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Improved Object Tracking with Particle Filter and Mean Shift

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***Abstract* - In this paper, we present a new object tracking algorithm based on particle filtering technique and the Mean Shift algorithm. The particle filtering technique is a powerful technique for tracking objects in image sequences with complex background. It has been proved to be a robust method of tracking in non-linear and non-Gaussian case. But two common problems of the particle filter technique are the degeneracy phenomenon and the huge computational cost. To solve these problems, our new tracking algorithm uses the Mean Shift algorithm inside the particle filter. With the help of the Mean Shift algorithm, we can sample more particles of higher weights, and discard those particles whose contribution to the tracking is almost zero. The experiment results show that the new algorithm reduces the degeneracy problem and the computational cost of the particle filter.**

Keywords - Particle filtering, Mean Shift, Object Tracking, Color distribution.

I. INTRODUCTION

Particle filter [1][12] is a powerful and reliable tool for object tracking because it neither limits to linear systems nor require the noise to be Gaussian. It apply a recursive Bayesian filter based on propagation of sample set over time, maintain multiple hypotheses at the same time and use a stochastic motion model to predict the position of the object.

A common problem with the particle filter is the degeneracy phenomenon. The variance of the importance weights can only increase time, and thus, it is impossible to avoid the degeneracy phenomenon. As the degeneracy problem is an undesirable effect in particle filter, a simple approach to reducing its effect is to use a great number of particles. This will increase the computational cost.

In order to reduce the effects of degeneracy, many particle filters introduce a resampling procedure whenever a significant degeneracy is observed. The basic idea of resampling is to eliminate particles that have small weights and to concentrate on particles with large weights. But the resampling step introduces other practical problems, such as the problem of sample impoverishment.

The mean shift algorithm [16, 17] is a simple and fast adaptive tracking procedure that finds the maximum of the Bhattacharyya coefficient given a target model and a starting region.

By introducing the Mean Shift in the particle filter, our new approach decreases the degeneracy problem. The Mean Shift algorithm is used on every particle. This makes every particle move to a better position which is near (or equal to) their original position. The new position has better Bhattacharyya coefficient, which means it is more likely to be the tracking object candidate. After the Mean Shift process, particles are gathered in a smaller area and moved to have large weights. This will efficiently overcome the degeneracy problem and reduce the cost of computation.

The paper is organized as follows. Section 2 states the generic particle filter algorithm. Section 3 introduces the Mean Shift algorithm. In Section 4 describes our new Particle Filter algorithm based on Mean Shift. Section 5 shows the experiment results of object tracking in video sequences. Finally, Section 6 draws the conclusions and discusses the open issues for future research.

II. GENERIC PARTICLE FILTER

A key idea of a particle filter is to represent the required posterior density function by a set of random samples with associated weights and to compute estimates based on these samples and weights. In order to avoid the degeneracy phenomenon of the particles, the resampling scheme is very important in particle filter [1, 2, 9, 11, 12, 13].

A generic particle filter is shown below [19].

(1) Initialization: $k=0$

(a) For $i=0 \dots N_s$

draw the states $x_0^{(i)}$ from the prior $p(x_0)$

End for.

(2) For $k=1,2\dots$

(a) For $i=1\dots N_s$

draw $x_k^i \sim q(x_k^i \mid x_{k-1}^i, z_k)$

assign the particle a weight w_k^i

according to
$$w_k^i \propto w_{k-1}^i \frac{p(z_k \mid x_k^i)p(x_k^i \mid x_{k-1}^i)}{q(x_k^i \mid x_{k-1}^i, z_k)}$$

End for.

(b) For $i=1\dots N_s$

Normalize the weights
$$w_k^i = w_k^i / \sum_{j=1}^{N_s} w_k^j$$

End for.

(c) Resample:

Multiply/Suppress samples $x_{0:k}^{(i)}$ with high/low w_k^i, obtain N_s random samples $x_{0:k}^{(i)}$ approximately distributed according to $p(x_{0:k} \mid z_{1:k})$,

For $i = 1 \ldots N_s$

set $w_k^i = 1/N_s$

End for.

III. MEAN SHIFT TRACKING

The Mean Shift Tracking method is based on target representation using a non-parametric isotropic kernel. Tracking involves target localization using a gradient descent based search procedure consisting of comparing the target model with the image. Detailed explanation of the method can be found in [3].

The process of mean shift tracking is shown below [4,8].

(1) Given the distribution $\{\hat{q}_u\}_{u=1\ldots m}$ of the target model and the estimated location $\hat{y}_0$, compute the distribution $\{\hat{p}_u(\hat{y}_0)\}_{u=1\ldots m}$, and evaluate

$$\rho[\hat{p}(\hat{y}_0), \hat{q}] = \sum_{u=1}^{m} \sqrt{\hat{p}_u(y_0)\hat{q}_u}.$$

(2) Derive the weights $\{w_i\}_{i=1\ldots n_h}$

$$w_i = \sum_{u=1}^{m} \delta[b(x_i) - u]\sqrt{\frac{\hat{q}_u}{\hat{p}_u(\hat{y}_0)}}.$$

where $b(x_i)$ associates the histogram bin corresponding to the color of location x_i.

(3) Based on the mean shift vector, derive the new location of the target

$$\hat{y}_1 = \frac{\sum_{i=1}^{n_h} x_i w_i g\left(\left\|\frac{\hat{y}_0 - x_i}{h}\right\|^2\right)}{\sum_{i=1}^{n_h} w_i g\left(\left\|\frac{\hat{y} - x_i}{h}\right\|^2\right)}.$$

Update $\{\hat{p}_u(\hat{y}_1)\}_{u=1\ldots m}$, and evaluate

$$\rho[\hat{p}(\hat{y}_1), \hat{q}] = \sum_{u=1}^{m} \sqrt{\hat{p}_u(y_1)\hat{q}_u}.$$

(4) While $\rho[\hat{p}(\hat{y}_1), \hat{q}] < \rho[\hat{p}(\hat{y}_0), \hat{q}]$

Do $\hat{y}_1 \leftarrow \frac{1}{2}(\hat{y}_0 + \hat{y}_1)$.

(5) If $\left\|\hat{y}_1 - \hat{y}_0\right\| < \varepsilon$ Stop.

Otherwise Set $\hat{y}_0 \leftarrow \hat{y}_1$ and go to Step 1.

The tracking consists in running for each frame the optimization algorithm described above. Thus, given the target model, the new location of the target in the current frame minimizes the distance in the neighborhood of the previous location estimate.

IV. IMPROVED OBJECT TRACKING ALGORITHM

A. Introduction of the Improved Algorithm

Our improved object tracking algorithm is based on particle filtering technology and mean shift algorithm. Figure 1 shows its structure.

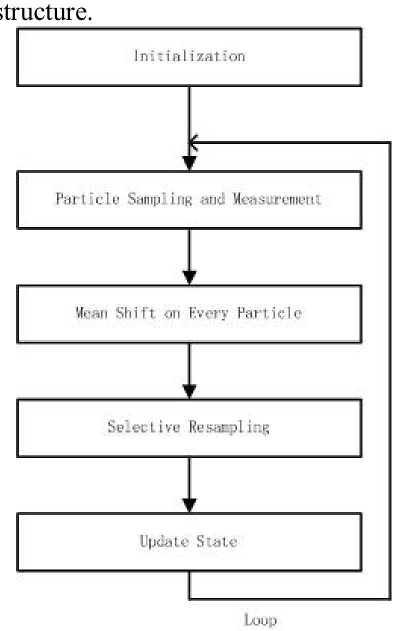


Fig. 1: Block diagram of improved object tracking

B. Color Distribution Model

Our improved object tracking algorithm is in a color-based context [5, 6, 7, 10, 15]. Color distributions are used as target models. The color distribution model has to be defined in a way to favor candidate color histograms close to the reference histogram. We use $8 \times 8 \times 4$ bin histograms in the three channels of hue, saturation, value (HSV) color space [14].

A distance metric which is appropriate to make decisions about the closeness of two histograms $\hat{h}_1 = \sum_{c\in\{H,S,V\}} h^c_{x_1}$ and $\hat{h}_2 = \sum_{c\in\{H,S,V\}} h^c_{x_2}$ is the Bhattacharyya similarity distance

$$d(\hat{h}_1,\hat{h}_2) = \sqrt{1-\rho(\hat{h}_1,\hat{h}_2)},$$

where $\rho(\hat{h}_1,\hat{h}_2)$ is the Bhattacharyya coefficient,

$$\rho(\hat{h}_1,\hat{h}_2) = \sum_{i=1}^{m}\sqrt{\hat{h}_{1,i}\,\hat{h}_{2,i}}$$

The larger the coefficient $\rho(\hat{h}_1,\hat{h}_2)$ is, the more similar the distributions are. The Bhattacharyya distance values are within the interval $[0,1]$. For two identical normalized histograms we obtain $d=0 \quad (\rho=1)$ indicating a perfect match.

Based on this distance, the color distribution model can be defined by

$$L(z\mid x) \propto \exp\Big(-\sum_{c\in\{H,S,V\}}[d(h^c_x,h^c_{ref})]^2/2\sigma_C^2\Big),$$

where the standard deviation σ_C specifies the Gaussian noise in the measurements, h^c_x is the current histogram of the target, and h^c_{ref} is the reference histogram [14].

C. Initialization of the Particle Filter

At the initialization step, we manually select a region of interest (ROI) in the first image of the video sequences. The ROI contains the object which is going to be tracked. In order to reduce the influence of the background, we set the ROI slightly larger the object. The histogram of the initial ROI is saved. The Bhattacharyya similarity distances are calculated by the initial saved histogram and other histograms.

D. Weighted Histogram

In order to reduce the influence of the background, a weighted histogram is used to compute the target histogram. The weighted histogram is created by a kernel profile $k(r)$ which assigns higher weight to pixels near the center of the region. Our kernel profile is defined as

$$k(r) = \begin{cases} 1-r^2 : r<1 \\ 0 : otherwise \end{cases}$$

where r is the distance from the region center. Thus, we increase the reliability of the colour distribution when these boundary pixels belong to the background or get occluded.

E. Selection of the Particles

The particles are sampled from the pixels of the image. We set the position of the sample pixel as the center of the search area. The search area is the same size as the initial ROI. Then the weighted histogram is calculated from the search area, and compared with the initial histogram. The Bhattacharyya distance shows the similarity of the two histograms [18, 19].

F. The Improved Object Tracking Algorithm

The algorithm is shown below.

(1) **Initialization**: k=0

(a) For $l=1\ldots N$

Generate samples $\{x_0^{(l)}\}$ from the initial distribution $p(x_0)$.

End for.

(2) For $k=1,2,\ldots$

(a) **Sample**.

For $l=1\ldots N$

Sample $x_{k+1}^{(l)} \sim p(x_{k+1}\mid x_k^{(l)})$

End for.

(b) **Mean Shift Search**.

For $l=1\ldots N$

Mean Shift search on samples, generate modified samples $x'^{(l)}_{k+1}$

End for.

(c) **Weight**.

For $l=1\ldots N$

Compute the weights $W_{k+1}^{(l)} \propto L(x_{k+1}\mid x'^{(l)}_{k+1})$.

Normalize the weights $\hat{W}^{(l)}_{k+1} = W^{(l)}_{k+1}/\sum_{i=1}^{N} W^{(l)}_{k+1}$.

End for.

(d) **Resampling**.

For $l=1\ldots N$

Multiply/suppress samples $x'^{(l)}_{k+1}$ with $\hat{W}^{(l)}_{k+1}$

Obtain N new random samples approximately distributed according to $p(x^{(l)}_{k+1}\mid Z^{k+1})$

End for.

(e) **Output**.

Compute the posterior mean $E[x_{k+1}\mid Z^{k+1}]$

Where $\hat{x}_{k+1} = E[x_{k+1}\mid Z^{k+1}] = \sum_{l=1}^{N}\hat{W}^{(l)}_{k+1}\,x'^{(l)}_{k+1}$.

V. EXPERIMENTS AND RESULTS

In this section, we will show the experiment results of the improved object tracking algorithm. Our algorithm is The video sequences are captured at 25 frames per second by a digital camera. The experiments are done in Visual C++ on a 3.0 GHz Pentium IV. The particle numbers are 50.

In Figure 2 (a) to (f), we track a ball in a video sequence. The video sequence numbers are 1, 5, 9, 14, 19, 25. The ball is running on the floor. In Figure 2 (a) to (c), it runs from right to left. In Figure 2 (d) to (f), it runs from left to right. Our tracking algorithm is used in our program to try to track the running of the ball. We draw a green rectangle on each image to indicate our tracking result of the position of the ball. From these images, we can see that the green tracking rectangle fits the position of the ball well.

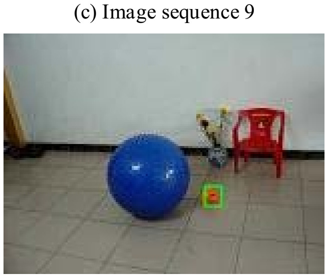
In Figure 3 (a) to (f), we track a boy in a video sequence. The video sequence numbers are 1, 15, 28, 44, 59, 73. The boy is playing on a square. At the initialization step, we set the initial search rectangle slightly smaller than the area of the boy. So in all the images, the boy's foot is not in our track rectangle. Despite that, the tracking result is good.

(a) Image sequence 1

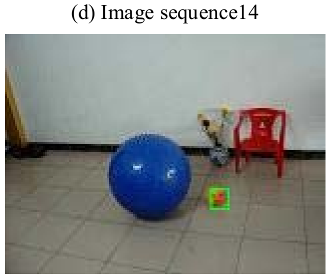
(b) Image sequence 5

(c) Image sequence 9

(d) Image sequence14



(e) Image sequence 19



(f) Image sequence 25

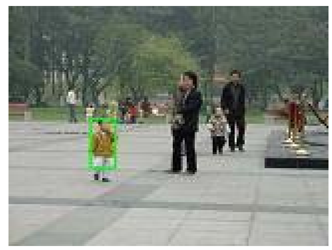
Fig. 2: The tracking of a ball.

(a) Image sequence 1

(b) Image sequence 15

(c) Image sequence 28

(d) Image sequence44



(e) Image sequence 59

(f) Image sequence 73

Fig. 3: The tracking of a boy.

VI. CONCLUSIONs

This paper has presented a new object tracking algorithm based on particle filter and mean shift. We used these two object tracking methods both for better effect and less computational cost. Experiments results show that the new algorithm overcome the degeneracy problem of conventional particle filters and require less computational cost.

Current and future areas for research include tracking objects under complex background, multiple objects tracking, efficient tracking when there are occlusions.

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