Adaptive Multi-feature Fused Particle Filtering Algorithm in Player Tracking Model

Shenshen Liu, Pu Zhou

College of Physical Education, Langfang Teacher's University,
Langfang 065000, Hebei, China

Yubing Wang

Oriental College, Beijing University of Chinese Medicine,
Langfang 065001, Hebei, China

Abstract
Standard particle filtering algorithm still exists the problems of low precision and high sensitiveness to the outside condition in the player tracking in sports video. In view of this situation, this paper puts forward a target tracking model based adaptive and multi-feature fused particle filtering algorithm. It firstly establishes the model with color histogram distribution to realize the distribution of target so as to improve the performance in the problem of non-rigidity, scale and rotation, then optimizes the target posture and illumination with a first-in first-out target histogram with L sequence length, and finally optimizes its hotspot in the particle filter to accelerate the operation. Experiment results show that the proposed algorithm has a better tracking effect in the basketball, volleyball and football sports videos.
Key words: PARTICLE FILTERING ALGORITHM, PLAYER TRACKING, ADAPTIVE MULTI-FEATURE FUSION, COLOR HISTOGRAM, ASYMPTOTIC PROPERTY OPTIMIZATION

1. Introduction

Moving object tracking is a core subject in computer vision field whose core idea is to quickly and accurately capture the moving object with the comprehensive utilization of image processing and video analysis techniques [1]. With the development of modern sports training level, how to conveniently understand the athlete's training level and extract the motion parameter of athletes and provide help for the athlete's daily training, has become a urgent affair for the majority of sports science and technology workers [2]. In order to obtain all kinds of technical parameters of athletes in training, the traditional method is to add various sensors in the athlete's body to obtain the motion parameters. However this method doesn’t consider the influence of sensor technology on the action of athletes. Therefore, it is an urgent need to provide a new technical means to better gain athletes’ motion parameters [3].

Scholars at home and abroad have conducted a lot of researches on moving object tracking problem. Haritaoglu et al. established the statistical model for each pixel in the scene with the use of maximum difference and maximum and minimum intensity of two consecutive frames, and periodically updated background. This algorithm can quickly adapt to the scene changes and precisely detect the moving target, but it cannot achieve the complete extraction for smaller target [4]. Stauffer and Grimson proposed a background subtraction algorithm based on adaptive mixed Gauss background model. Through the hybrid Gauss modeling for each pixel and updating the model parameters by pixel iteration, the influence of illumination change and branches sway is effectively overcome, but this algorithm is easy to generate isolated noise when dealing with some complex background, which causes inaccuracy of target test together with complex calculation [5]. Li Jinhui studied a kind of moving object detection method based on optical flow field and wavelet image fusion. This algorithm has better target segmentation effect, but the complete contour extraction of moving target and connectivity still have some limitations [6]. Tomas et al used the color distribution of each pixel in the image to establish the regional model, and tracked the moving object with the help of edge contour features. This algorithm is better for target tracking in the rotation, translation and contraction changes, but it still has large amount of calculation [7]. Koschan proposed a moving object tracking algorithm based on adaptive color model which can basically achieve effective tracking of targets, but when the target color is close to background color or the target color changes greatly, the tracking accuracy is very low [8]. Based on a watershed image segmentation algorithm to obtain contour points of the moving object, Sang-Cheol used the maximum likelihood estimation method to predict the target position in the next time, and accurately obtain the position information of the target through the Hausdorff distances. The algorithm can overcome partial influence of occlusion and light interference, but the real-time function is poor [9]. Generally speaking, the domestic and foreign scholars have made some achievements in the research on the intelligent video surveillance detection and tracking of moving target, but there are still many challenges, such as the size and shape change, mutual occlusion, velocity difference, the effect of illumination change and shadows and other external factors.

According to the requirement of athletes target tracking in the sports video, this paper put forward a tracking model based on adaptive and multi-feature fused particle filter algorithm. It optimized the modeling approaches, asymptotic property, object posture, luminance effect and operation efficiency of particle filter algorithm.

2. Particle filter algorithm analysis

Compared with Kalman filter, particle filter is a nonlinear filter algorithm. It is the optimal regression Bayes filtering algorithm based on Monte Carlo simulation technology [10].

Suppose the state space model of the dynamic system is,

$$\begin{cases} x_k = f_k(x_{k-1}, v_k) \\ y_k = h_k(x_k, v_k) \end{cases} \tag{1}$$

where $x_k \in R^n$ is a system state, $y_k \in R^n$ is the measured value, $v_k \in R^n$ and $w_k \in R^n$ is the independent and identically distributed system noise sequence and mensuration noise sequence.

The principle of Bayes filter is to use all the known information to estimation the posterior probability density of the system state variable. It firstly uses the system model to predict the prior probability density, then adjusts it with latest mensuration value and finally gets the posterior probability density. Through the mensuration data $y_{1:k}$ to recur the confidence $p(x_k|y_{1:k})$ of state x_k at different values, the optimal estimation is obtained. Therefore, Bayes filter includes prediction and updating.

(1) Prediction

If the initial probability density of state is $p(x_0|y_0) = p(x_0)$ and the probability density of state at time $k-1$ is $p(x_{k-1}|y_{k-1})$, then for first order Markoff process(the state at $k-1$ only relates to the state at $k-2$), according to the Chapman-Kolmogorov equation the prediction equation at k is,

$$p(x_k|y_{1:k-1}) = \int p(x_k|y_{k-1})p(x_{k-1}|y_{1:k-1})dx_{k-1} \tag{2}$$

That is, the prior probability of mensuration value at k is not included, and calculated from the state transfer probability $p(x_k|x_{k-1})$.

(2) Updating

This step is an amendatory step with the latest mensuration value y_k and the prior probability $p(x_{k-1}|y_{1:k-1})$ at k to realize the derivation of $p(x_k|y_{1:k})$.

The latest mensuration value is acquired with the help of Bayes equation $p(a|b)=\frac{p(b|a)p(a)}{p(b)}$,

$$p(x_k|y_{1:k})=\frac{p(y_{1:k}|x_k)p(x_k)}{p(y_{1:k})} \tag{3}$$

In order to get out the y_k, $p(y_{1:k}|x_k)$ and $p(y_{1:k})$ can be represented as,

$$p(y_{1:k}|x_k)=p(y_k,y_{1:k-1}|x_k) \tag{4}$$

$$p(y_{1:k})=p(y_k,y_{1:k-1}) \tag{5}$$

Adding Equation (3) and (4) into Equation (2), there is,

$$p(x_k|y_{1:k})=\frac{p(y_k,y_{1:k-1}|x_k)p(x_k)}{p(y_k,y_{1:k-1})} \tag{6}$$

According to conditional probability density expression $p(a|b)=p(b|a)p(a)$,

$$p(y_k,y_{1:k-1})=p(y_k|y_{1:k-1})p(y_{1:k-1}) \tag{7}$$

According to joint probability density formula $p(a,b|c)=p(a|b,c)p(b|c)$, there is,

$$p(y_k,y_{1:k-1}|x_k)=p(y_k|y_{1:k-1},x_k)p(y_{1:k-1}|x_k) \tag{8}$$

From Bayes equation,

$$p(y_{1:k-1}|x_k)=\frac{p(y_k|y_{1:k-1})p(y_{1:k-1})}{p(x_k)} \tag{9}$$

Adding Equation (6), (7) and (8) into Equation (5), there is,

$$p(x_k|y_{1:k})=\frac{p(y_k|y_{1:k-1})p(x_k|y_{1:k-1})p(y_{1:k-1})p(x_k)}{p(y_k|y_{1:k-1})p(y_{1:k-1}|x_k)} \tag{10}$$

Because each mensuration value is independent, then

$$p(y_k|y_{1:k-1},x_k)=p(y_k|x_k) \tag{11}$$

Adding Equation (10) into (9), there is,

$$p(x_k|y_{1:k})=\frac{p(y_k|x_k)p(x_k|y_{1:k-1})}{p(y_k|y_{1:k-1})} \tag{12}$$

The whole recursion process from prior probability density to posterior probability density is realized from Equation (2) to Equation (12).

The particle filtering algorithm proposed by Gordon introduced the similar Bayes method into the discrete-time recursive filtering. The core of this algorithm is to establish posterior probability density function based on sample. We sample the particle from the posterior probability density function $p(x_{0:k}|z_{1:k})$ and express the particle swarm set with $\{x_{0:k}^i,\omega_k^i\}_{i=1}^N$. Here, $\{x_{0:k}^i, i=1,\ldots,N\}$ is the support sample set, $\{\omega_k^i, i=1,\ldots,N\}$ is the corresponding weight, $\sum_{i=0}\omega_k^j=1$. The posterior probability can be expressed approximately as,

$$p(x_{0:k}|z_{1:k})\approx\sum_{i=0}^{N}\omega_k^j\delta(x_{0:k}-x_{0:k}^i) \tag{13}$$

Therefore, the discrete method with weight can be used to express the real posterior probability $p(x_{0:k}|z_{1:k})$. Then the mathematical expectation can be calculated,

$$E(g(x_{0:k}))=\int g(x_{0:k})p(x_{0:k}|z_{1:k})dx_{0:k} \tag{14}$$

Approximated by,

$$E(g(x_{0:k}))=\sum_{i=0}^{N}\omega_k^j\delta(x_{0:k}^i) \tag{15}$$

3.Adaptive and multi-feature fused particle filter algorithm

3.1.Target modeling based on color histogram

There are many methods that use the adoptive histogram to track the target from the literature. Chen et al gave the high tolerance model based on probability distribution. In fact, they established the model through Gauss distribution and adjusted the parameters in the condition of changing the lamination.

This paper put forward an adaptive particle filter tracker based on color. They realized the distribution of target through color histogram so as to improve the performance in the problem of nonrigidity, scale and rotation.

Because the color histogram can effectively deal with the rotation, partial cover and non-rigidity problem, this paper takes the color histogram to model. It took the oval to model the object. This histogram can be calculated from other color space or simple grey space with the main selection method of inputting series. When the histogram is adopted, the partial lost space information can be processed. Both Mmmiaro and Perez introduced the weight of different pixel of the oval to increase the stability of color histogram. That with small weight was far away from the center of the oval due to the different importance for a subject described by the entire pixel in a similar region. They took the weighting function to sample the target to establish the histogram, namely,

$$K(r)=\begin{cases}1-r^2 & r<1\\ 0 & otherwise\end{cases} \tag{16}$$

Here, r represents the distance from the particle to the center. For each acceptor U, the target model is updated with following equation.

$$q_t^{(u)}=(1-\alpha)q_{t-1}^{(u)}+\alpha p_{E[st]}^{(u)} \tag{17}$$

Where α is the weight of state histogram to objective model q_{t-1}. In order to keep constant of the model when the tracker misses the tracking object, the condition $\pi_{E[xt]} > \pi_{thres}$ should be met where $\pi_{E[xt]}$ is the average observation probability and π_{thres} is the threshold. Threshold π_{thres} and parameter α is constant here. Jcaquot proposed that when the scene changed a lot, the model should be updated. Therefore, they came up with the idea that when $\pi_{E[xt]} > \pi_{thres}$, the model histogram was updated.

3.2. Asymptotic property optimization based on histogram parameter

The number of the histogram box is a key element and should be determined automatically. Much more boxes in the histogram cannot deal with lamination change or shape change of model, which fails to track the target. Conversely, little boxes don't have good identification ability to the target, and the tracking also fails.

In most current algorithms, the number of box is arbitrary and constant in the whole tracking process. Nothing can prove the classification is optimal when we want to estimate the density of n samples. If we can find an optimal classification, the tracker will be very effective.

There were many ways to determine the optimal box number through data. These methods are based on approximation with some disadvantages. For example, when the sample is small, due to the gradualness of the particle, these methods will lose their effectiveness. In addition, many methods require determining the prior density information. The statistic method of a model selection is that the simpler model will predict well if both of them can well accord to the given data. Therefore, this paper will briefly summarize the determination of optimal boxes in the histogram.

The goal is to make some partition $\{I_1,\cdots,1_k\}$ in $[0,1]$ can form k interval with same length and to find the histogram estimation f. $X_1, X_2, \cdots, X_n$ is the n sample of which we want to estimate the density f. K is given by following equation.

$$K = \arg\max_K (L_n(K) - penalty(K)) \quad (18)$$

Where $L_n(K)$ is the log-likelihood function of k boxes in histogram, namely

$$L_n(K) = \sum_{j=1}^{k} M_j \log(\frac{KM_j}{n}) \;\; M_j = \sum_{i=1}^{n} 1_j(X_i) \quad (19)$$

1_j is the index function, defined by following expression,

$$1_j(x) = \begin{cases} 1 & if \quad x \in 1 \\ 0 & otherwise \end{cases} \quad (20)$$

Punishment function is given as,

$$penalty(K) = K - 1 + (\log(K))^{2.5} \quad for \;\; K \geq 1 \quad (21)$$

This is a typical model selection method, making a well compromise between the complex function and the fidelity of data.

3.3. Object posture and illumination optimization

To overcome the posture change of the tracking object and illumination change, this paper considers a target histogram with first-in first-out queue L. The histogram is calculated by the weighted average of each box histogram. The weight of each histogram is the index and applied in each channel. This model can be calculated from the recursive operation. Suppose $h(j)$ is the histogram of queue j, and at the same time, $H(t)$ represents the histogram at time t, as follows,

$$H(1) = h(1) \quad (20)$$

$$H(t) = \alpha \times h(j-1) + (-\alpha) \times H(t-1) \quad (21)$$

Thus, the latest histogram will cause effect on the histogram of the whole model. In a tracking method, new observed results will be added into each step to update the estimated state. Therefore, we need a similarity measure based on color distribution. A popular method is to give Bhanacharyya algorithm between two distribution $p(u)$ and $q(u)$,

$$p[p,q] = \sum_{u=1}^{m} \sqrt{p(u)\square q(u)} \quad (22)$$

Generally, this paper takes the Gauss density to deal with the likelihood function of the measured color histogram, as follows.

$$p(y_t | x_t) = \frac{1}{\sqrt{2\pi\delta}} e^{\frac{1-p[p,q]}{2\sigma^2}} \quad (23)$$

The standard deviation of Gauss density is a flexible parameter σ. It is known that choosing an average state as a target is not a good solution, for it very depends on the spread of each frame and the number of particle. This paper selected the most similar particle as the target. Resampled particle is based on their likelihood function and acceptable weight.

3.4. Operation efficiency optimization

In the particle filter, the hotspot of the procedure can be parallelized to accelerate the operation. The sampling algorithm of particle filter can be described as,

(1) $\left[\{x_k^i, w_k^i\}_{i=1}^{N_s}\right] = SIS\left[\{x_{k-1}^i, w_{k-1}^i\}_{i=1}^{N_s}, Z_k\right]$

(2) For $i = 1, 2, \cdots, N_s$, to calculate the sample particle $x_k^i \cdot q(x_k | x_{k-1}^i, Z_k)$

(3) To normalize the weight $\sum_{i=1}^{N_s} w_k^i = 1$

And the pseudo-code of the resampling algorithm is described as,

(1) $\left[\left\{x_k^i, w_k^i, i^j\right\}_{j=1}^{N_s}\right] = \mathrm{Re}\,sample\left[\left\{x_k^i, w_k^i\right\}_{i=1}^{N_s}\right]$

(2) To initialize the probability cumulative distribution function, $C_1 = 0$

(3) For $i = 2 : N_s$, the probability cumulative distribution function is calculated, $C_1 = C_{i=1} + w_k^i$

(4) To set $i = 1$

(5) To take an initial point $u_1 \cdot U\left[0.N_s^{-1}\right]$ following the uniform distribution

(6) For $j = 1 : N_s$, to move in the probability cumulative distribution function $u_j = u_1 + N_s^{-1}(j-1)$, when $u_j > c_i$, $*i = i+1$, the sample is valued as $x_k^{j^*} = x_k^i$, the weight is value as $w_k^j = N_s^{-1}$, and the index is valued as $i^j = i$.

Finally, a complete particle filtering algorithm can be described as,

Initialization: When $k = 0$, N uniformed distributed particle set S_{k-1} is sampled for the target and the target model is established.

$$\hat{q} = f\sum_{i=1}^{I} k\left(\left\|\frac{x_0 - x_i}{a}\right\|^2\right)\delta\left[h(x_i) - u\right] \qquad (24)$$

It is known that the tracking result is $S_{k-1}(E)$ at time $k-1$, the particle set $S_{k-1}(i)$, the weight $w_{k-1}(i)$, the cumulative probability $C_{k-1}(i)$, $i = 1.\cdots, N_{k-1}$, particle number N_{k-1} and the color modulate q_N^k at time k.

The specific steps are as followed.

Resampling S_{k-1} according to the weight $w_{k-1}^{(n)}$ of each sample particle

Firstly calculating normalized cumulative probability function C_{k-1} to generate uniform distributed random number $r \in [0,1]$, then searching the minimum j that meets $C_{k-1}^{(j)} \geq r$, and finally $S_{k-1}^{(n)} = S_{k-1}^{(j)}$.

Solving the particle set at time k from the particle set $S_{k-1}^{(n)}$ at time $k-1$ through dynamic equation $S_k^{(n)} = AS_{k-1}^{(n)} + v_{k-1}^{(n)}$ where $v_{k-1}^{(n)} \cdot N(0,\sigma^2)$

State estimation

Calculating weighted average state $S_k(E) = \sum_{n=1}^{N} w_k^{(n)} S_k^{(n)}$.

4. Simulation experiment

To test the effectiveness of the proposed algorithm, this paper conducted the simulation experiment. We made the athletes target tracking test on the basketball, volleyball and football video.

Figure 1. Basketball player video object tracking results

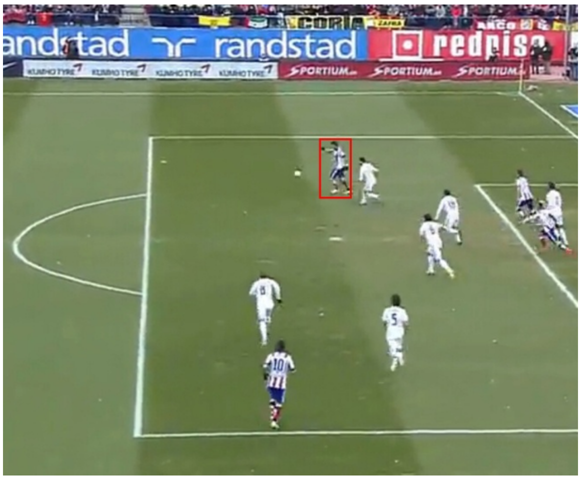

Figure 2. Football player video object tracking results

Figure 3. Volleyball player video object tracking results

From the simulation result, the proposed player target tracking model based on adaptive multi-feature fused particle filter algorithm has better application performance.

5. Conclusions

Moving target tracking technology plays an important role in the area of sports video analysis. Through the real-time tracking, the moving trail of an athlete is analyzed to judge the standardization of his action. For example, in the diving, the moving track of a player is analyzed to judge whether his taking off, tuck dive and entry is correct and continuous. In the weightlifting training, the movement track of the barbell is tracked to help analyze the player's essential of exercise. This paper put forward an improved athlete tracking model base on the adaptive and multi-feature fused particle filter algorithm. The simulation experiment shows that the proposed algorithm has good performance.

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