Basketball player tracking model of hierarchical multiple feature fusion particle filter

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Abstract
As the standard particle filter algorithm has the problems that the tracking accuracy is not so good and the robustness is poor in the application of motion object detection, this paper proposes a basketball player tracking model based on hierarchical multiple feature fusion particle filter. First of all, use the color histogram distribution to model the target, and use a weighted function to take samples of target to establish the histogram, and then optimize the progressive nature of the histogram parameters to ensure the fidelity of complex function and data, then according to the characteristics of the shape, use the SIFT to execute shade optimization for the particle filter, finally construct the basketball player target tracking model incorporating the above methods. Simulation experiment shows that the improved algorithm shows excellent tracking performance whether there is a shelter or not.
Key words: PARTICLE FILTER, HIERARCHICAL, MULTIPLE FEATURE FUSION, ATHLETE TRACKING

Introduction

Detection and tracking players in sports video has very important significance, it is helpful to realize the automatic analysis of sports video, which provide advanced tool and means for the sports training [1].The movement of athletes in sports video is irregular, their attitude changes in the process of movement. Athletes may be similar with the color of the scene, the athletes often exists shading each other. The particularity of sports video brings many challenges to the detection and tracking process [2].

Because of the moving target detection and tracking technology in many areas are playing an very important role, many researchers at home and abroad in recent years launched a lot of research in this respect. The defense advanced research projects agency set up headed by

Carnegie Mellon university and the Massachusetts institute of technology and universities to participate in the visual monitoring major projects VSAM, they mainly research the automatic video understanding technology used in battlefield and ordinary civil scene monitoring [3].The university of Reading in England did the related research of tracking and interaction identification of vehicles and pedestrians[4]. Companies such as IBM and Microsoft also gradually applied the gesture recognition interface based on vision to the using in the business field [5].Moving target detection and tracking technology have been successfully applied to many fields, mainly including: intelligent video surveillance, perceptual user interface, motion analysis, etc. For example, the real-time visual surveillance system can detect and track human body movement developed by university of Maryland, it was applied to the bank, homes and other places[6]. Freeman, etc use the moving target detection and tracking technology to track face and body in video in the perception of the user interface, and understand people's behavior, in order to achieve a more natural way of human-computer interaction [7].Huang etc, using the motion analysis technology based on moving object detection and tracking to analyze the biological characteristics, it was used for long-distance identification and authentication. Moving target detection and tracking technology's application in the field of sports video analysis is becoming more and more widely [8]. Pennsylvania state university CGISD system is developed, and it was used to help the diving coaches and athletes to strengthen the understanding of the whole body posture in the diving process [9].Chen etc, through the analysis of the trajectory judgment of tennis players in the tennis match to judge the volley ball or the bottom line [10]. Tsinghua university "diving posture research based on video analysis" use the target detection and tracking technology in diving video to extract the moving object, and the moving object was video composed, in order to achieve the purpose of eliminating background influence [11].

In this paper, based on the problems existing in the particle filter moving target tracking model, this paper proposes a basketball player tracking model based on hierarchical multiple feature fusion particle filter, and experimental simulation was done on it to verify the validity of the model.

Moving target tracking model based on particle filter

Particle filter is one of efficient tools for dealing with nonlinear and non-Gaussian problems, it has been widely applied in the field of image target tracking. The steps of moving target tracking model based on particle filter are as follows:

A dynamic system state space model is:

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

Among them $x_k \in R^n$ —system state, $y_k \in R^n$ —measurement value, $v_k \in R^n$, $w_k \in R^n$ — independent identically distributed system noise and measurement noise sequences.

Bayesian filtering principle is to use all the known information to estimate the posterior probability density of system state variables, first of all, using system model to predict prior probability density of states, and then using the latest measurement value to correct, finally getting a posteriori probability density. Using the observation data $y_{1:k}$ to recursive confidence coefficient $p(x_k | y_{1:k})$ when the computational state x_k has different value. Through this get the optimal estimates of the status. Therefore, the Bayesian filter including the forecast and update these two steps

(1) Forecast

Assuming the probability density of the system initial state is $p(x_0 | y_0) = p(x_0)$, and the probability density is $p(x_{k-1} | y_{k-1})$ at $k-1$, For the first order Markov process (The state of $k-1$ is related with $k-2$), According to the Chapman Kolmogorov equation, the prediction equation in time k is:

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

Then get the prior probability which is not consist of observed value at time k, and it is calculated by the state transition probability $p(x_k | x_{k-1})$ of the system.

(2) Update

This step is a process of correction, using the latest observation y_k and the prior probability $p(x_{k-1} | y_{1:k-1})$ obtained by last step at k moment to realized the derived of $p(x_k | y_{1:k})$.

After getting the latest observation, by using Bayes formula $p(a|b) = \frac{p(b|a)p(a)}{p(b)}$:

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

In order to bring y_k to independence, $p(y_{1:k} | x_k)$ and $p(y_{1:k})$ can be expressed as:

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

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

Make type (3) and (4) into type (2):

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

By the conditional probability density formula $p(a|b) = p(b|a)p(a)$:

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

By the joint probability density formula $p(a,b|c) = p(a|b,c)p(b|c)$:

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

By the Bayes formula :

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

Make type(6), (7), (8)into type(5) :

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

Due to the observed value is independent, then

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

Make type (10) into type(9) :

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

By type (2) into type (12) realize the recursive process from the prior probability density to posteriori probability density.

Gordon proposes particle filter algorithm, introduce approximate Bayesian method into the discrete time recursive filtering. The core of the algorithm is to construct a posterior probability density function based on sample. Here we sampling particles from the posterior probability density function $p(x_{0:k}|z_{1:k})$, use $\{x_{0:k}^i, \omega_k^i\}_{i=1}^N$ to express the particle swarm collection. Among them, $\{x_{0:k}^i, i=1,\dots,N\}$ is support sample set, $\{\omega_k^i, i=1,\dots,N\}$ is the corresponding weights of particles, and it satisfies $\sum_{i=0} \omega_k^j = 1$, posterior density can be expressed as:

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

(13)

So the discrete weighted approximate representation can be used to represent the true posterior density $p(x_{0:k}|z_{1:k})$, so it also can calculate the mathematical expectation of questions:

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

It is similar to the equation below.

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

Sequential sampling method of basic particle filter algorithm has certain blindness, it is prone to have particle K deficiency phenomenon, with the increase of time, only a minority of particles produced by prior probability at a high likelihood area. Thus importance weights may only focus on a few particles, the use of these particles cannot express a posteriori probability density function, resulting in a decline in the diversity of the particles, though, which can be propagated through the subsequent re-sampling particles, but it still cannot change the problem of insufficient particle diversity, as shown in figure 1.

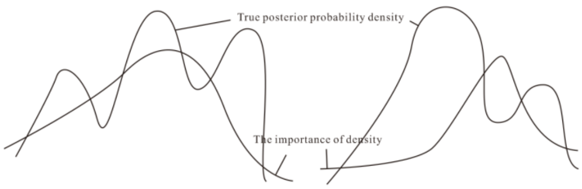

Figure 1. Particle degradation

In target tracking, the particle phenomenon of the lack of diversity will directly affect the target state prediction ability, reduce the estimate performance of likelihood observations result. When particle degradation happens, that is, there are power value particle is multiple choice, it causes the results of the calculation sample contains too many repeated points, lost the diversity of particles, at this time, if there is a big weight of particle deviates from the real target state, it is likely to see the final estimated position of tracking system is deviated, and it has great deviation with the true state of target.Therefore, in order to avoid in the process of tracking particle degradation phenomenon, we need to optimize the particle sampling to increase the diversity of particles and improve the effect of each particle.

Basketball player tracking model based on hierarchical multiple feature fusion particle filter

(1) Histogram optimization based on the color characteristics

Particle filter based on color feature is put forward in this paper, their goal was achieved by color histogram distribution, thus in face of the non-rigid, scale, rotation problems, it increases performance significantly.

Due to the color histogram can effectively deal with the rotation of the target, partial sheltering and non-rigid problems, therefore, this article uses color histogram distribution to model for target. Suppose this distribution can be divided into k boxes. This article uses the oval for modeling. The histogram can through other color space or sample gray space to be calculated, choice of method depends largely on the input sequence. When using histogram, it is able to handle part loss of spatial information, through the different weights of ellipse to increase the reliability of color histogram, the one whose pixel weight is relatively small will be far away from the ellipse center, because the importance of all the pixels in the same area to describe an object is unequal, using a weighted function of target samples to establish histogram,then.

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

Among them r is the distance that is particle to the center. For each receiver U , update their target model with the type:

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

Among them α is the weight that histogram to the target model q_{t-1}. In order to ensure when the tracking lost track objects, the model is not updated, the update conditions $\pi_{E[xt]} > \pi_{thres}$ should be fulfilled at this time, $\pi_{E[xt]}$ is the observation probability of average state, π_{thres} is the threshold value. Here, threshold value π_{thres} and parameter α is stationary.

Then, the progressive nature of histogram parameters should be optimized again, the purpose is to make the partitions $\{I_1, \cdots, 1_k\}$ in $[0,1]$ be k same length intervals, find a histogram estimate f . $X_1, X_2, \cdots, X_n$ are n samples of the unknown density f which we want to estimate. K can be get by the equation bellow:

$$K = \arg\max_K (L_n(K) - penalty(K)) \tag{18}$$

Among them $L_n(K)$ is the log-likelihood function of k boxes in histogram, then

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

1_j is indicator function, it is given by the equation definition below:

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

Penalty function is given by the type:

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

This method is a typical mode selection, the method makes complex function and data fidelity can achieve a good compromise.

(2) SIFT optimization based on shape feature

In view of the particle filter exists real-time and target occlusion, and so on tracking failure problems, based on SIFT features has good matching with target rotation, shield such problems, and particle filter is suitable for the non-Gaussian nonlinear characteristics, this paper uses SIFT to keep out optimized for particle filter. Using color histogram and SIFT to describe target, and using the particle filter to predict the coarse location and target location, SIFT feature matching method for precision positioning.

Feature points matching use two steps to complete, at the beginning, using the minimum Euclidean distance to match, then using projection transformation model to remove the "point" of feature point matching.

(1) Beginning matching of feature points

Feature points' similarity measurement usually adopts the method of distance measurement, such as the Euclidean distance, Markov distance, etc. This article will use the Euclidean distance measurement, this method first obtains the nearest points p_1、 p_2 to feature point p, and calculate the Euclidean distance $Ed(p, p_1)$ 、 $Ed(p, p_2)$ to point p separately. If the specific value of $Ed(p, p_1)$ and $Ed(p, p_2)$ is smaller than threshold value T_d , p and p_1 are a pair of matching feature points.

$$\frac{Ed(p, p_1)}{Ed(p, p_2)} < T_d \tag{22}$$

(2) Removed the "outside point"

On the premise of ignoring imaging abnormalities, and different perspectives of the same scene video image has a one-to-one relationship. Under the homogeneous coordinate system, images $X(x, y, 1)^T$ and $X'(x', y', 1)^T$ meet the projection transformation relationship:

$$X' \sim HX = \begin{bmatrix} h_1 & h_2 & h_3 \\ h_4 & h_5 & h_6 \\ h_7 & h_8 & h_9 \end{bmatrix} X \tag{23}$$

Among them, "$\sim$"represents left and right sides are proportional to the relationship, matrix H has 8 independent variables, the projection transformation relations for specific expression:

$$x' = \frac{h_0 x + h_1 y + h_2}{h_6 x + h_7 y + h_8} \tag{24}$$

$$y' = \frac{h_3 x + h_4 y + h_5}{h_6 x + h_7 y + h_8} \tag{25}$$

From the above formula, only need to get four control points corresponding to match, we can calculate the space transform relation between images. We can use random sampling consistency algorithm for iterative arithmetic to obtain maximum satisfy geometric feature points of the model. Transformation model between Image is calculated by using least square method:

$$Ax = b \Rightarrow x = [A^T A]^{-1} \tag{26}$$

To sum up, the specific steps of feature point extraction and matching based on SIFT optimization are:

(1) Determine the need of the total number of feature points N

According to 0.6% of the size of the input image divided by the original image information entropy to determine the total number of feature points, so as to ensure the operation speed and registration accuracy;

(2) Build DOG pyramid

According to the predefined number of feature points (N_{ol}), extracting the space extreme value point in each group of each layer of the image. The image was divided into n_cell regions, each region to obtain the number of feature points as follows:

$$n\_cell_i = 3\frac{N_{ol}}{n\_cell} \quad (27)$$

(3) Priority curvature filtering whose threshold value is of feature points is $gT_r = 10$ is done on feature points

(4) Calculating feature points' information entropy whose radius is 3σ.
Order is from big to small, then leave the n_cell_i feature points;

(5) Characteristics of extracted feature points are described according to the standard SIFT algorithm;

(6) Using the minimum Euclidean distance and projection model to match feature points;

In order to avoid the reduction of control points number, where the number of control points cannot reach a predefined, it will be extracted to compensate by other block or scale image.

Basketball player target tracking model based on improved particle filter

This article is based on the framework of particle filter algorithm, using the correlation coefficient as a decision-making basis, by default, the particle filter is adopted to basketball player tracking reservation, if it is high correlation, then output target position directly; Otherwise, do the SIFT feature precise matching.

(1) Initialize the target information, manual calibrate target, confirm target position and get target color histogram H_0 and SIFT feature S_0;

(2) Use the particle filter for tracking, get target forecast position and the candidate area target color histogram H' and SIFT feature S';

(3) Pap coefficient is used to calculate the histogram similarity $\rho(H_0, H')$;

If $\rho > 80\%$, the location which tracked by the particle filter is the target location, namely to jump to (4);

If $60\% < \rho < 80\%$, get the location of the particle filter area expanded β times, SIFT feature points of a rectangular area and the original goal SIFT feature points are matched, if meet the requirements, jump to (4);If matching failure, jump to (5);

If $\rho < 60\%$, there are eight consecutive frames appear this kind of situation, target is considered lost; Otherwise we think target is temporarily complete keep out, turn to (2);

(4) Output the target location which is calculated;

(5) Update the target model and take the next frame, turn to (2).

Algorithm performance simulation

In order to verify the performance of the improved algorithm proposed in this paper, simulation experiment is done on it, make a basketball video as example, in the first place in the case of without sunscreen to do the target tracking of basketball players, comparison results of the standard particle filter and the proposed improved particle filter is as shown in figure below.

Figure 2. Standard algorithm to track the results of unobstructed case

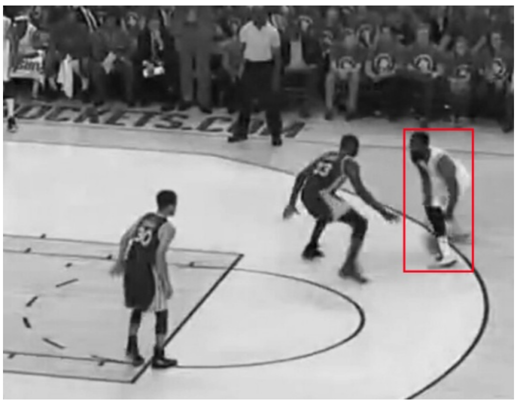

Figure 3. Improved algorithm to track the results of unobstructed case

Then, In the case of covered, target tracking is done on basketball player, the compared results of the standard particle filter and improved particle filter proposed in this paper is shown in figure below.

Figure 4. Standard algorithm to track results under occlusion

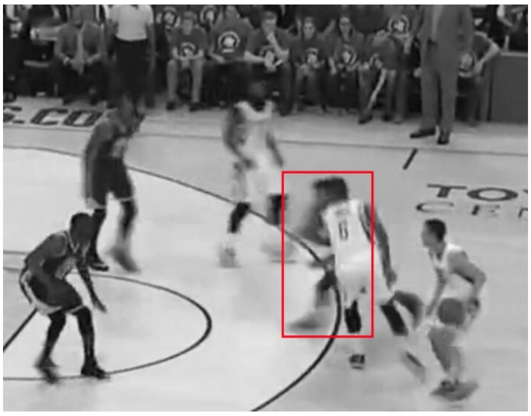

Figure 5. Standard algorithm to track results under occlusion

It can be seen from the above results, after the color and shape hierarchical multiple feature fusion optimization for standard particle filter, in case there are obstructions and without shelter, improved algorithm are showed excellent tracking performance.

Conclusion

Detecting athletes from the sports video not only can reduce time and calculation amount for video subsequent processing, but also can provide useful information for other high-level sports video processing, these information are important input in sports video to athletes tracking, event detection, behavior recognition, and so on. In this paper, based on the problems existing in the particle filter moving target tracking model, this paper proposes a basketball player tracking model based on hierarchical multiple feature fusion particle filter, the experimental simulation results show that under a shelter circumstances and without shelter, improved algorithm shows excellent tracking performance.

References

1. Jin Z.F. (2015) UAV Measuring Object Velocity Based on Moving Target Tracking and Orientation. *Opto-Electronic Engineering*, 42(2), p.p.59-65.
2. Zhang B. (2015) Moving Object Tracking Algorithm based on Variable Scale Global Search. *Laser Journal*, 36(2), p.p.30-34.
3. Huang S.Y. (2015) Tracking and Detection Algorithm of Motion Targets Based on Improved Gaussian Mixture Model. *Computer Measurement & Control*, 23(3), p.p.861-863.
4. Xia T.W. (2015) Robot Moving Target Tracking Algorithm Based on Adaptive Kalman Filter. *Computer Measurement & Control*, 23(1), p.p.173-175.
5. Hu F.J., Zhao Y.W., Chen J. (2014) SIFT Feature Points Detection and Extraction of Three-Dimensional Point Cloud. *WIT Transactions on Information and Communication Technologies*,13(60), p.p.603-611.
6. Hu F.J., Zhao Y.W., (2013) Comparative Research of Matching Algorithms for Stereo Vision. *Journal of Computational Information Systems*, 9(13), p.p.5457-5465.
7. Su Y.Z. (2015) Visual Tracking of Moving Object based on Double Layer Features Optimization. *Journal of Optoelectronics·laser*, 26(1), p.p.162-169.
8. Chen J.Y. (2014) Fast Moving Object Tracking Algorithm based on Hybrid Quantum PSO. *Control Engineering of China*, 21(6), p.p.812-817.
9. Xu H.F. (2014) Research on Moving Objects Tracking in Intelligent Video Surveillance System. *Tv Engineering*, 38(9), p.p.202-206.
10. Liao Y.Q. (2014) Kalman Particle Filter Algorithm for Moving Target Tracking Based on the Complex Dynamic Scene. *Laser & Optoelectronics Progress*, 51(9), p.p.89-96.
11. Lv, Z.H., Alex T., Franck D. S. (2013) Game on, Science-how Video Game Technology May Help Biologists Tackle Visualization Challenges. *Charly Empereur-Mot, Matthieu Chavent, and Marc Baaden*, 8(3), p.p. E57990.