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A moving object tracking based on color information employing a particle filter algorithm

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Abstract: In this paper, we present a new algorithm to track a moving object based on color information employing a particle filter algorithm. Recently, particle filter has been proven very successful for non-linear and non-Gaussian estimation problems. It approximates a posterior probability density of the state such as the object position by using samples which are called particles. The probability distribution of the state of the tracked object is approximated by a set of particles, where each state is denoted as the hypothetical state of the tracked object and its weight. The particles are propagated according to a state space model. In this paper, the state is treated as the position of the object. The weight is considered as the likelihood of each particle. For this likelihood, we consider the similarity between the color histogram of the tracked object and the region around the position of each particle. The Bhattacharya distance is used to measure this similarity. And finally, the mean state of the particles is treated as the estimated position of the object. The experiments are performed to confirm the effectiveness of this method to track the moving object.

Keywords: object tracking, color information, particle filter.

I. INTRODUCTION

Tracking objects through the frames of an image sequence is an elementary task in online and offline image-based applications including surveillance, human-machine interface, motion capture, and medical imaging, etc. Many researches of tracking object motion in image sequences have been proposed based on image subtraction such as background subtraction and inter-frame difference, optical flow, skin color extraction and probabilistic methods such as Kalman filter and particle filter. Recently, probabilistic methods become popular method among many researches. Kalman filter is a common approach for dealing with target tracking in the probabilistic framework. But it cannot resolve the tracking problem when the model is nonlinear and non-Gaussian. The extended Kalman filter can deal to this problem, but still has a problem when the nonlinearity and non-Gaussian cannot be approximated accurately.

Recently, particle filter has been proven very successful for non-linear and non-Gaussian estimation problems [1-4]. It approximates a posterior probability density of the state such as the object position by using samples which are called particles. As for one of the particle filters, the Condensation algorithm was introduced by M. Isard et al. [1]. This algorithm has been typically used for tracking problems of moving object contours. For another particle filter, Monte Carlo filter was introduced by Kitagawa [2] and Bayesian bootstrap filter was introduced by Gordon et al. [3].

The most important step in tracking based on color information is to establish color distribution model, which provides a basis for weight updating and target state estimation. There are different approaches to build the target model. McKenna et al. [5] use adaptive color threshold to distinguish the target from background, Olson et al. [6] use model intensity of each pixel of the target with a normal distribution and Isard et al. [7] use a mixture of Gaussian distribution to model pixel value. But in practical application, all these methods cannot provide robust and computationally efficient solutions when the background and target are in a complicated condition.

Comparatively, a color histogram has many advantages for target tracking as it is robust to partial occlusion, rotation and scale invariant, and is also easy to be implemented [8-9]. In this paper, we employ a particle filter to track a moving object based on color information. A target model is tracked using the particle filter by comparing its histogram with the histogram of every sample using the Bhattacharyya distance which makes the measurement matching and weight updating more reasonable.

The remaining of this paper is organized as following. In section 2, we describe a dynamic model of our system and the color histogram of the tracked object. The implementation of color histogram into particle filter is presented in section 3. Section 4 present some experimental results and finally section 5 is the conclusion of the paper.

II. TRACKING AND COLOR DISTRIBUTION MODEL

2.1. Tracking Model

We consider the motion of a target as the discrete time 2 dimensional motion with constant velocity. The state vector at a time step k is denoted by $\boldsymbol{x}_k$, which usually contains information about the coordinate of the current position of the object and the differential of it. Our dynamical model is described as

$$\boldsymbol{x}_k = F\boldsymbol{x}_{k-1} + G\boldsymbol{w}_k \tag{1}$$

where F is the transition matrix, G is the system noise matrix and $\boldsymbol{w}_k$ is a Gaussian noise vector. This dynamical model is used in the sampling step of particle filters. With the assumption that the object moves in constant velocity (uniform motion), we can describe the motion as following equations:

$$\begin{aligned} x_{k+1} &= x_k + (x_k - x_{k-1}) \\ y_{k+1} &= y_k + (y_k - y_{k-1}) \end{aligned} \tag{2}$$

where x_k, y_k represent the center of the target region at time step k, respectively. From this, the state vector $\boldsymbol{x}_k^{(i)}$ of the i-th particle at time step k, system matrices F and G and noise vectors $\boldsymbol{w}_k$ are defined respectively as follows:

$$\mathrm{x}_k^{(i)} = \left[x_k^{(i)}, y_k^{(i)}, x_{k-1}^{(i)}, y_{k-1}^{(i)} \right]^T \tag{3}$$

$$F = \begin{bmatrix} 2 & 0 & -1 & 0 \\ 0 & 2 & 0 & -1 \\ 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix},\ G = \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ 0 & 0 \\ 0 & 0 \end{bmatrix} \tag{4}$$

$$\boldsymbol{w}_k^{(i)} = \left[w_{xk}^{(i)}, w_{yk}^{(i)} \right]^T \tag{5}$$

2.2. Color Distribution Model

To achieve robustness against mixed color, rotation and variant illumination condition, we focus on weighted color histograms to represent the target model. The color histogram is used as the discretized color distribution. Let m be the number of segments of the segmented color space. The histograms are produced from the function $h(\boldsymbol{x}_i)$ that assign the color at location $\boldsymbol{x}_i$ to the corresponding bin. In this paper, we use RGB color space with $8\times8\times8$ bins.

We determine the color distribution of the object inside a rectangular region. To increase the reliability of the target model, smaller weight are assigned to the pixels that are further away from region center by employing a weighting function

$$g(r) = \begin{cases} 1 - r^2 & r < 1 \\ 0 & otherwise \end{cases} \tag{6}$$

Here, r is the distance from the center of the region.

The color histogram $p_{\boldsymbol{y}} = \left\{ p_{\boldsymbol{y}}^{(u)} \right\}_{u=1,\ldots,m}$ at location $\boldsymbol{y}$ is calculated as

$$p_{\boldsymbol{y}}^{(u)} = f \sum_{j=1}^{I} g\left(\frac{\left\| \boldsymbol{y} - \boldsymbol{x}_j \right\|}{a} \right) \delta\left[h\left(\boldsymbol{x}_j \right) - u \right] \tag{7}$$

Where I is the number of pixels in the region, $\boldsymbol{x}_j$ is the position of pixels in the region, δ is the Kronecker delta function, a is the normalization factor, and f is the scaling factor defined as

$$f = \frac{1}{\sum_{i=1}^{I} g\left(\frac{\left\| \boldsymbol{y} - \boldsymbol{x}_i \right\|}{a} \right)} \tag{8}$$

to ensures that $\sum_{u=1}^{m} p_{\boldsymbol{y}}^{(u)} = 1$.

The similarity between two color histograms $\boldsymbol{p} = \left\{ p^{(u)} \right\}_{u=1,\ldots,m}$ and $\boldsymbol{q} = \left\{ q^{(u)} \right\}_{u=1,\ldots,m}$ is measured using Bhattacharyya distance defined as

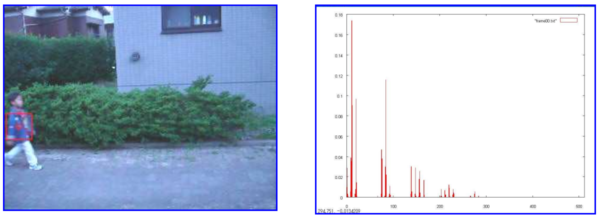
$$d = \sqrt{1 - \rho[\boldsymbol{p}, \boldsymbol{q}]} \tag{9}$$

where

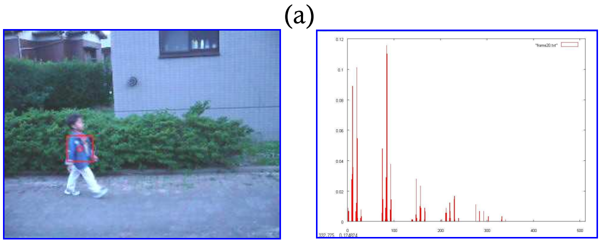
$$\rho[\boldsymbol{p}, \boldsymbol{q}] = \sum_{u=1}^{m} \sqrt{p^{(u)} q^{(u)}} \tag{10}$$

From this equation, the larger ρ shows the more similar the distributions. For two identical histograms we obtain ρ=1, indicating a perfect match.

Fig.1. shows an example of reference color histogram at time step k_o and the candidate color histogram at time step k with hypothesized state $\boldsymbol{x}_k$.



(a)



(b)

Fig.1. Color histogram used for tracking. (a) a reference color histogram at time step k_o (b) candidate color histogram at time step k

III. IMPLEMENTATION OF PARTICLE FILTER

In the particle filter, the probability distribution of the state of the tracked object is approximated by a set of particles $\boldsymbol{s}^{(i)}=\{\boldsymbol{x}^{(i)}, \pi^{(i)}\}$ $(i=1,2,\dots,N)$ where each $\boldsymbol{x}^{(i)}$ is denoted as the hypothetical state of the tracked object and $\pi^{(i)}$ is its weight. In this paper, the state is treated as the position of the object. The particles are propagated according to a system model. Then, the mean state of the particles is treated as the estimated position of the object. The weight is considered as the likelihood of each particle. For this likelihood, we consider the similarity between the color distributions of the tracked object and the region around the position of each particle using Bhattacharya distance.

The weight $\pi^{(i)}$ of i-th state $\boldsymbol{x}^{(i)}$ is calculated as

$$\begin{aligned}\pi^{(i)} &= \frac{1}{\sqrt{2\pi\sigma}}\exp\left(-\frac{d^2}{2\sigma^2}\right)\\ &= \frac{1}{\sqrt{2\pi\sigma}}\exp\left(-\frac{\left(1-\rho\left[\boldsymbol{p}\left(\boldsymbol{x}^{(i)}\right),\boldsymbol{q}\right]\right)}{2\sigma^2}\right)\end{aligned} \tag{11}$$

Where $\boldsymbol{p}(\boldsymbol{x}^{(i)})$ and $\boldsymbol{q}$ are the color histogram of sample and target, respectively. From this equation we can see that small Bhattacharya distance corresponds to large weight. During resample step of particle filter, samples with a high weight may be chosen several times leading to identical copies, while others with relatively low weights may be ignored.

The proposed tracking algorithm is performed by four steps as following:

1. Initialization:
   - Given the color histogram of tracked object:
     $$\boldsymbol{q} = \left\{q^{(u)}\right\}u = 1,\dots,m$$
   - Initialize the N particles.

2. Important sampling : For each particle do the following:
   - Propagate each sample according to system model of Eq. (1).
   - Calculate the color histogram $\boldsymbol{p}^{\boldsymbol{u}}_{\boldsymbol{x}_k^{(i)}}$ from Eq. (7).
   - calculate the Bhattacharya coefficient
     $$d_{\boldsymbol{x}_k^{(i)}} = \sqrt{1-\rho[\boldsymbol{p}\left(\boldsymbol{x}_k^{(i)}\right),\boldsymbol{q}]}$$
   - calculate the weight
     $$\pi_k^{(i)} = \frac{1}{\sqrt{2\pi\sigma}}\exp\left(-\frac{\left(1-\rho\left[\boldsymbol{p}\left(\boldsymbol{x}_k^{(i)}\right),\boldsymbol{q}\right]\right)}{2\sigma^2}\right)$$

3. Estimated position of $\boldsymbol{x}_k$ according to mean estimate :
   $$E(\boldsymbol{x}_k) = \sum_{i=1}^{N}\pi_k^{(i)}\boldsymbol{x}_k^{(i)}$$

4. Resampling : Generate a new set of samples
   $$\left\{\boldsymbol{x}_k^{(i)},\pi^{(i)}\right\}i = 1,\dots,N$$
   - Calculate the normalized cumulative probability $c_k^{'(i)}$:
     $$c_k^{(0)} = 0,\ c_k^{(i)} = c_k^{(i-1)} + \pi_k^{(i)},\ c_k'^{(i)} = \frac{c_k^{(i)}}{c_k^{(N)}}$$
   - Generate Uniformly distributed number $r\in[0,1]$. Find, by binary search, the smallest j for which $c_k^{'(j)} \geq r$ and set $\boldsymbol{x}_k^{(i)} = \boldsymbol{x}_k^{(j)}$

IV. EXPERIMENTAL RESULT

We have done the experiment to track a moving object with our proposed method. The experiments are implemented on Pentium IV with 2.53 GHz CPU and 512 MB RAM. The resolution of each frame is 320×240 pixels image.

Initially, we prepared the color histogram of the tracked object and the region to make the histogram was set to 30×30 pixels. We performed the experiment using 100 and 300 particles. Fig.2 and Fig.3 show the experimental results of the tracking object. The red circle shows the estimated position of the tracking object and the red square shows the region of the tracked object used in color histogram. As shown in those figure, the accuracy of the tracking result using 100 particles is lower than using 300 particles. However, in both case, satisfactory experimental results are achieved with RMSE for each case is 6.48 and 2.28, respectively.

V. CONCLUSION

This paper presented a new method to track the moving object based on color information employing particle filter algorithm. The experimental results showed the satisfactory performance on each frame.

Furthermore, the performance of the tracking of the moving object needs more improvement. There are many aspects in tracking the moving object that are not considered yet in this paper. The problem of occlusions between object and speed up the computational time are examples of related studies conducted by existing researchers. Taking them into consideration could lead to some improvement. These are remaining for our future works.

REFERENCES

[1] M. Isard and A. Blake (1998), CONDENSATION –Conditional Density Propagation for Visual Tracking, Intl. J. of Computer Vision, 29(1): 5-28.

[2] G. Kitagawa (1996), Monte Carlo filter and smoother for non-Gaussian nonlinear state space models, J. Comput. and Graph. Stat. 5(1):1–25.

[3] N.J. Gordon, D.J. Salmon and A.F.M. Smith (1993), Novel approach to nonlinear/non-Gaussian Bayesian state estimation, IEE Proceeding on Radar and Signal Processing, 140(2):107-113.

[4] P. Li and T. Zhang (2003), Visual contour tracking based on particle filters, Image and Vision Computing, 21(1):111–123.

[5] S. McKenna, Y. Raja, S. Gong (1999), Tracking color objects using adaptive mixture models, Image and Vision Computing, 17: 225–231.

[6] T. Olson and F. Brill (1997), Moving object detection and event recognition algorithm for smart cameras, Proceeding of the DARPA Image Understanding Workshop, 159-175.

[7] M. Isard and J. McCormick (2001), A Bayesian multiple-blob tracker, International Conference on Computer Vision, 2:34–41.

[8] K. Nummiaro, E. Koller, L.V. Gool (2002), A color-based particle filter, 1st Intl. WS on GMBV, 53–60.

[9] P. Perez, C. Hue, J. Vermaak et al [2002], Color-based probabilistic tracking, Proceeding of the 7th European Conference on Computer Vision, 661–675.

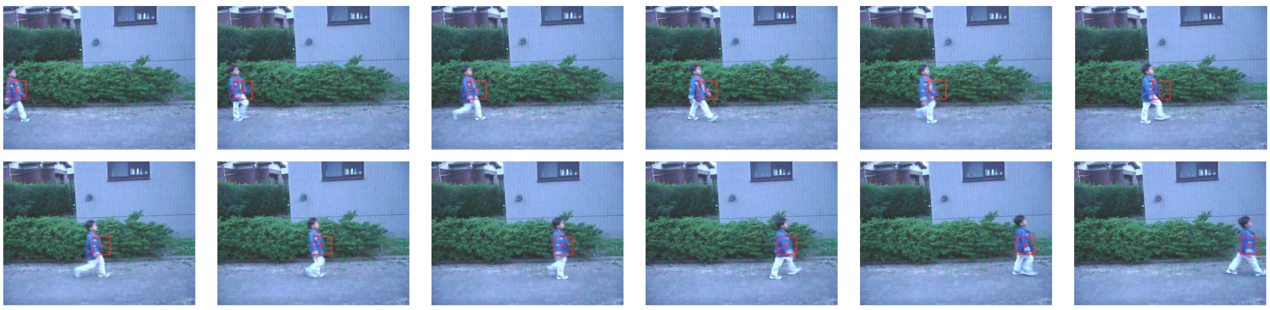


Fig.2. Tracking result using 100 particles

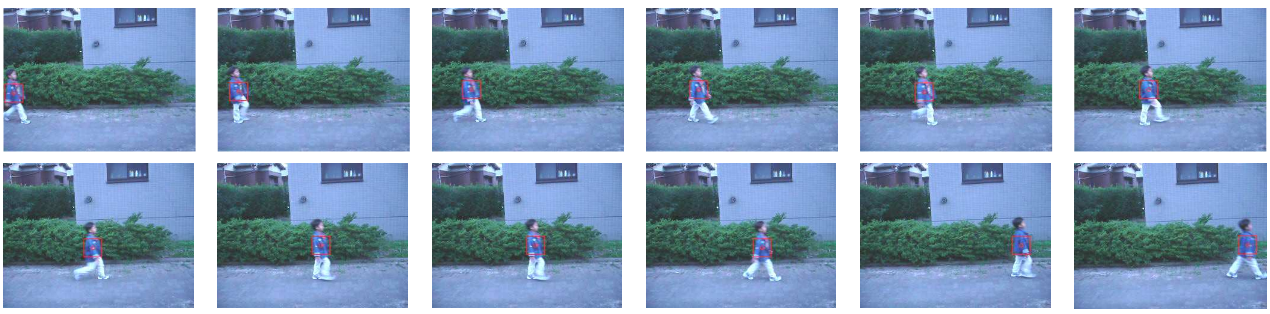


Fig.3. Tracking result using 300 particles