreme of $\sum_{i=1}^{M} \sqrt{\sum_{j=1}^{D} [X_{i,n}^{j} - \overline{X}_{n}^{j}]^2}$. Namely, to obtain the optimal distribution of $\begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1D} \\ x_{21} & x_{22} & \cdots & x_{2D} \\ \cdots & \cdots & \cdots & \cdots \\ x_{m1} & x_{m1} & \cdots & x_{mD} \end{bmatrix}$, which makes the optimal population diversity. $\sum_{i=1}^{M} \sqrt{\sum_{j=1}^{D} [X_{i,n}^{j} - \overline{X}_{n}^{j}]^2}$ can be expanded as:

$$\begin{aligned}\sum_{i=1}^{M} \sqrt{\sum_{j=1}^{D} [X_{i,n}^{j} - \overline{X}_{n}^{j}]^2} &= \sqrt{\sum_{j=1}^{D} (x_{1j} - \frac{1}{D}(x_{11} + x_{12} + ... + x_{1D}))^2} \\ &+ \sqrt{\sum_{j=1}^{D} (x_{2j} - \frac{1}{D}(x_{21} + x_{22} + ... + x_{2D}))^2} \\ &+ ......\sqrt{\sum_{j=1}^{D} (x_{mj} - \frac{1}{D}(x_{m1} + x_{m2} + ... + x_{mD}))^2}\end{aligned} \qquad (14)$$

Minimum value can be obtained by expanding $\sum_{i=1}^{M} \sqrt{\sum_{j=1}^{D} [X_{i,n}^{j} - \overline{X}_{n}^{j}]^2}$, namely:

$$\frac{2(x_{11} - \frac{1}{D}(x_{11} + x_{12} + ... + x_{1D}))(1 - \frac{1}{D})}{2\sqrt{(x_{11} - \frac{1}{D}(x_{11} + x_{12} + ... + x_{1D}))^2}} = 0 \quad (15)$$

We will find the population diversity completely lost by solving the equation (15), when

$$\begin{aligned}[x_{11}, x_{12}, ..., x_{1D}] &= [x_{21}, x_{22}, ..., x_{2D}] \\ &= ...... = [x_{M1}, x_{M2}, ..., x_{MD}]\end{aligned} \qquad (16)$$

According to Jun et al. analysis of the quantum particle swarm optimization algorithm in the middle and late evolution, most particle converge to local optimum location, according to the description of the dropped Euclidean distance between particles of formula (14), the population diversity d_n reduces and the particles' global expansion ability is not enough, so there is a need to increase d_n ,thus helping the particle global expansion to avoid the local premature convergence, and there is a need to $Max(d_n)$ in a certain evolution algebra, Namely, to maximize the $\sum_{i=1}^{M} \sqrt{\sum_{j=1}^{D} [X_{i,n}^{j} - \overline{X}_{n}^{j}]^2}$. Assuming the effective flight range hypothesis particle (the value range of variables) is $x_i \in [a,b]$, obtaining the maximum of the equation (17) by maximizing $\sum_{i=1}^{M}\sqrt{\sum_{j=1}^{D}[X_{i,n}^{j}-\overline{X}_{n}^{j}]^{2}}$.

$$L=\sum_{i=1}^{M}\sqrt{\sum_{j=1}^{D}(x_{i,j}-\overline{x_i})^2}+\sum_{i,j}\lambda_{i,j}(a-x_{i,j})+\sum_{i,j}\eta_{i,j}(x_{i,j}-b) \quad (17)$$

We can find that $[x_{i1}, x_{i2}, ..., x_{iD}]$ uniformly distributed in the boundary when making the derivation of formula (17), or we can obtain the maximum of formula (13) when the particle' relative distance is the largest. Therefore, human participation in boundary diffusion of particle' distribution can effectively increase the particle population diversity, this paper design a hybrid quantum particle swarm algorithm based on Euclidean distance, when in the appropriate algebra of the particles evolution, we can scatter parts of particles, thus increase the diversity of population.

3.3.2 Hybrid quantum particle swarm algorithm（HQPSO）

According to the analysis of 3.3.1,Some scholars have put forward the method to improve the performance of particle swarm based on the particles' diversity, Different from the fixed diffusion mode proposed by Jun[11], when the evolution to a certain algebra and the diversity is $d_n < d_r$, let part particles diffuse towards the boundary rather than continuing to convergence. The particle population can be divided into two subgroups according to the Euclidean distance, firstly, calculate the average distance between each particle and $mbest$, the particles whose distance is smaller than the average distance are divided into a group, denoted by P_N; The rest particles are divided into another group, denoted by P_F . As shown in figure 1:

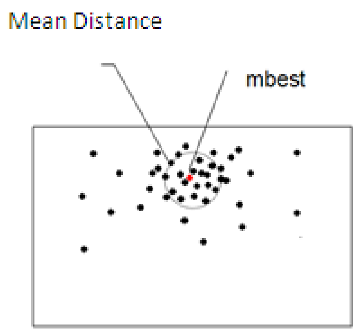

Fig.1. the divided schematic diagram of the HQPSO algorithm

The basic idea of HQPSO is:

(1) In the search space, generate a group composed of M parameters randomly, initialize the related parameters; Set the population diversity threshold diversity $d_r = d_n^0 / 2$ (When half the population diversity lost, it begins to divide the groups and diffuse the operation)

(2)Calculate the population diversity, when $d_n^t < d_r$, select the population by constituting the collection P_N whose distance is less than the average distance the collection of particles, then the rest particles constitute P_F , the intersection of collection P_N and P_F is empty.

(3)Select appropriate parameters for the two subgroups respectively, iterate, calculate the next position of particles, and then adjust it. Evolve P_N according to the original trace, and diffuse particles of P_F toward to the boundary which is equivalent to use the rejection of the particles current center point, that is, instead of the formula (11), the formula (18) update the particle's position, and the figure is shown in figure 2.

$$x_{i,n+1}^{j}=x_{i,n}^{j}-r\times(\overline{x_{n}^{j}}-x_{i,n}^{j}), r\in[0,1] \quad (18)$$

(4)Reconstruct groups which are the union of P_N and P_F

(5) If meet the terminal conditions, then end the algorithm. Otherwise, go back to (2).

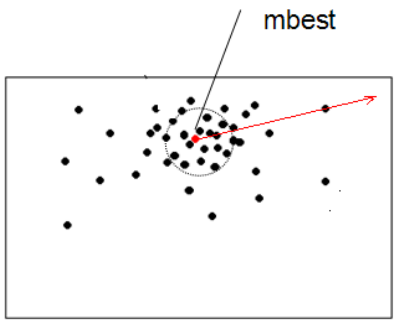

Fig.2. particles move toward the opposite direction of centre position in the HQPSO algorithm, thus realize the attraction of boundary to particles

3.3.3 Function optimization based on HQPSO

To verify the HQPSO algorithm performance, optimize the unimodal and multimodal function respectively, compared to the standard PSO algorithm(PSO)、QPSO algorithm, chaotic particle swarm optimization algorithm (CPSO) and PSO the division strategy, Where Sphere function, Ackley function, Trid function and Sum Squares function are all unimodal functions, denoted by f1, f2, f3, f4 respectively. Rastrigin function, Griewank function, Schwefel function are multimodal functions, denoted by f5, f6, f7. And Rosenbrock function is a typical metamorphosis of the quadratic functions, denoted by f8. The comparison of the optimal solution is shown in Table 1. Set the number of iterations is 2000,the particle swarm is 20 and the dimension is 10,then run 20 times, take the average record of optimal value each time in table 1, we can get HQPSO compared with other four kinds of PSO algorithm and obtain the optimal solution when optimize the test function.

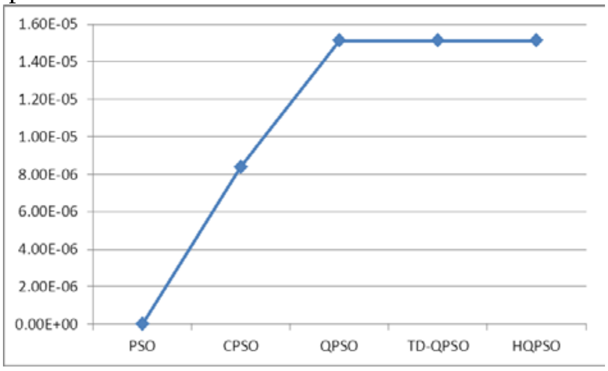

Fig.3. the running time(second) of HQPSO algorithm and other PSOs optimization f6 function

HQPSO shows good optimization accuracy in the optimization of unimodal and multimodal function, with the f6 function as an example, from Figure 3,we can verify the computation time is almost the same with the comparation between its computational time complexity and the traditional QPSO, thus provide the basis for its further application in fast object tracking algorithm.

4 Fast moving object tracking algorithm based on HQPSO Mean Shift and implementation

Mean Shift algorithm use color histogram to represent the target, let the tracking window gradually approaching the target position after several iterations based on Bhattacharyya distance between candidate model and target model. The traditional Mean Shift algorithm iterations affect the target tracking speed, if the targets move fast, then the Mean Shift exist the situation of "lost". Besides, the iteration of traditional Mean Shift algorithm to calculate nuclear center position of the window exist deviation, thus leading to inaccurate tracking.

In order to solve the problem above, HQPSO algorithm mentioned above can optimize the characteristics of function rapidly, This paper proposes the Mean Shift algorithm based on HQPSO and optimize the Bhattacharyya distance with HQPSO, then find the minimum value corresponding to the coordinates of the window as the Mean Shift tracking nuclear center coordinates, thus we can obtain the nuclear center location with the optimization process of HQPSO rather than traditional Mean Shift iteration. The process of Mean Shift target tracking algorithm based on HQPSO is shown as the following figure.

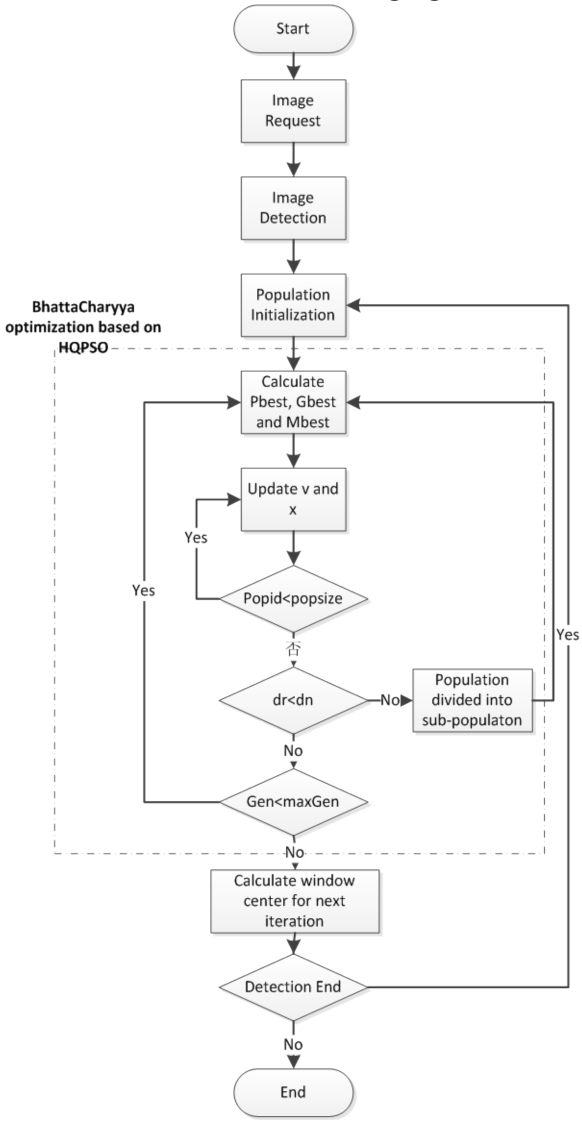

Fig.4. Fast moving object tracking algorithm flow chart of the Mean Shift algorithm based on HQPSO

The particle swarm initialization is selected randomly in the rectangular area which regards the detecting target as the center, considering the continuity of the moving object, although speed is fast, it won't surpass the rectangular range. According to the relationship of group diversity $d_n < d_r$ in the HQPSO evolution process to determine whether to group evolution or not, thus the particles far from center position can scatter toward the border, this is in accordance with the principle 3.3.2 of this article.

5 Experiment and analysis

This paper makes a contrast on the traditional Mean-Shift algorithm and the algorithm proposed in this paper, video collects from the camera in real-time, the image size is 320 x 240 pixels, the processor is Intel dual core E7400 2.8GHz,Windows7 operating system environment, VS2010 development environment and OpenCV 2.3.0. Computation is mainly concentrated on modeling and matching in the candidate region, HQPSO iteration to obtain the window core position, the detection and matching of the feature point of two frames of adjacent tracking window.

The experiment selects two group videos of different background and the traffic video shot in traffic lights, the speed is as high as 70-100 kilometers per hour, which is in accordance with the requirements of fast moving objects. Figure 5 is the tracking results of traditional Mean Shift, which is the tracking results of 6, 11, 16, 21, 26 frame, we can see the target displacement from the initial frame to 6, 21 frame change greatly, that is to say, the object move very quickly, the traditional Mean has been appeared to the problem of "lost" when it tracks to the 21 frame. Figure 6 is the proposed tracking algorithm based on QHPSO Mean Shift, the tracking window positioning is between the target and similar background objects, as shown in (c) (d)of Figure 6. From the tracking results of the 6, 11, 16, 21, 26 frame, the proposed algorithm can realize tracking completely which overcomes the "lost" problem of the traditional Mean Shift.

6 Conclusion

This paper analyzes local exploration and global scalability of the quantum particle swarm algorithm and proposes HQPSO algorithm based on population diversity model, the main idea is to quantify the current population diversity in the evolution process, introduce the principle of population evolution with P_N and P_F When it below to a certain threshold, Then P_N flies according to the evolution principle of QPSO, and P_F diffusing towards the boundary far from center according to the analysis of the population diversity, thus can realize the goal of maintaining the population diversity in the late stage of evolution and find the global optimal solution. Besides the verification of the standard test functions, this paper also applies HQPSO in fast moving object tracking.

Effective tracking of fast moving targets is very important to the effective implementation of the intelligent monitoring, Mean Shift algorithm is a kind of parameter estimation algorithm, its real-time requirements is in accordance with the requirements of fast tracking. with the "lost" problem in fast object tracking, on the basis of the fast object tracking algorithm of HQPSO Mean Shift and proving the HQPSO can effectively solve the unimodal and multimodal function optimization problems without the significant increase in the time complexity, this paper design the Bhattacharyya distance function that HQPSO can optimize the Mean Shift and replace the original Mean Shift iteration, which can realize accurate and fast exploration to find the center position of moving object, thus overcoming the shortcomings of the traditional "lost" problem of Mean Shift, this offers the possibility for further application of Mean Shift.

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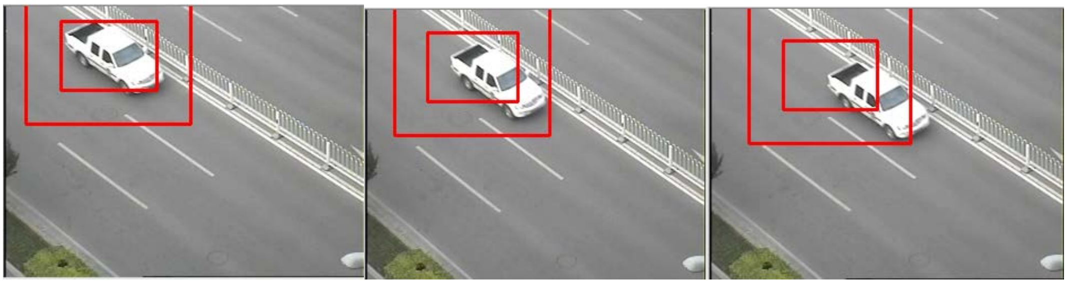
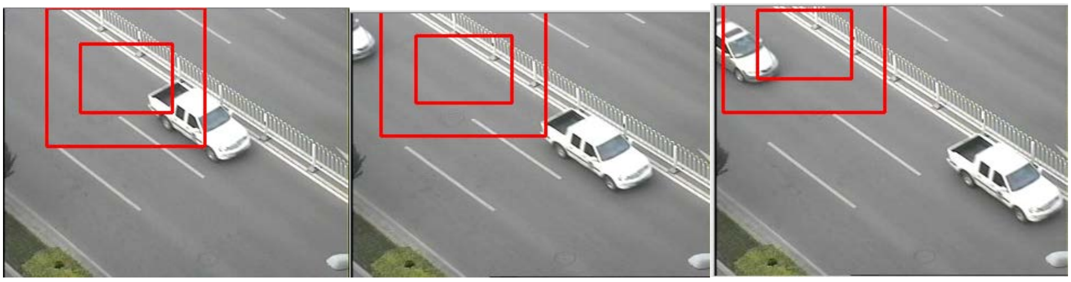
Table 1 the optimization results comparison of text function of various PSO algorithm

Text function	PSO	CPSO	QPSO	TD-QPSO	HQPSO
f1	0.0619157	1.02756e-53	2.88245e-80	1.27615e-94	**3.64218e-108**
f2	2.0619	**1.84081**	**1.84081**	**1.84081**	**1.84081**
f4	0.404795	1.49764e-52	8.66076e-100	3.12587e-88	**1.62628e-105**
f5	19.3628	6.96471	2.98488	3.97984	**2.98488**
f6	1.11782e-5	1.59699e-54	1.19873e-110	1.27279e-99	**1. 2233e-112**
f7	1698.16	1758.5	118.438	236.877	**118.438**

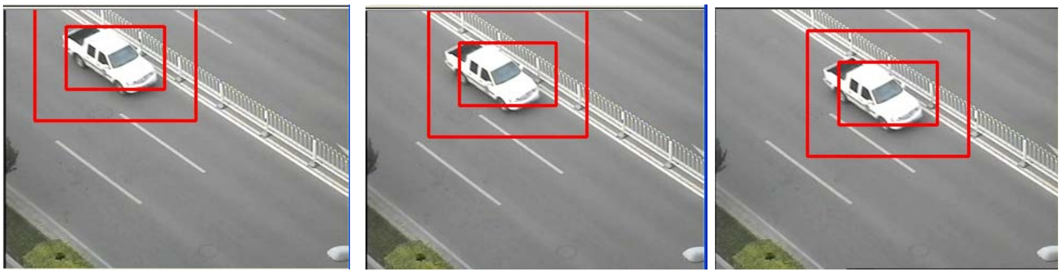


(a) the 1 frame (b) the 2 frame (c) the 3 frame

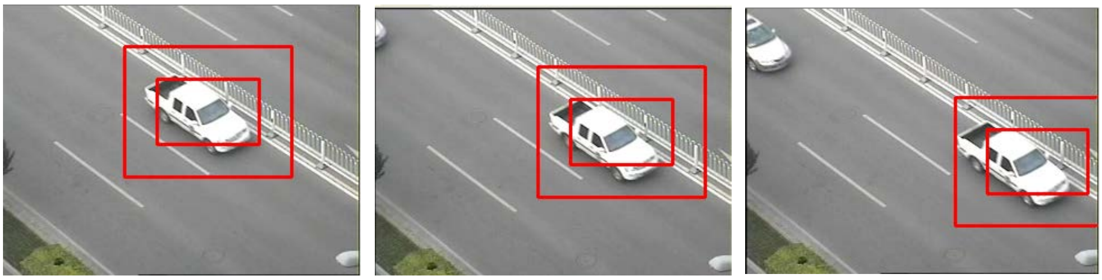


(d) the16 frame (e) the 21frame (f) the 27 frame

Fig.5. fast moving object tracking results based on the traditional Mean Shift algorithm



(a) the 1 frame (b) the 6 frame (c) the 11 frame



(d) the 16 frame (e) the 21 frame (f) the 27frame

Fig.6. fast moving object tracking results based on the HQPSO of the Mean Shift algorithm