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Visual Tracking Using Quantum-Behaved Particle Swarm Optimization

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Abstract: Visual tracking is one of the most important applications in computer vision. Since the tracking process can be formed as a dynamic optimization problem. PSO, an effective algorithm to solve optimization problem, has been used in tracking widely. However, it has been proved that the traditional PSO is easy to converge to local optimum. In this paper, we adopt quantum-behaved particle swarm optimization (QPSO) for visual tracking. QPSO has better global convergence compared with the PSO, and can overcome the shortcomings of PSO algorithm. In order to achieve better tracking performance, we improve the traditional tracking framework based on PSO and propose a sequential QPSO based tracking algorithm in this paper. We conduct numerous experiments, and the results have shown the effectiveness of our method, even when the object undergoes abrupt motion or large changes in illumination, scale and appearance.

Key Words: Visual tracking, premature, QPSO, global optimum

1 Introduction

Visual tracking is an important and challenging research due to its widely usage and complex working environment. The importance of visual tracking comes from numerous useful tasks, such as automated surveillance, motion based recognition, human-computer interaction, intelligent transportation and so on. Given the initialized state (e.g., position and size) of an object in a video frame, the aim of visual tracking is to estimate the state of the object in the subsequent frames. Although robust visual tracking algorithm remains a huge challenge due to numerous factors, e.g. illumination variation, occlusion, abrupt object motion, appearance variation and so on, much progress has been made by researchers in recent decades, e.g. representation scheme, search mechanism, model update. With the development of these basic researches, numbers of tracking algorithms were proposed.

Most state-of-art tracking algorithms can be formed as an optimization process, i.e. searching for the optimization state of the object in a new frame, and the tracking algorithms can be categorized into two groups, one is deterministic methods [1, 2, 3] and the other is stochastic methods [4, 5, 6, 7]. Deterministic methods usually involve an optimal algorithm to minimize (or maximize) a cost function. For example, the snakes model [1] proposed by Kass et al. The method builds an energy function, and minimizes the function to obtain a tight contour enclosing the object. The widely used tracking method, mean shift [8], is also a kind of deterministic method. It was firstly proposed as a method to estimate the gradient of a density function. Comaniciu et al. [3] applied it to visual tracking and achieved success. In mean shift method, the cost function is described by the distance between two color histograms, and then the mean shift iteration is used to minimize the distance. In general, the advantage of the deterministic method is that they are usually computationally efficient, and the disadvantage is that they easily become trapped in local optimum.

Unlike the deterministic methods, the state of object in tracking algorithms which using stochastic methods is non-deterministic (i.e. “random”) so that subsequent state of the object is determined probabilistically. Stochastic methods have been proved to have good performance in tracking algorithm. A typical example is particle filter [4, 5]. Particle filter is a Bayesian inference process for predicting the unknown state according to the previous results. Particle filter and its variation are widely used for visual tracking. Compared with deterministic methods, stochastic methods are relatively insensitive to local optimum, and more robust. However, the main disadvantage of them is that they are usually computing expensive, especially when they are used in high-dimensional state space. Although numbers of work has already been done, there still need an efficient and robust tracker that can deal with complex environment.

Particle swarm optimization (PSO) [9, 10], proposed by Kennedy and Eberhart [9], has received more and more attention because of its good performance in solving nonlinear, and multimodal optimization problems. Different from the independent particles in other particle based optimization techniques (e.g., genetic algorithm and particle filter), the particles in PSO interact with each other and with their environment. This is similar to the cooperative behavior of animal swarm. Furthermore, PSO is simple and has low number of parameter. This makes it a faster and cheaper method compared with other optimal algorithms. However, PSO is a local convergence algorithm, i.e. it is easy to converge to local optimum. The main reason of the problem is that the trajectory of each particle is fixed, results in the search space of every generation is limited.

Inspired by quantum mechanics and the trajectory analysis of PSO, Sun et al. [11] proposed quantum-behaved particle swarm optimization (QPSO). Particles in QPSO have quantum behavior, and they move according to wave functions. The particles in QPSO are released from the bondage of trajectories, so that the QPSO is insensitive to local optimum and has a better performance in searching for the global best compared with PSO.

In this paper, we improve the tracking algorithm based on PSO and propose a novel effective and robust tracking method base on QPSO. We regard the tracking problem as an optimization problem, then adopted the QPSO algorithm into tracking to form a sequential QPSO based tracking framework. The proposed framework can deal with challenging tracking tasks even when the object undergoes abrupt motion or large changes in illumination, scale and appearance. Numerous experiments are conducted to illustrate both effectiveness and efficiency of the proposed method.

The remaining part of this paper is structured as follows. In Section 2, we provide the relevant algorithms that motived this work. In Section 3, the details of the proposed sequential QPSO are described. Section 4 presents the tracking framework based on sequential QPSO. The results of numerous experiments and performance evaluation are presented in section 5. Finally, we conclude this paper in section 6.

2 Related Work and Motivation

Numerous of work have been done by researchers in visual tracking and more detail information can be found in [12, 13]. We discuss the algorithms that are important for our research and put this work in proper context in this section.

2.1 Quantum-Behaved Particle Swarm Optimization

Standard PSO algorithm is initialized with a set of particles. Each particle is represented by its state x_i and velocity v_i. The following equations are the evolutionary equation:

$$v_i(t+1) = v_i(t) + c1 * r1 * (p_i(t) - x_i(t)) \\ + c2 * r2(t) * (p_g(t) - x_i(t)) \tag{1}$$

$$x_i(t+1) = x_i(t) + v_i(t+1) \tag{2}$$

In equations (1) and (2), $c1$ and $c2$ are the accelerated coefficients. $r1$ and $r2$ are random numbers uniformly distributed on (0, 1). p_i is the personal best of a particle and p_g is the global best particle.

Sun et al. [11] took uncertainties into account. Based on quantum mechanics and standard PSO algorithm, they proposed the quantum-behaved particle swarm optimization (QPSO). In QPSO, the searching strategy is a probability searching technique and the search space in QPSO is quantum space. So the movement of particles is similar to the ones in the quantum mechanics.

The main idea of QPSO is to use the wave principle of the particles in the quantum space. Based on the wave principle, the QPSO is realized effectively. The iteration process of QPSO is described as the following. First, initialize the states of the particles, and then the particles search for the global optimum in search space according to the wave function. The particles in QPSO could move and appears anywhere in the search space with a certain probability. And the particles update their states according to the following equations without using velocity information:

$$mbest = \left(\frac{1}{N}\sum_{i=1}^{N} p_{i1}, \frac{1}{N}\sum_{i=1}^{N} p_{i2}, \ldots \frac{1}{N}\sum_{i=1}^{N} p_{id}\right) \tag{3}$$

$$p_i(t+1) = \varphi * p_i(t) + (1-\varphi) * p_g \tag{4}$$

$$x_i(t+1) = p_i(t+1) \pm \alpha * \left| mbest - x_i(t) \right| * \ln\left(\frac{1}{u}\right) \tag{5}$$

where $mbest$ is the mean state and $p_i(t+1)$ contains the personal best of a particle and the global best. N is the number of particles. φ and u are two random numbers uniformly distributed on (0, 1). α, the only parameter, is called creativity coefficient, it is used to balance the local and global search of the algorithm during the iteration process.

Both experiment and theory has proved that the QPSO can overcome the shortcoming of standard PSO and outperforms standard PSO.

2.2 Motivation of This Work

PSO has been proved that it can be used in tacking [14], and experiments have shown good performance in some tacking algorithms. But the shortcoming limits the use of PSO. This is because the objects are usually under hard environment and trackers based on PSO are easily converging to the local optimal. As is discussed above, the QPSO can overcome the shortcoming of PSO. Under this background, the main contribution of this paper is that we try to introduce QPSO into tracking and propose a sequential QPSO based tracking framework. Experiments have shown that our work can achieve improvements compared with PSO based tracking algorithm. What's more, our work has good performance in many difficult datasets.

3 Sequential QPSO

In this section, we will introduce the tracking process in optimization view to show the details of sequential QPSO used in tracking.

Similar to the PSO based tracking algorithm [14], the sequential QPSO based tracking algorithm is essentially a particle filter with QPSO iterations to optimize the states of particles in every new frame. As illustrated in Fig. 1, through the QPSO iterations, the particles sampled in a new frame move towards the region where the likelihood of observation has larger values. Finally, after the QPSO iteration, the particles are relocated to the dominant modes of the likelihood. The QPSO iteration makes tracking process more robust and the states of particles are more close to the real state of the object, which means we can decrease the number of particles and achieve better robust ability at the same time. The computation cost will be decreased.

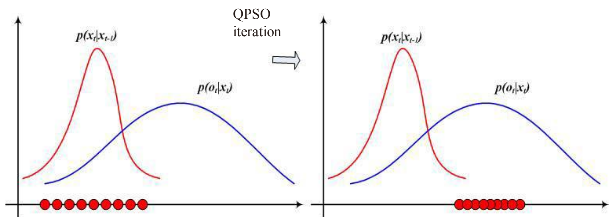


Fig. 1: illustration of QPSO iteration

To give a clear view of our tracking algorithm, the flowchart of the tracking algorithm is displayed in Fig.2. It contains three major steps. First, propagate the particles from the previous optimization randomly according to a Gaussian distribution to enhance their diversities. Then, the QPSO is used to search for the global best. Finally, we use a convergence criterion to decide whether the QPSO iteration stops or not. The three major steps described above can be concluded as: random propagation, QPSO iteration and convergence criterion, we will introduce them in the remaining contents in Section 3.

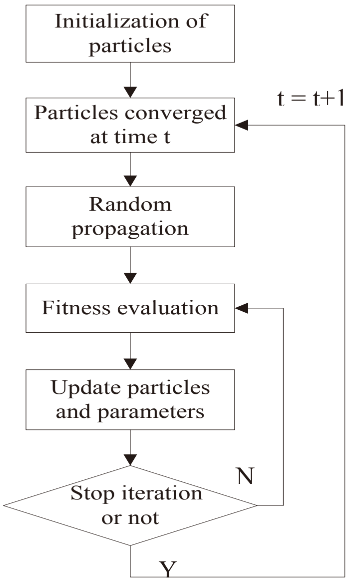


Fig.2: Overview of the sequential QPSO tracking framework

3.1 Random Propagation

The major problem of the proposed tracking method is the diversity loss of particles, which decreases the robustness of tracking algorithm in long time tracking task. Thus, a re-diversification mechanism is needed in the QPSO iteration.

An effective re-diversification mechanism is usually based on the motion information of the tracked object. In this paper, re-diversification mechanism is based on a Gaussian distribution. The mean of the Gaussian distribution is the previous personal best of the particle, and we use a predicted velocity of the object to define the covariance matrix. As is discussed above, the Gaussian distribution contains the motion information of the object, and the particle set is randomly propagated according to the proposed Gaussian distribution. The detail description of the re-diversification mechanism is the following:

Given the personal best of a set of particles $\{p_i(t)\}_{i=1}^{N}$ converged at time t, the re-diversification strategy used in this paper is described in (6):

$$x_{i,0}(t+1) \sim \mathrm{N}(p_i(t), \Sigma) \tag{6}$$

where Σ in equation (6) is the covariance matrix of the Gaussian distribution. The diagonal elements of Σ are proportional to predicted velocity $v_{pre}(t+1)$.

$$v_{pre}(t+1) = g(t) - g(t-1) \tag{7}$$

The randomly propagation discussed above is simple but effective, because we just use it to produce an initial states of particles for a subsequent search for the optimum.

3.2 QPSO Iteration

After the random propagation process, particles begin to search for the global optimum, i.e. the QPSO iteration. As is introduced above, compared with standard PSO, the advantages of QPSO are the following. First, QPSO is more simple and easy to implement, because there is only one parameter i.e. the creativity coefficient needs to be controlled. Second, QPSO is computationally more efficient. What's more, the probability searching technique in QPSO results in a better performance in searching for the global optimum.

In this paper, the creativity coefficient α in equation (5) is described in equation (8):

$$\alpha = (1-0.5) * \frac{\max IterNum - j}{\max IterNum} + 0.5 \tag{8}$$

where $\max IterNum$ is max number of QPSO iterations, and j ($j < \max IterNum$) represents the current number of iteration. What more, the method of updating the personal and global best of particles is similar to the method in standard PSO. According to the proposed discussion, the detail of the QPSO iteration process is presented in Algorithm 1.

Algorithm 1: QPSO iteration

Initialization: at time t+1

- a population of particles $\{x_i^0(t+1)\}_{i=1}^{N}$ (N is number of particles)
- fitness value of each particle $\{f(x_i^0(t))\}_{i=1}^{N}$ and their personal best $\{p_i(t)\}_{i=1}^{N}$
- global best of the particles $p_g(t)$ and the corresponding fitness value $f(p_g(t))$

for j=0 **to** maxIterNum **do**

for i=1 **to** N **do**

1. Update particles according to equations (3), (4), (5), the new states of particles: $\{x_i^j(t+1)\}_{i=1}^{N}$
2. Calculate the fitness values of particle in new state according to an appearance model
3. Update personal best and global best of particles according to the following equations:
$$p_i(t+1) = \begin{cases} x_i^j(t+1), f(x_i^j(t+1)) > f(p_i(t+1)) \\ p_i(t+1), else \end{cases}$$
$$p_g(t+1) = \arg\max_{p_i(t+1)} f(p_i(t+1))$$
4. Check for the convergence condition
if the particles are converged **then**
Terminate the QPSO iteration
else Continue iteration
end if

end for

end for

Output the particle set $\{x_i(t+1)\}_{i=1}^{N}$

3.3 Convergence Criterion

There should be a convergence criterion in the QPSO iteration. Because there is no need for all for all particles converge to the global best. In this paper, convergence criterion is designed as:

The fitness value of the global best is smaller than a predefined threshold T, and all the personal best are in a neighborhood of the global best, as shown in Fig.3. Or the number of iteration reaches to the maximum.

According to the convergence criterion, the object to be tracked can be efficiently identified and the convergent particle set provides a compact initialization while avoiding the sample impoverishment problem which can cause damage to tracking algorithm in the next optimization process.

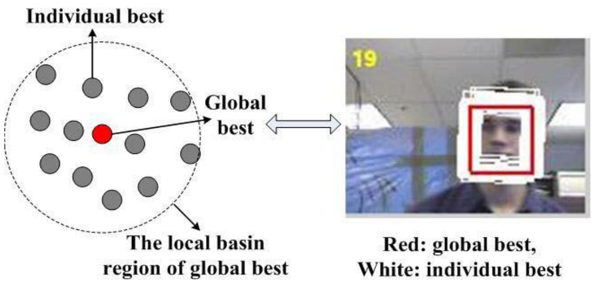


Fig. 3: The convergence criterion

4 Tracking Framework using Sequential QPSO

We will introduce the proposed tracking framework that based on sequential QPSO in this section. The tracked object in each image frame in our algorithm is located by a rectangular window, and the motion of the object between two consecutive frames is described by an affine image warping. In details, the motion is characterized by the state of the particle $x(t)=(x,y,\theta,s,\alpha,\beta)$ where x,y describe the 2-D translation parameters and θ,s,α,β are deformation parameters. The appearance model used in the tracking framework is a MOG (mixture of Gaussian) based appearance model, and the fitness value of each particle is evaluated according to the appearance model. In the following parts, we first introduce the MOG based appearance model, and then give a detailed description of the proposed tracking framework.

4.1 MOG Based Appearance Model

Similar to [15], [16], there exist three components in our appearance model：S, W and F component, where the S component describes temporally stable images, the W component characterizes the two-frame variations, and the F component is a fixed template of the target to prevent the model from drifting away. Based on the appearance model, we can calculate the fitness value of particles in QPSO according to equation (9):

$$f(x(t)) = p(o(t)\,|\,x(t)) = \prod_{j=1}^{d}\left\{\sum_{l=s,w,f}\pi_{l,j}(t)\mathrm{N}(o_j(t);\mu_{l,j}(t),\sigma_{l,j}^2(t))\right\} \tag{9}$$

where $\{\pi_{l,j}(t),\mu_{l,j}(t),\sigma_{l,j}^2(t), l=s,w,f\}$ represent the mixture probabilities, mixture centers and mixture variances of the S, W, F components respectively, $o(t)$ is the candidate image correspond to the state of particle $x(t)$ at time t, and d is the number of pixels inside the candidate image $o(t)$. In equation (9), $\mathrm{N}(\cdot)$ is a Gaussian density defined in (10):

$$\mathrm{N}(x;\mu,\sigma^2) = (2\pi\delta^2)^{-1/2}\exp\{-\frac{(x-\mu)^2}{2\sigma^2}\} \tag{10}$$

A robust tracking algorithm should have an appearance model that can change over time, i.e. the appearance model should be an online model. In this paper, we update the MOG based appearance model by update the parameters in it. What's more, we use a forgotten factor to avoid storing all the data from previous frames. This makes the model parameters depend more on the most recent observation while the previous observation is exponentially forgotten.

Finally, an online EM algorithm is used to estimate the parameters of the three components and is described as the following:

Step1 (E-step):

The ownership probability of each component is computed as:

$$m_{l,j}(t) \propto \pi_{l,j}(t)\mathrm{N}(o_j(t);\mu_{l,j}(t),\sigma_{l,j}^2(t)) \tag{11}$$

which fulfills $\sum_{l=s,w,f} m_{l,j}(t)=1$.

The mixing probability of each component is computed as:

$$\pi_{l,j}(t+1) = \partial m_{l,j}(t) + (1\text{-}\partial)\pi_{l,j}(t); l=s,w,f \tag{12}$$

And the first- and second-moment images are defined in (13)

$$M_{k,j}(t+1) = \partial o_j^k(t)m_{s,j}(t) + (1-\partial)M_{k,j}(t)$$
$$k=1,2$$

(13)

where $\partial = 1-e^{-1/\tau}$ is used as a forgotten factor, and τ is predefined.

Step2 (M-step):

The mixture centers and the variances are estimated in the M-step:

$$\mu_{s,j}(t+1)=\frac{M_{1,j}(t+1)}{\pi_{s,j}(t+1)}, \sigma_{s,j}^2(t+1)=\frac{M_{2,j}(t+1)}{\pi_{s,j}(t+1)}-\mu_{s,j}^2(t+1)$$
$$\mu_{w,j}(t+1)=o_j(t), \sigma_{w,j}^2(t+1)=\sigma_{w,j}^2(1)$$
$$\mu_{f,j}(t+1)=\mu_{f,j}(1), \sigma_{f,j}^2(t+1)=\sigma_{f,j}^2(1)$$

4.2 Sequential QPSO Based Tracking Algorithm

We embed the MOG based appearance model into sequential QPSO based tracking algorithm for the fitness value evaluation. The sequential QPSO based tracking algorithm is presented in Algorithm 2.

Algorithm 2: Sequential QPSO Based Tracking

Input: Given the personal best of particles $\{p_i(t)\}_{i=1}^N$ and global best $p_g(t)$ at time t

1. Randomly propagate the particles to enhance the diversities of them according to the transition model defined in equation (6).
$$x_i^0(t+1) \sim \mathrm{N}(p_i(t),\Sigma)$$
2. Compute the fitness value of each particle according to equation (9).
$$f(x_i^n(t+1)) = p(o_i^n(t+1)\,|\,x(t+1))$$
3. Update the personal best $\{p_i(t+1)\}_{i=1}^N$ and the global best $p_g(t+1)$ of particles.
4. Carry out the QPSO iteration according to the proposed Algorithm 1.
5. Check the convergence criterion: if satisfied, continue, otherwise go to step 2

Output: Global optimum: $p_g(t+1)$

5 Experiment Results

Our tracking algorithm is implemented in MATLAB on a PC with Intel i5 CPU (2.27 GHz) with 4 GB memory. For each sequence, the state of the target object is manually set in the first frame. Each candidate image corresponding to a particle is rectified to a 32×32 patch.

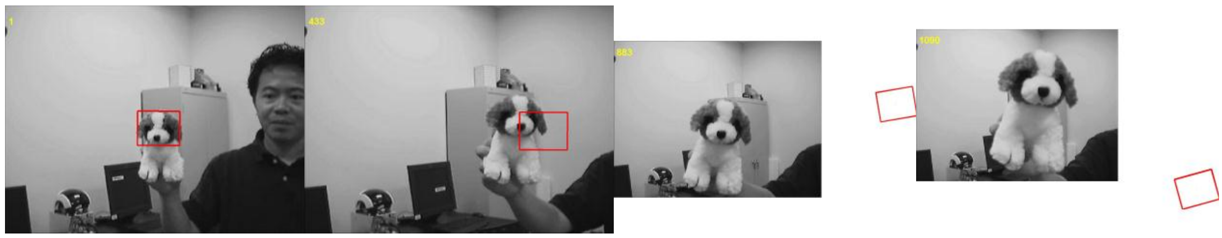
5.1 Compared sequential QPSO tracker with similar tracking algorithm

In this section, we conduct a comparison experiment among the sequential QPSO based tracking algorithm, a standard PF (particle filter) and the sequential PSO based tracking algorithm [14] on two videos with ground truth. One video sequence is “Dog”, which is a simple dataset contains a dog face moving to the left and right with appearance and scale variation. Another dataset is “Boy”, which is a harder dataset contains a boy moving quickly.

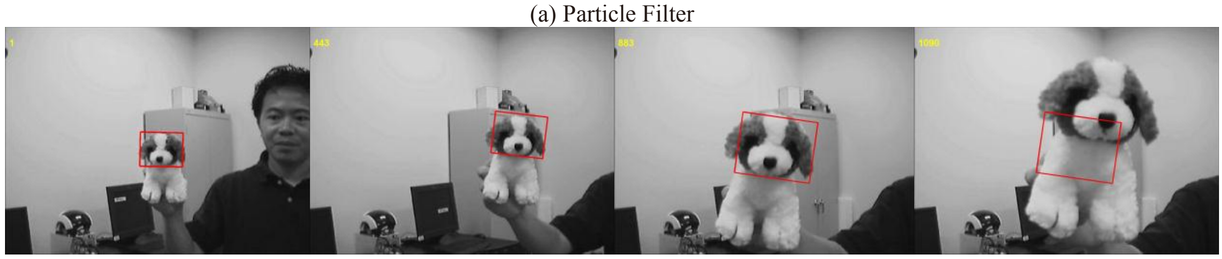
The experiment results can be seen in Fig. 4 and Fig. 5. As shown in Fig. 4(3), our tracking algorithm performs well, successfully finish the tracking task. However, in Fig. 4(b) the sequential PSO based tracker fails after frame 883, and the tracking window stop moving. This is because the tracker converges to the local optimum as time goes on. On the other hand, in Fig. 4(a), the PF performs poorly, it fails after frame 433. The result shows that out tracking framework is a robust tracker in the simple tracking task. What’s more, compared with sequential PSO based tracker, our tracker has a better performance when searching for the global optimum in a long tracking task. Although the sequence is simple, it is effective to show the advantages of our algorithm.

In Fig. 5, the results of performances of the three trackers are displayed. As can be seen in Fig. 5, the results are similar to the ones in Fig. 4. PF tracker fails after frame 90 due to the fast motion of the object. The sequential PSO based tracker performs better. However, the tracking window fails to cover the object after frame 230, and it fails after frame 265 when the object is under a motion blur. Our tracker still has the best performance even in a harder dataset. The result shows that the sequential QPSO based tracking framework is a relatively robust tracking algorithm.

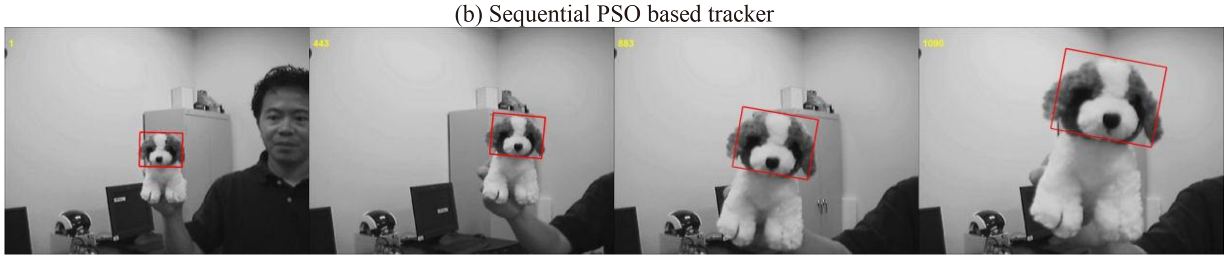
Furthermore, we conduct a quantitative evaluation of the algorithms, and have a comparison in the following aspects: MSE (mean square error) between the estimated position and the labeled groundtruth, and the frames of successful tracking. If the distance between the predicted object and the groundtruth is less than 20 pixels, the tracking process in this frame is successful. Besides, the MSE calculated here only takes the successful frame in to consideration. The comparison result is displayed in Table 1 and Table 2. We can see from the tables that our tracker achieves very favorable performance in terms of both accuracy and successful rate.



(a) Particle Filter



(b) Sequential PSO based tracker



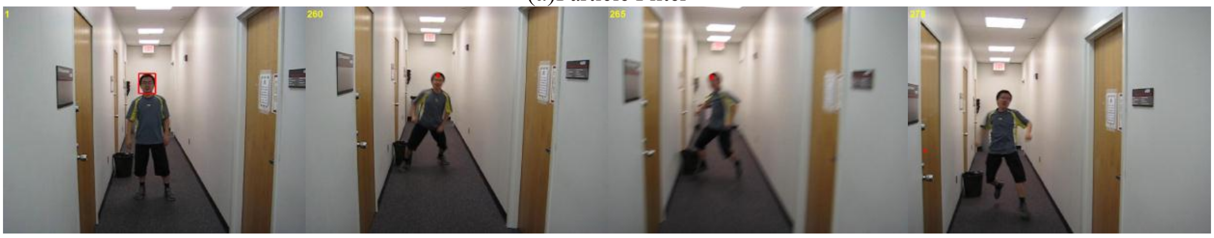
(c) Sequential QPSO based tracker

Fig. 4: Tracking performances of “Dog” sequence

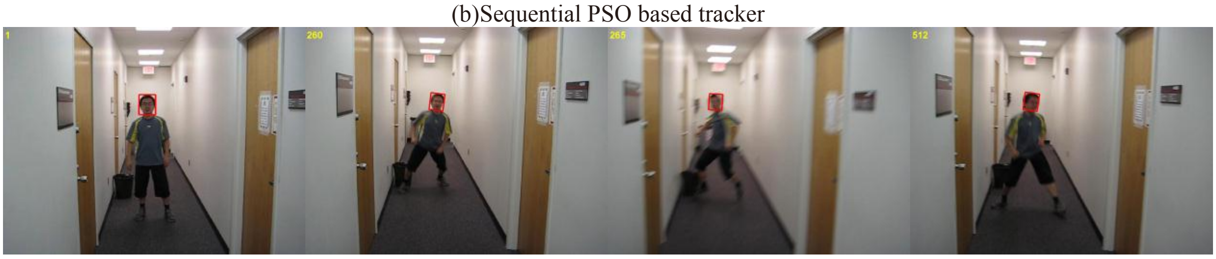
Table 1: Tracking performances of “Dog” dataset

Tracking Framework	MES of Position	Frames Tracked	Successful?
PF	8.3145	433/1350	N
PSO based Tracker	5.2527	883/1350	N
QPSO based Tracker	4.0847	1350/1350	Y

(a)Particle Filter



(b)Sequential PSO based tracker



(c) Sequential QPSO based tracker

Fig. 5: Tracking performances of "Boy" sequence

Table 2: Tracking performances of "Boy" dataset

Tracking Framework	MES of Position	Frames Tracked	Successful?
PF	5.3145	90/512	N
PSO based Tracker	4.3123	278/512	N
QPSO based Tracker	2.2851	512/512	Y

Fig. 6(a):" Sylvester" dataset, the object undergoing illumination variation, rotation, pose and scale variation

Fig. 6(b):"Jumping" dataset, object undergoing fast motion and motion blur

Fig. 6 (c):"Fish" dataset, object is static with illumination variation, and the camera is abruptly moving

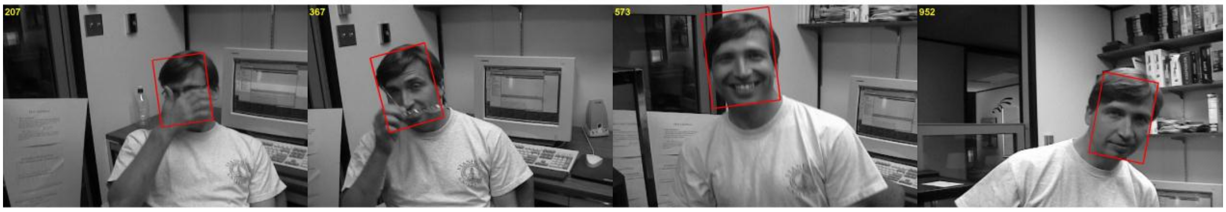


Fig. 6(d):”Dudek” dataset, the object undergoing scare and illumination, partial occlusion, fast motion rotation and background clutters

Fig. 6: Tracking results of different scenes

5.2 Experiments on Challenging Image Sequences

In this section, in order to further evaluate the performance of the sequential QPSO based tracking framework, we adopt eight challenging image sequences dataset from previous work [13]. The challenges of these sequences include partial occlusion, illumination variations, pose change, background clutter, motion blur and so on. All the results are displayed in Fig. 6.

The first video is “Sylvester”, shown in Fig. 6(a), contains a doll moving in changing lighting conditions, pose, and scale. The result shows that, our tracking algorithm is able to track the object as it experiences large pose change (#65, #272, #364, #521, #550), a cluttered background (#65, #450,#521), scale change (#65, #225), and lighting variation (#225, #364, #450).

Results in Fig. 6(b), demonstrate that the proposed tracker performs well when the tracked objects undergo fast and abrupt motion. In Fig. 6(b), the object is also under quick appearance variation (#129, #197, and #227) and motion blur(#266 and #354).

Sequence in Fig. 6 (c) is a static object with camera motion. Besides, the object is under illumination variation (#157, #183, #310, #388, #437, and #453). Once initialized in the first frame, our algorithm is able to track the target object correctly.

The last dataset, “Dudek”, describes a person undergoing large pose, expression, appearance, and lighting change, as well as partial occlusions. This is a hard dataset and the time of the video is long. The result in Fig. 6 (d) shows that our tracker finishes the task successfully.

6 Conclusion

In this paper, we improve the tracking algorithm based on PSO and propose a sequential quantum-behaved particle swarm optimization (sequential QPSO) framework for visual tracking. The proposed tracking framework can deal with tracking tasks with objects undergo pose, illumination, scale, appearance variation, partial occlusion, abrupt and fast motion and other environments. The appearance model we used is a MOG (mixture of Gaussian) based model which is updated during the tracking process. In experiments, the sequential QPSO based tracker has a favorable performance compared with the particle filter and the sequential PSO based tracker both in terms of accuracy and robustness, demonstrating that the sequential QPSO based tracking framework is an effective framework for visual tracking.

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