Optimal Analysis of Target Dynamic Tracking Strategy Based on Computer Vision

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***Abstract*—Computer vision is a highly intensive interdisciplinary subject which combines artificial intelligence and advanced algorithms, and its target tracking has become a hot research topic at present. At the operational level of target tracking, PF(Particle Filter) technology has its own technical advantages in processing image interpretation interference and target movement change. In order to meet the dual requirements of dynamic intelligent capture and timeliness at the next moment of target tracking, on the one hand, BPNN(Back Propagation Neural Network) technology is introduced to improve the diversity of particles and improve the accuracy of target information at the next moment; on the other hand, PSO(Particle Swarm Optimization) technology is introduced to prevent particle degradation and quickly find the global optimal solution of particle information. The simulation results show that the method of using BPNN + PSO to improve the particle filter algorithm, not only improves the accuracy of target tracking information, but also reduces the time-consuming of target tracking.**

Keywords—Computer vision; Target tracking; particle filter; BPNN; PSO

I. INTRODUCTION

As an interdisciplinary and knowledge-intensive technology, computer vision is widely used in image processing, pattern recognition, target tracking and other fields[1]. Among them, target tracking plays an important role in computer vision research system[2,3]. Target tracking can be understood as acquiring relevant features in frame sequence, such as contour, texture, color and gradient, and constructing related problems, so as to accurately locate the position of the target in the frame sequence and obtain the target motion trajectory. At the same time, it provides a key data source for motion analysis.

In the process of dynamic target tracking, the timeliness and accuracy of target information acquisition is a very challenging systematic research work. Considering the actual dynamic target tracking process, the target change has the characteristics of non-linearity and randomness, and the particle filter(PF) technology has certain technical advantages in obtaining the state information of the actual moving target[4]. However, particle filter has two shortcomings. A large number of samples lead to a large amount of computation and resampling process will lead to sample degradation[5].

In order to make up for the shortcomings of particle filter itself, the algorithm from two dimensions will be optimized, and then the optimization and analysis of target dynamic tracking strategy based on computer vision will be realized[6].

II. DESIGN OF OPTIMIZATION ANALYSIS FRAMEWORK FOR TARGET DYNAMIC TRACKING STRATEGY BASED ON COMPUTER VISION

Aiming at the optimization design of dynamic target tracking strategy in computer vision, particle filter is used to construct the state and observation model of the target; back propagation neural network(BPNN) is used to adjust and update the weights to improve the diversity of particles and optimize the dynamic tracking target information[7]. The global optimization ability of particle swarm optimization (PSO) is used to perform the speed-displacement model operation on the resampled particle set to improve the efficiency of locking dynamic tracking targets[8].

The specific framework design is shown in Fig. 1.

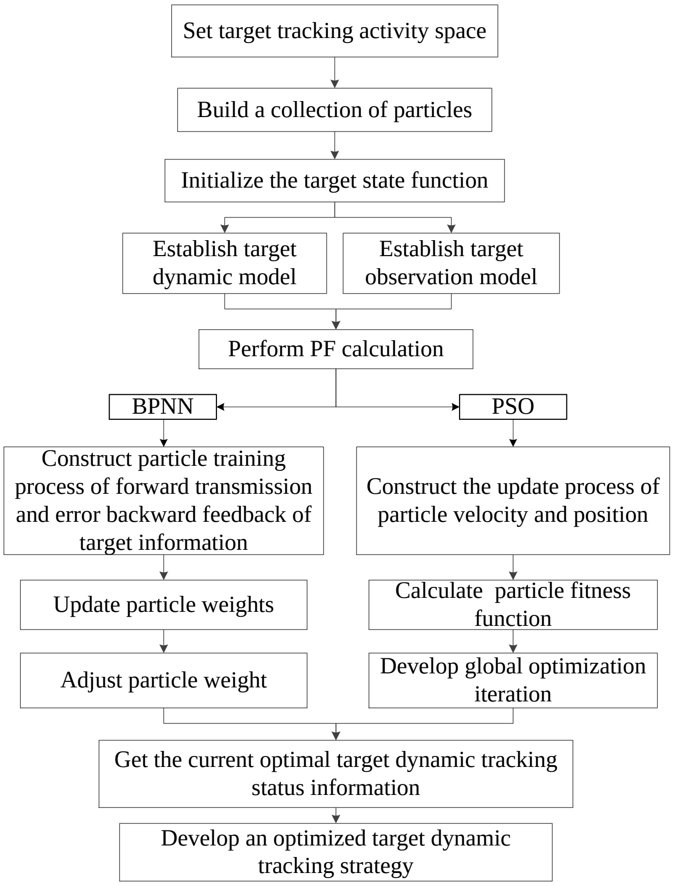

Fig.1 Analytical framework for optimizing target dynamic tracking strategy based on computer vision

III. MATHEMATICAL MODEL OF TARGET TRACKING BASED ON OPTIMIZED PARTICLE FILTERING

A. *Mathematical Modeling of PF*

The basic principle of particle filter: Firstly, according to the empirical condition distribution of the system state vector, a set of random samples is generated in the state space, these samples are called particles; then, according to the observation quantity, the weight and position of particles are constantly adjusted, and the initial empirical condition distribution is corrected by adjusting the information of the particles. It can be applied to any dynamic state space model. Particle filter is particularly important in dealing with non-linear and non-Gaussian problems[9].

a. Target Motion Model

Assuming that the motion of the target from the current moment t_{now} position to the next moment t_{next} position is entirely driven by noise, the equation of motion in three-dimensional space is shown in the formula (1).

$$Target_{t_{next}} = Target_{t_{now}} + V_{t_{now}} T + \frac{1}{2} a_{t_{now}} T^2 + N_{t_{now}} \tag{1}$$

In the formula (1), $Target_{t_{next}}$ represents the state information vector of the target at the next moment, $Target_{t_{now}}$ represents the state information vector of the target at the current moment, T is the sampling period of target tracking, $V_{t_{now}}$ represents the current velocity vector of the target, $a_{t_{now}}$ represents the current acceleration vector of the target, $N_{t_{now}}$ represents the noise vector of the target at the current position.

b. Target observation model

Since each particle represents a possible prediction of the target state, the purpose of system observation is to obtain a larger weight for particles that are close to the actual situation and a smaller weight for particles that are far from the actual situation.

Assume that the probability density function of the target observation is shown in formula (2).

$$p(Target) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{D^2_{Target}}{2\sigma^2}\right) \tag{2}$$

In the formula (2), σ is the Gaussian variance, and D_{Target} is the distance between the target observation state value and the true value.

B. *Model optimization of particle filter based on BPNN*

a. Model optimization of particle filter based on BPNN

BPNN, also known as error Back Propagation algorithm learning process, is mainly divided into two processes: one is the forward propagation of information, the other is the reverse propagation of error[10]. The forward transmission of information is mainly the neurons in the input layer to accept the external information, and then passed to the neurons in the middle hidden layer. The hidden layer can effectively transform the information, and finally the hidden layer will transmit the information to the output layer, thus realizing the forward transmission of information. The error direction transfer is that the error passes through the output layer, and the weight of each layer is adjusted and modified by the gradient descent method, so as to realize the reverse transfer to the hidden layer and the input layer.

Particle filter model optimization principle based on BPNN: through continuous forward transmission of particle state information and reverse transmission of particle state error, the particle weight is repeatedly adjusted, and the training and learning process of the neural network is iterated. In the process of solving the minimum value of particle state error through BPNN, the error is continuously changed along the direction with negative gradient by means of gradient descent method after repeated training, and finally converges to the minimum point, and the speed of convergence is related to the given initial value and the function used for transmission.

Particle filter model weight optimization steps based on BPNN are as follows.

a. Suppose the particle input sample of the tracking target is $P_I=[p_{I1}, p_{I2,\ldots,} p_{In}]$, and the final output tracking result is $P_O=[p_{O1}, p_{O2},\ldots,p_{om}]$.

b. The BPNN hidden layer output is used in the particle filter calculation is shown in the as formula (3).

$$H_j = f\left(\sum_{j=1}^{m} \omega_{ij} p_{Ii}\right) \tag{3}$$

In the formula (3), H_j is the output of the ith node of the hidden layer, ω_{ij} is the link weight of the input layer and the hidden layer, p_{Ii} is the input of the ith particle of the particle input layer, $f()$ is the activation function, $f(x)=1/(1+e^{-x})$, $f(x) \in (0,1)$.

c. According to the output H_j of the hidden layer, the result value of the output layer is calculated.

$$P_{Hk} = f\left(\sum_{j=1}^{m} \omega_{jk} H_j\right) \tag{4}$$

In Formula (4), ω_{jk} is the link weight of the hidden layer and the output layer.

d. Calculating particle sample error

$$e_k=P_O-P_{Hk} \tag{5}$$

In formula (5), P_O is the expected output of the algorithm, and P_{Hk} is the predicted output of the hidden layer calculation.

e. According to the error, gradient descent is used to adjust and correct the weights of each layer

$$\Delta\omega_{ij} = \omega_{ij}(t_{next}) - \omega_{ij}(t_{now}) = -\sum_{q=0}^{Q} \varepsilon \frac{\partial \sum_{k=1}^{m} e_k}{\partial \omega_{ij}} \tag{6}$$

In formula (6), ε is the correlation coefficient of BPNN learning.

C. *Model optimization of particle filter based on PSO*

The problem of sample depletion caused by the resampling work is one of the important defects of particle filter technology. To compensate for the above defects, PSO is introduced. PSO is used to manipulate the resampled particle set and make the particles cooperate intelligently[11]. PSO has good global and local optimization ability to continuously update the position and velocity of the particle, and better approximate the true posterior probability distribution of the system.

Particle filter model optimization principle based on PSO: after introducing PSO, if the particle sets are all distributed near the real state, the fitness of each particle in the particle swarm is very high. Conversely, if the individual optimal values for each particle in the particle swarm and the global optimal value of the particle swarm are low, the particles are not distributed near the real state. At this time, particle set uses PSO to constantly update the speed and position of each particle according to the optimal value, so that the particle is constantly approaching the real state. By moving the particle swarm closer to the optimal particle, PSO essentially drives all the particles to move to the high likelihood probability region.

Particle filter model weight optimization steps based on PSO are as follows.

a. Define the particle fitness function

The particle swarm searches for the optimal solution by updating the speed to find the optimal position. The particle population is regarded as a filter particle, the fitness function is regarded as the posterior probability function, and the particle swarm algorithm is integrated into the particle filter. The fitness function of the target tracking is shown in the formula (7).

$$Fitness_{Target} = \exp[-\frac{1}{2\sigma}(V_{now} - V_{pre})^2] \tag{7}$$

In the formula (7), σ is the Gaussian error of the target observation, V_{now} is the observed value of the current target observation and V_{pre} is the predicted observation value.

b. Start the resampling process and calculate the cumulative weight of the particle sample set

c. Carry out particle filter optimization work

The PSO global optimal solution iteration search is carried out, and the particle weight dynamic adjustment strategy is used to realize that the current particle value is constantly compared with the current optimal value in the search process. The velocity and position iteration formula of PSO algorithm is used to update the speed and position of each particle, so that the particle moves to the real state of the system.

$$[(p_t^i, \omega_t^i)_{i=1}^N] = PSO\_PF[(p_t^i, \frac{1}{N})_{i=1}^N, p_{Rt}] \tag{8}$$

In the formula (8), $\frac{1}{N}$ represents the initial weight value of N particles, p_t^i represents the state information of the ith particle at time t, ω_t^i represents the weight of the ith particle at time t, p_{Rt} represents real state information of real target dynamic tracking.

d. According to the re-adjusted particle weight, the particle filter global state information is re-assigned to the target dynamic tracking motion model and observation model

IV. Simulation and Analysis

A. Description of related parameters in the simulation environment

The description of the relevant parameters of the simulation environment of the target dynamic tracking strategy optimization based on the computer vision is shown in Table 1.

TABLE.1 EXPLANATION OF PARAMETERS RELATED TO SIMULATION ENVIRONMENT

NO.	Parameter	Value
1.	Target tracking activity space	2*2*2m^3
2.	Target tracking frame rate	50fps
3.	Code rate	1000kbps
4.	Resolution ratio	2K
5.	Number of particles	100

B. Simulation experiment analysis

Target tracking response time and tracking accuracy are used as two dimension evaluation indicators. The performance of target dynamic tracking strategy based on computer vision is compared in PF, PF with BPNN, PF with PSO, PF with BPNN+PSO.

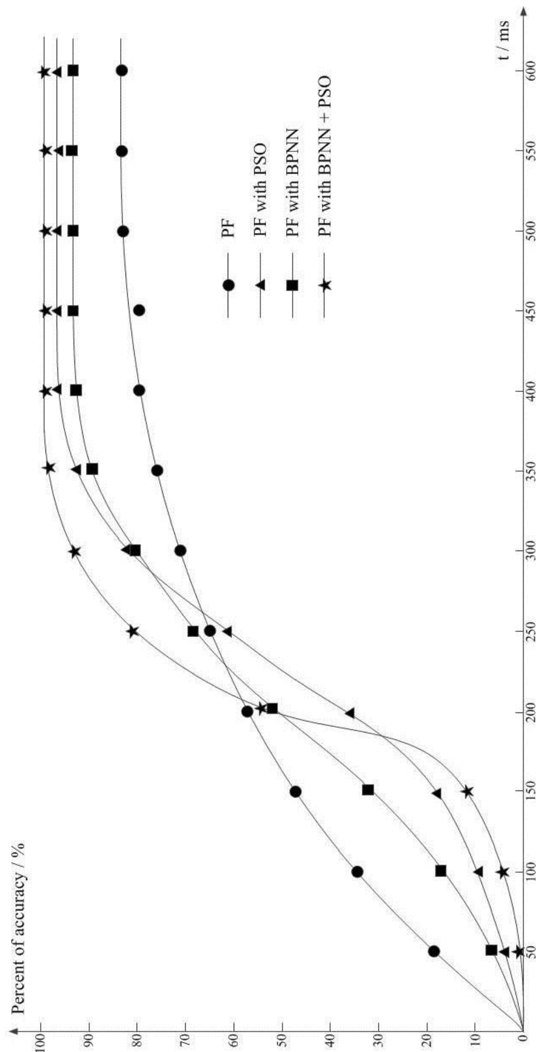

Fig.2 Comparison of simulation effects

It can be seen from Fig. 2 that PF: when $t \approx 541.6$ ms, the degree of approaching the true value of target tracking is 82.8%; PF with PSO: when $t \approx 424.9$ ms, the degree of approaching the true value of target tracking is 94.1%; PF with BPNN: when $t \approx 441.3$ ms, the degree of approaching the true value of target tracking is 90.9%; PF with BPNN + PSO: when $t \approx 379.5$ ms, the degree of approaching the true value of target tracking is 98.6%.

Through the above comprehensive comparison, PF with BPNN + PSO has obvious advantages over PF, PF with PSO and PF with BPNN in terms of response time and target tracking true value fitting.

V. CONCLUTION

Based on the optimization of target dynamic tracking strategy in computer vision, this paper improves PF method by combining BPNN and PSO artificial intelligence method. The improved method effectively balances the contradiction between the degree of approaching the real dynamic target and the response time of target tracking. It not only improves the accuracy of target tracking information, but also reduces the time-consuming of target tracking.

This achieves the goal of optimizing the target dynamic tracking strategy. At the same time, the joint innovation mode of optimizing the existing technology by multiple algorithms will become the development trend of interdisciplinary research in the future.

[1] Szeliski R. Computer Vision[M]. 2011.

[2] Mahmoudi N, Ahadi S M, Rahmati M. Multi-target tracking using CNN-based features: CNNMTT[J]. Multimedia Tools & Applications, 2018(9):1-20.

[3] Ying Z, Su X. Performance Analysis of a Moving Target Tracking Method Based on Computer Vision[C]// Eighth International Conference on Measuring Technology & Mechatronics Automation. 2016.

[4] Khithov V, Petrov A, Tishchenko I, et al. Toward Autonomous UAV Landing Based on Infrared Beacons and Particle Filtering[M]// Robot Intelligence Technology and Applications 4. 2017.

[5] Liu B , Jin Y . A Particle Filter based Multi-Objective Optimization Algorithm: PFOPS[J]. 2018.

[6] Lin Z , Chen G , Guo W , et al. PSO-BPNN-Based Prediction of Network Security Situation[C]// International Conference on Innovative Computing Information & Control. IEEE Computer Society, 2008.

[7] Sehgal S . uman Activity Recognition Using BPNN Classifier on HOG Features[C]// 2018 International Conference on Intelligent Circuits and Systems (ICICS). IEEE Computer Society, 2018:286-289.

[8] Havangi R. An adaptive particle filter based on PSO and fuzzy inference system for nonlinear state systems[J]. Automatika, 2018, 59(1):94-103.

[9] Karkus P , Hsu D , Lee W S . Particle Filter Networks with Application to Visual Localization[J]. 2018.

[10] Ye J, Hu D, Xia G, et al. An advanced BPNN face recognition based on curvelet transform and 2DPCA[C]// International Conference on Computer Science & Education. 2013.

[11] Messerschmidt L, Engelbrecht A P. Learning to play games using a PSO-based competitive learning approach[M]// Learning to Play Games Using a PSO-Based Competitive Learning Approach. 2004.