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The object segmentation technology research on tennis match video based on particle filter and a priori probability model

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ABSTRACT

Segment complete video results for a moving object can reduce the search amount of moving target and have great help for effectively enhance the tracking speed and precision. The purpose of video segmentation is to extract a moving target in video sequences from the background and to achieve segmentation of the foreground and background. The traditional method for extracting is the pixel value in the background is in accordance with the Gaussian model and conduct image segmentation according to 3σ rule. Although the rules can preferably extract the background, there will still be the case where foreground can be divided as the background by mistake. Therefore, this paper uses particle filter and a priori probability model to predict the moving target in the next frame, and then obtain a adaptive segmentation threshold to achieve video object segmentation according to the prediction value. This algorithm reduces the ratio that foreground points are divided into background points by mistake in the segmentation results, and it has improved for image segmentation compared with 3σ rule. Through the analysis and implementation of the algorithms, it provides a theoretical basis for the tennis tournament video object segmentation and better analytical methods for the technique improvement of all kinds of sports.

KEYWORDS

Bayesian estimation;
Monte carlo algorithm;
Priori probability model.

INTRODUCTION

Video analysis of human motion is mainly targeted at image sequence of human motion, involving image processing and analysis, pattern recognition, computer vision, mathematics, kinesiology and computer images and others. Its handling process includes video segmentation and extraction of human motion, dynamic trajectory tracking of joints, three-dimensional modeling of human motion, motion parameters equations establishment, parameter calculation and video animation reproduction. This year Digital Entertainment is also under vigorous development, computer human body animation technology as important technology in the digital entertainment industry also will be more advanced; more professionals, such as automated production line experts, physicians and sports researchers are interested in video analysis.

As video technology and computer continues to evolve, more and more sports technology and level of training has been significantly improved. For tennis technology research many people made efforts from the physical and a statistical point of view, but purely theoretical studies are difficult to accurately and efficiently guide it, so the study of the actual details became the focus. The best way of actual details studies is through the actual video analysis, and video object segmentation for video analysis is an important research content in computer vision, and it is extremely important for accurate subsequent human motion tracking and target behavior. By analyzing the particle filter algorithm and a priori probability model principle, this paper designs a new algorithm combining both methods, uses the new algorithm presented in this paper to compare the experimental results with the 3σmethod, and provides a theoretical basis for tennis video analysis.

PARTICLE FILTERINGALGORITHM

Particle filter algorithm is a Monte Carlo method based on Bayesian estimation, the basic idea is to describe the probability distribution of a random sample of certain weight and the sample called "particle." Based on the observed sample, update the location and the weight value of the random sample, and use it to estimate the approximation of the real probability distribution. The algorithm can not only be implemented on a computer, but also is able to be used in the situation when the observation information is abnormal. Under normal circumstances, a dynamic system is characterized by formula (1):

$$\begin{cases} x_{k+1} = f_k\left(x_k, w_k\right) \\ z_k = h_k\left(x_k, v_k\right) \end{cases} \quad \textbf{(1)}$$

In Formula (1), x_k represents the system state at time k ; f_k indicates that the system transfer function; w_k represents system noise, and it obeys zero-mean Gaussian distribution; z_k represents the systematic observation value at time k ; h_k indicates systematic observation function; v_k represents observation noise, which obeys the zero-mean Gaussian distribution.

Filtering is to calculate the occurrence probability of x_k in the case of known observed sequence values $z_{1:k}$; the mathematical expression is as equation (2) below:

$$p\left(x_k \middle| z_{1:k}\right) \quad \textbf{(2)}$$

Formula (2) can be calculated according to Bayes formula, the calculation results are shown in formula (3):

$$p\left(x_k \middle| z_{1:k}\right) = \frac{p\left(z_k \middle| x_k\right) p\left(x_k \middle| z_{1:k-1}\right)}{p\left(z_k \middle| x_{1:k-1}\right)} \quad \textbf{(3)}$$

The purpose is to predict x_{k+1} on the basis of the calculated $z_{1:k}$, the mathematical expression and the calculation method are shown in the formula (4) below:

$$p\left(x_{k+1} \middle| z_{1:k}\right) = \int p\left(x_{k+1} \middle| x_k\right) p\left(x_k \middle| z_{1:k}\right) dx_k \quad \textbf{(4)}$$

The $p\left(x_k \middle| z_{1:k}\right)$ in Formula (4) can be calculated by the formula (3)), and calculate the corresponding $\bar{x}_k$ when the error value of the estimated value and the actual value is the minimum using Bayesian estimation, the calculation method is shown as formula (5) below:

$$\bar{x}_k = \int x_k d\left(p\left(x_k \middle| z_{1:k}\right)\right) \quad \textbf{(5)}$$

Because the formula $p\left(x_k \middle| z_{1:k}\right)$ is generally cannot be explained, $p\left(x_k \middle| z_{1:k}\right)$ can be approximated as the form of kalman filtering. Taking into account the probability distribution of $p\left(x_k \middle| z_{1:k}\right)$ is generally non-analytic situation, so we need to use Monte Carlo random sampling method to approximately deal with $p\left(x_k \middle| z_{1:k}\right)$ with a group of weight particle sets. By Monte Carlo method we can know the approximation way of $p\left(x_k \middle| z_{1:k}\right)$ is in the formula (6):

$$p\left(x_k \middle| z_{1:k}\right) = E\left(I_{\{xk\}}(x) \middle| z_{1:k}\right) \quad \textbf{(6)}$$

In Formula (6), when $x = x_k$, the value of $I_{\{xk\}}(x)$ is 1, otherwise 0; $E\left(I_{\{xk\}}(x) \middle| z_{1:k}\right)$ is able to approximate its sample means, as shown in the formula (7):

$$E\left(I_{\{xk\}}(x) \middle| z_{1:k}\right) \approx \frac{1}{N} \sum_{i=1}^{N} I_{\{xk\}}\left(x^j\right) = \frac{1}{N} \sum_{i=1}^{N} \delta\left(x - x_k^i\right) \quad \textbf{(7)}$$

In Formula (7), x_k^i indicates the i –th sample value of x_k , generally use importance sampling method to approximate $p\left(x_k \middle| z_{1:k}\right)$, with the importance sampling $E\left(I_{\{xk\}}(x) \middle| z_{1:k}\right)$ can be represented by the formula (8):

$$E\left(I_{\{xk\}}(x) \middle| z_{1:k}\right) \approx \frac{1}{N} \sum_{i=1}^{N} w_k^i \delta\left(x - x_k^i\right) \propto \sum_{i=1}^{N} w_k^i \delta\left(x - x_k^i\right) \quad \textbf{(8)}$$

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Suppose the important function is $q(x_k|z_{1:k})$, then there is formula (9):

$$w_k^i \propto \frac{p(x_k^i|z_{1:k})}{q(x_k^i|z_{1:k})} \quad \textbf{(9)}$$

By the formula (9), when directed to a specific x_k, for each sampling time and when $x = x_k$, w_k^j is a fixed value; from the probabilistic sense it refers to randomly collect samples for N times from x ,when $x = x_k$, the corresponding $\delta(x - x_k^j)$ is equal to 1, in this case it corresponds to a weight w_k^j .

ALGORITHM IMPLEMENTATION

General idea of the algorithms

When the moving foreground moves according to a particular velocity, we can predict area coordinate of the moving foreground in current frame according to the moving foreground area coordinate of previous frame and the horizontal and vertical movement rate of the foreground. In accordance with the system and observation equations N predicted value of foreground region can be derived using a particle filter, then you can calculate the probability that pixels fall in this area is in foreground, then that you can get the probability of the background. When the sample number is determined, the occurrence probability of an event is P; in the N samples that has been sampled, the occurrence probability of an event is below P; and in the rest of the $N - M$ samples the occurrence probability of the event is relatively large; If the segmentation algorithm can use the event's priori probability for adaptive segmentation, the robustness of the algorithm will increase accordingly. The algorithm described herein is to enhance the robustness of the segmentation from the above two angles. When pixel value of each point (i, j) in the previous frame is x, the way to judge whether this point belongs to the background is decided by the average value of the probability particle filtering predicts the point as the background and the probability a priori probability model predicts the point as the background. Wherein each point (i, j) of the image is the background, distribution of pixel values is of the Gaussian distribution; when it is the background, distribution of each pixel value is also of the Gaussian distribution.

The overall flow chart of the algorithm is shown in Figure 1:

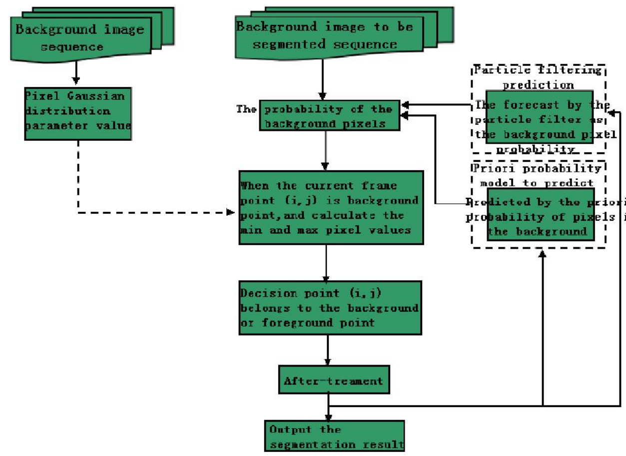

Figure 1 : Overall algorithm flow chart

Background determination

If the pixel (i, j) falls on the interval determined by $P(x_1 < X < x_2) = P(B)$, (i, j) belongs to the background, shown in formula (10):

$$x(i, j) = \begin{cases} \text{Background} & , x(i, j) \in [x_1, x_2] \\ \text{Foreground} & , x(i, j) \notin [x_1, x_2] \end{cases} \quad \textbf{(10)}$$

$P(B)$ Represents the probability when the point (i, j) belongs to the background when the known sample video frame is n and pixel value of the current frame point is x, and its calculation method is in formula (11):

$$P(B) = \frac{P(N) + P(M|x)}{2} \quad \textbf{(11)}$$

In Formula (11), $P(M|x)$ means probability that the pixel x belongs to the background when in the known prior probability frame n the background pixel (i, j) is background and the pixel value is x; $P(N)$ Means the probability of the pixel belongs to the background when predicting the particle.

As background pixel value of point (i, j) can be approximated as Gaussian distribution; if we take $f(x)$ to indicate that the probability density function of the Gaussian distribution, the mean μ and variance σ^2 of the parameter can be obtained by statistical methods, the calculation is as formula (12):

$$\begin{cases} \int_{-\infty}^{x_2} f(x)dx = 1 - \left[\frac{1 - P(B)}{2}\right] \\ x_2 - \mu = \mu - x_2 \end{cases} \quad \textbf{(12)}$$

In Formula (12), μ represents the average value of pixel (i, j) on the current background.

Particle filtering prediction

Particle filtering prediction is divided into five parts, namely particle initialization, foreground region prediction and the pixel belongs to the background probability calculations, particle weight calculation, important adoption and post-processing.

Particle initialization is to use the initial set of particles to approximate the distribution of X_n based on observation equation, wherein the observation equation is as in formula (13):

$$Y_n = X_n + V_n \quad \textbf{(13)}$$

In Formula (13), V_n represents observation noise, which obeys the standard normal distribution. Particle standard initialization process: use the coordinates of the foreground region in the first frame segmentation results to form N 8-dimensional state vector, that is particles, that is N particles, the state vectors is in the formula (14) as follows:

$$(x_0, y_0, u_0, v_0, x_1, y_1, u_1, v_1) \quad \textbf{(14)}$$

In Formula (14), (x_0, y_0) means the coordinate value of top left corner in the target area, (x_1, y_1) means the coordinate value of lower right corner in the target area, (u_0, v_0) means the horizontal velocity and vertical velocity in upper left corner of the target area, (u_1, v_1) means the horizontal velocity and vertical velocity in lower right corner of the target area,. Initially we have $(u_0, v_0) = (0,0)$ and $(u_1, v_1) = (0,0)$; and then, to add normal random noise on the state vector, get N new state vectors; finally, attach a weight $\frac{1}{N}$ on each new state vector; thus we can get a set of initial particles of particle filter.

Using the initial set of particles or particle set obtained by sampling to predict the foreground region of the next frame shown in the system equation of the formula (15):

$$\begin{cases} x_0^{n+1} = x_0^n + u_0^{n+1} + w_n, y_0^{n+1} = y_0^n + v_0^{n+1} + w_n \\ u_0^{n+1} = u_0^n, v_0^{n+1} = v_0^n \\ x_1^{n+1} = x_1^n + u_1^{n+1} + w_n, y_1^{n+1} = y_1^n + v_1^{n+1} + w_n \\ u_1^{n+1} = u_1^n, v_1^{n+1} = v_1^n \end{cases} \quad \textbf{(15)}$$

By the formula (15) the N prediction values of the foreground region in the next frame can be drawn. The accuracy of prediction is according to the calculation method of particle weights shown in formula (16):

$$\frac{P(Y_n | X_n^*(i))}{\sum_{j=1}^{N} P(Y_n | X_n^*(j))} \quad \textbf{(16)}$$

According to formula (16) calculate particle weights, and then normalize them, one can calculate the accumulation weight of each particle. The accumulation weight of each particle can divide [0,1] space into N regions. And then uniformly sample in the space to generate N random numbers. Lastly reproduce the corresponding particle into a new particle that the random number belongs to a region. So the adoption of a new set of particles can be done. In the important sampling process particles with larger weights have corresponding larger space region, the probability to copied to new particles is greater.

Using the connected component analysis to conduct the noise elimination; this article does not describe the treating process after completed.

Priori probability forecast

$$P(M|x) = \begin{cases} 1 & , \text{When} \quad P(W|x) < P(A) \\ \dfrac{p(A)}{p(w)} & , \text{When} \quad P(W|x) \geq P(A) \end{cases} \quad \textbf{(17)}$$

In Formula (17) $P(M|x)$ represents the predicted probability value of frame point (i, j) of the known sample n when the pixel value is x and belongs to the background, and $P(W|x)$ represents the probability of point (i, j) when the pixel value is x and belongs to the background, its calculation method can be obtained according to Bayes' theorem, as shown in the formula (18):

$$P(W|x) = \frac{P(Wx)}{P(x)} = \frac{P(W)P(x|W)}{P(W)P(x|W) + P(V)P(x|V)} \quad \textbf{(18)}$$

In Formula (18) $P(V)$ indicates the probability of point (i, j) belonging to foreground, and assuming $P(x|V)$ obey Gaussian distribution, then using statistical methods we can find the estimates of the parameters and the estimated value of $P(V)$, in a similar way $P(W)$ can also be estimated using Gaussian distribution

RESULT ANALYSIS

Conduct image segmentation on the 5 videos, segment them separately based on 3σ method and a prior probability model with particle, compare the following five aspects: the total number of pixels, mistaken points that the background point is divided into foreground, mistaken points that the foreground point is divided into background, the ratio that the background point is divided into foreground and the ratio that the foreground point is divided into background, as shown in TABLE 1:

Seen from TABLE 1, this paper based on particle filter algorithm and priori probability model on the whole is better than 3σ method.

TABLE 1 : The comparison table of experimental results

Classification	algorithm selection	pixels	Mistaken foreground point	Mistaken background point	Mistaken foreground point ratio	Mistaken background point ratio
Video 1	Method 1	207360000	2818020	38672640	1.359%	18.650%
	Method 2	207360000	2954880	19838130	1.425%	9.567%
Video 2	Method 1	207360000	9053330	52047360	4.366%	25.100%
	Method 2	207360000	9092730	16914360	4.385%	8.157%
Video 3	Method 1	207360000	2596140	44893440	1.252%	21.650%
	Method 2	207360000	2193860	15336340	1.058%	7.396%
Video 4	Method 1	207360000	2421960	37698040	1.168%	18.180%
	Method 2	207360000	2411590	22415610	1.163%	10.810%
Video 5	Method 1	207360000	4053880	38900730	1.955%	18.760%
	Method 2	207360000	4281980	21233660	2.065%	10.240%

Note: Method 1 is the 3σ method, Method 2 is method based on the a priori probability model and particle algorithm

CONCLUSIONS

1) This paper introduces the algorithm based on particle filtering method and a priori probability model, and compares with the 3σ methods; the experimental data shows that this algorithm is superior to 3σ method;
2) Particle filter has better prediction results in a nonlinear non-Gaussian case;
3) Video segmentation based on priori probability model has good predictive effect in the case of pixel changes significantly;
4) This algorithm combines the advantages of two algorithms, when performing image segmentation it can effectively reduce the error in the case of background dynamically changes in a large range, and it can achieve better segmentation results in diving, gymnastics and tennis.

REFERENCES

[1] Bing Zhang, Yan Feng; The Special Quality Evaluation of the Triple Jump and the Differential Equation Model of Long Jump Mechanics Based on Gray Correlation Analysis. International Journal of Applied Mathematics and Statistics, **40(10)**, 136-143 **(2013)**.

[2] Chen Jian, Wang Wen-cheng et al.; Markerless Human Motion Tracking from Monocular Videos. Journal of Computer Aided Design & Computer Graphics, **17(9)**, 2033-2039 **(2005)**.

[3] Chen Rui, Liu Tun-yi, Zhao Guo-ying; 3D Human Motion Tracking Based on Sequential Monte Carlo Method. Journal of Computer Aided Design & Computer Graphics, **17(1)**, 85-92 **(2005)**.

[4] Deng Yu, Li Zhen-bo, Li Hua; Design and Realization of Vision-Based 3D Human Body Motion Tracking System. Journal of Computer Aided Design & Computer Graphics, **19(6)**, 769-780 **(2007)**.

[5] J.Barron, D.Fleet, S.Beauchemin; Performance of optical flow techniques International Journal of Computer Vision, **12(1)**, 42-77 **(1994)**.

[6] Li Qing-you; Study on Receive a Service of Tennis. China Sport Science and Technology, **42(5)**, 62-65 **(2006)**.

[7] Pi Wen-kai, Liu Hong et al.; Motion Detection for Human Bodies Basing Adaptive Background Subtraction by Using an Omnidirectional Camera. Acta Scicentiarum Naturalum Universitis Pekinesis, **40(3)**, 458-462 **(2004)**.

[8] S.McKenna, S.Jabri, Z.Duric et al.; Tracking groups of people. Computer Vision and Image Understanding, **80(1)**, 42-56 **(2000)**.

[9] Xia Bing-hu; Comparison of first three beats technical and tactical characteristics of Asia and the world's top male tennis players. Contemporary Sports Technology, **2(19)**, 82-84 **(2012)**.

[10] Zheng Shun-yi; Human Motion Capture from Video Sequences. Editorial Board of Geomatics and Information Science of Wuhan University, **29(4)**, 359-361 **(2006)**.