Improved color feature arrangement for mean shift tracking

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Abstract: In order to reduce redundant empty bin capacity in the probability representation, we present a new color feature arrangement mechanism for mean shift tracking objects. In the proposed mechanism, the important optimal color, or we call it optimal color vector, is clustered by closing Euclidean distance which happens inside the original RGB color 3-D spatial domain. After obtaining clustering colors from the reference image RGB spatial domain, novel clustering groups substitute for original color data. So the new color substitution distribution is as similar as the original one. And then target region in the candidate frame is mapped by the constructed optimal clustering colors and the cluster Indices. In the final, mean shift algorithm gives a performance in the new optimal color distribution. Comparison under the same circumstance between the proposed algorithm and conventional mean shift algorithm shows that the former has a certain advantage in computation cost.

Key words: color feature arrangement; optimal color vector; cluster; redundant bin

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0 Introduction

Mean shift[1-3] theory is one efficient way for application of object tracking. Generally speaking, inside the entire tracking algorithm, mean shift computation cost is relatively low, which locates the object in each frame by means of color histogram difference between reference and candidate frame.

Continuous mean shift, which uses iterative histogram procedure based on two sequential video clips, tracks the object in total video clips. Inside each iterative procedure, previous frame's color or other feature statistic distribution is compared by current frame feature statistic distribution. After comparing the previous and current statistic distributions, new location position can be obtained by iterative convergence.

Numerous approaches for tracking objects have been proposed in the real environment surveillance. Mean shift algorithm has received lots of interest since it was developed by Dorin et al[4]. In their papers, the use of color histogram and kernel function reduced computation cost efficiently and effectively. So the follow-up researches related to mean shift have been brought to the forefront in recent years. In the past, mean shift trackers, most of them followed a traditional partition of feature space, especially for the color space. Methods for mean shift tracking have been invented. Collins[5] made a parametric control kernel scale in the original mean shift tracking process. In order to reduce computation cost, Gauss model transform was accepted by YANG et al[6]. Spatial histogram has been implemented to obtain the spatial relationship of pixels[3,6]. Scale space information was added into the feature structure in the paper[5,6]. ZHAO et al. made spatial information incorporated into object representation, by using color correlogram as a feature[7].

Color features are free of transformation and rotation, which have attracted lots of attention from vision processing field. In the tracking object's process, color usually can be represented by pixel value histogram. Histogram is the best representation showing a visual impression of the distribution of data. It is also a direct estimation of the color variables' probability distribution.

Mean shift tracker with object color information is simple and convenient. It offers good performances in the real environment. Because of color's robustness for object poses' variance and partial occlusion, application of color model histogram has been increasingly popular in the tracking field.

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Commonly, color model of the means shift tracker is represented by kernel-based probability distribution and measured by Bhattacharrya distance, which takes charge of statistics' distribution similarity comparison[3,8].

In this paper, the utilization of distance clustering based on similar colors (color vectors) facilitates robustly optimal color substitutions. Those substitutions help the statistic distribution analysis from 3-D RGB spatial domain to 1-D histogram representation. Statistic iteration convergence is facilitated by reduced empty-bins procedures and original data substitutions namely, cluster indices. Closing color statistics' clustering offers several advantages in the context of tracking process.

1) It offers new color data representation format: Optimal color vectors take the place of conventional RGB data. Obviously, histogram distribution is also replaced by new substitutions that greatly simplify the color statistics distribution.

2) Distance clustering is used to find the closing group in the original data distribution. We employ a sampling strategy according to the target window capacity of each reference frame. After color components clustering in the reference frame, fast voting map based on optimal color is presented to efficiently remove the redundant empty bin modes. Euclidean mapping between cluster indices from reference frame to candidate frame accelerates the construction of candidate frame data distribution.

3) Computation cost is reduced by the limited bin numbers. The simplified color clusters' distribution enables the real-time surveillance system.

1 Color feature arrangement in the conventional mean shift tracking

Almost all the mean shift tracking projects follow uniform probability arrangement when they construct the statistical histogram[9-13], as shown in Figs. 1 and 2.

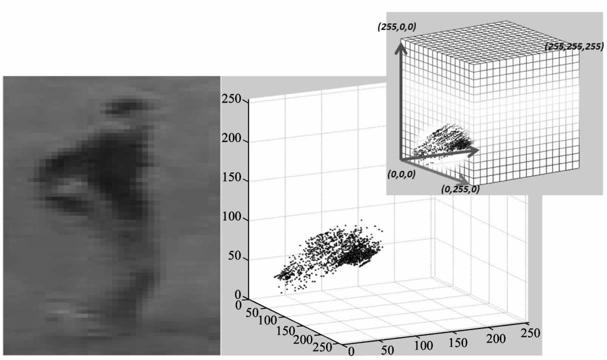

Fig. 1 Color arrangement

Fig. 2 gives the uniform histogram of the pixel. In this figure, the color space is divided by $5 \times 5 \times 5$ bins. R, G and B axis is divided averagely by 5. One index of yellow sub-box is 24. This histogram construction ignores the immense relationship of the real useful data. Lots of boxes are empty which waste the limited valuable storage. As shown in Fig. 3, lots of yellow boxes own nothing, but they still exist in the histogram space.

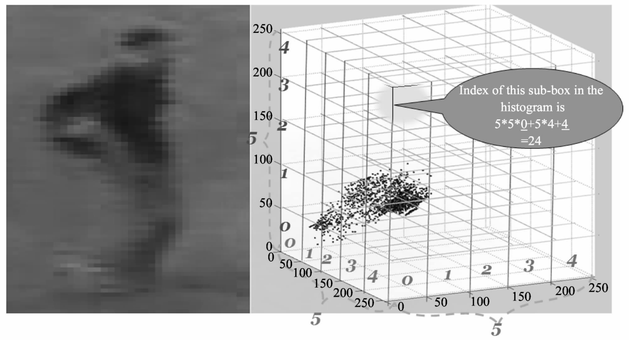

Fig. 2 Conventional histogram of color arrangement

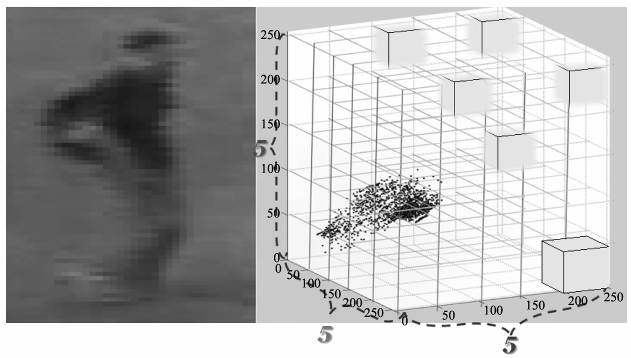

Fig. 3 Redundant bins in conventional uniform histogram

2 Clustering color based mean shift algorithm for object tracking

2.1 Clustering colour arrangement

In order to reduce such yellow empty bins and improve the rate of utilization. We use the clustering method to only focus on the useful pixel. As shown in Fig. 4, several clusters are arranged into the original pixel vectors.

The procedures is shown in Fig. 5.

As we known, one pixel in the original image has RGB-3 attributes, which can be projected into RGB vector space (see Fig. 1). According to Euclidean distance gathering, we firstly select several initial centers randomly and then assign the remaining data to their closest cluster center. After calculating a new cluster center for each cluster, we repeat it until the cluster centers do not change.

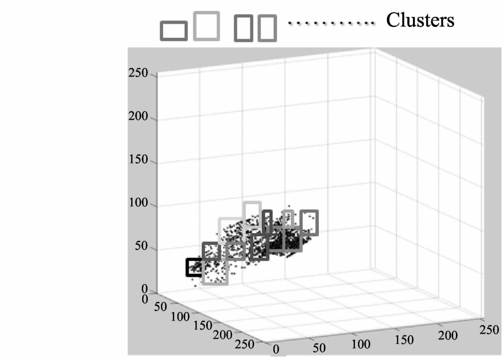

Fig. 4 New clustering color arrangement

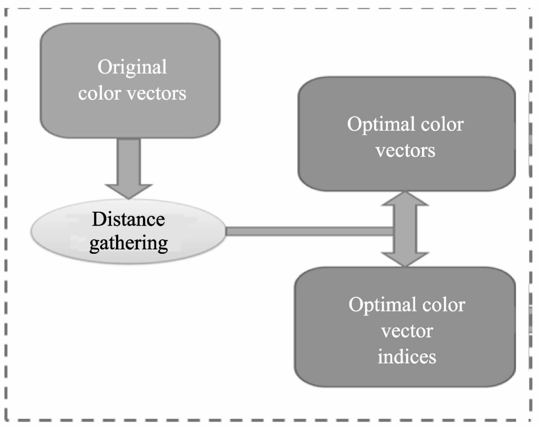

Fig. 5 Pixel rearrangement procedures

$$Eva = \sum_{j=1}^{N} \sum_{i=1}^{t} \| \boldsymbol{y}_i^{(j)} - \boldsymbol{p}_j \|^2 . \quad (1)$$

Eq. (1) shows the measurement about Euclidean distance between color vector $\boldsymbol{p}_j$ and the cluster centroid $\boldsymbol{y}_i^{(j)}$.

When *Eva* gets the minimum in each cluster, the clustering stops. Meanwhile, each cluster's mean value is calculated by

$$m_i = \frac{\sum (C_i)}{n}, \quad (2)$$

where C_i is the i-th cluster, m_i is the mean value of the i-th cluster. In our definition, m_i is named by optimal color vector (OPC) and which can be indexed by value.

2.2 Mean shift based on cluster color arrangement

Mean shift process based on OPC facilitates the histogram construction. New color substitution, OPC, not only represents the limited kinds of color but also owns the influence from the optimal color neighborhood.

Our representation about optimal color model gives a cunning mechanism to organize the color statistics distribution. In the mean shift process, color distribution of the reference image interest area (RIA) is able to be transformed into histogram of OPC modes. We only arrange the histogram about OPC, so that we can control the total infomation about the whole color distribution of RIA. Statistic density is described in the RIA as histogram of OPC. For the same reason, the candidate interest area (CIA) is also able to be described by histogram of OPC, as shown in Fig. 6.

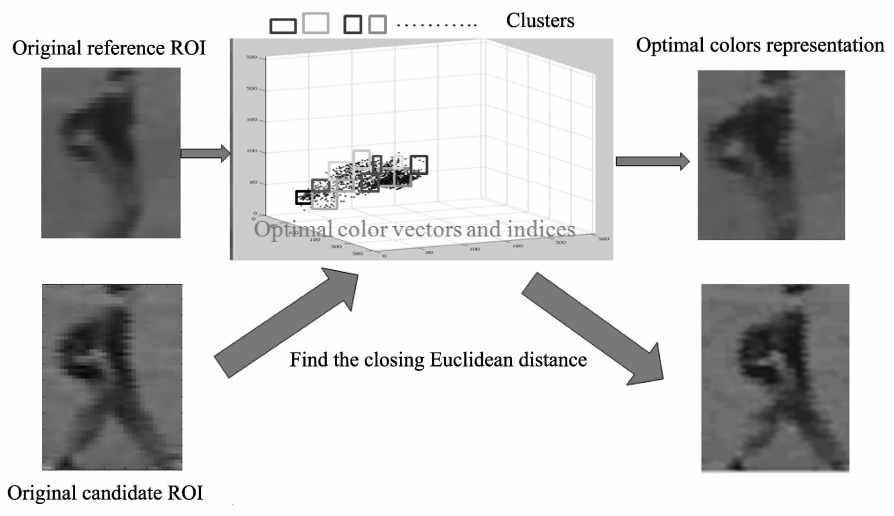

Fig. 6 RIA and CIA projection results

To obtain OPC in RIA and CIA, we initialize a target location in the reference frame as $P_r(x_r, y_r)$, and make a target rectangular window W_r according to the initial location P_r. Window size is $ih \times iw$. Then we cluster the color vectors in W_r and obtain OPC. Now a group of OPCs substitute original W_r density attributes. Histogram of each OPC also can be obtained easily.

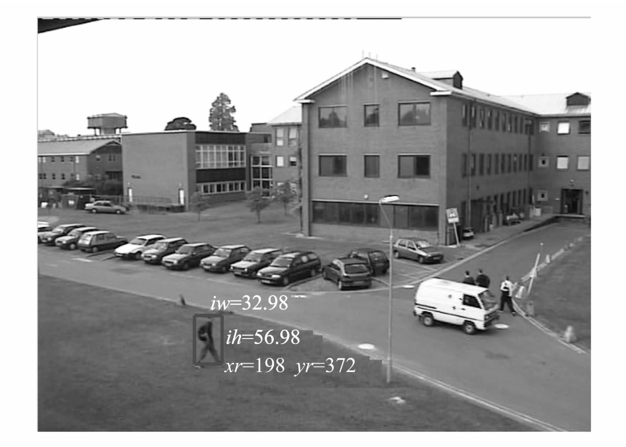

Fig. 7 Select initial position in RIA

The probability p of OPC u in W_r is

$$p_u = \sum_{i=1}^{iw \times ih} k \left\| \frac{P_r - Q_{r_j}}{\sqrt{(ih/2)^2 + (iw/2)^2}} \right\| \times \delta(b(Q_{r_j}) - u), \qquad (3)$$

where Q_{r_j} $(j = 1, \cdots, iw \times ii)$ denotes pixel (color vector) locations of target centered at P_r; $b(Q_{r_j})$ denotes the OPC bin of the u; k denotes the kernel function.

For CIA frame:

1) Extract the same size W_r from the same position P_r in the candidate frame. The pixels (color vectors) from the candidate interest area (CIA) can be mapped by Eq. (1).

The probability q_u of OPC u in CIA can be obtained by Eq. (3).

2) The matching OPC of u in RIA and CIA can be compared by

$$w_u = \sum (\sqrt{p_u / q_u}), \qquad (4)$$

$$Z_c = \frac{\sum_{u=1}^{n_h} w_u Q_r}{\sum_{u=1}^{n_h} w_u}. \qquad (5)$$

While $W_u(P_u(Z_c), q_u) < W_u(P_u(Q_r), q_u)$, the new position Z_c is replaced by $(Z_c + Q_r)/2$, as shown in Eq. (5).

3 Experiment

In our experiments, we manually select a target object at the initial frame (reference frame) and model it using the proposed OPC histogram model. The experimental results are shown in Figs. 8-11.

The program is written in MFC environment on a computer with 2.8-GHz Intel Pentium (R) CPU and 2.0-GB memory. Tracking time cost is presented in Table 1.

Fig. 8 Tracking Man _ passage result (400 **frames, size:** 640×480) **using the proposed algorithm**

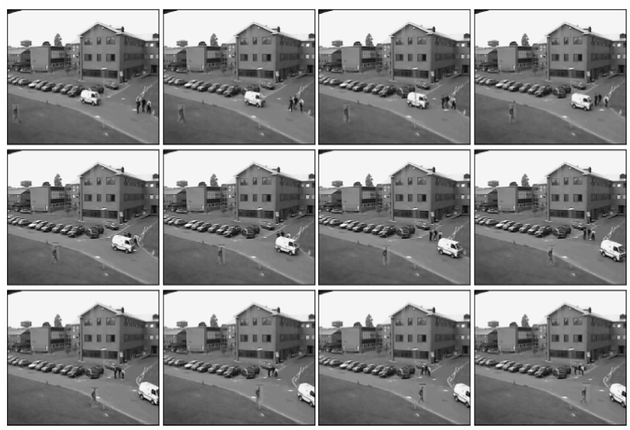

Fig. 9 Tracking Pedestrian _ 1 **result** (240 **frames, size:** 640×480) **using the proposed algorithm**

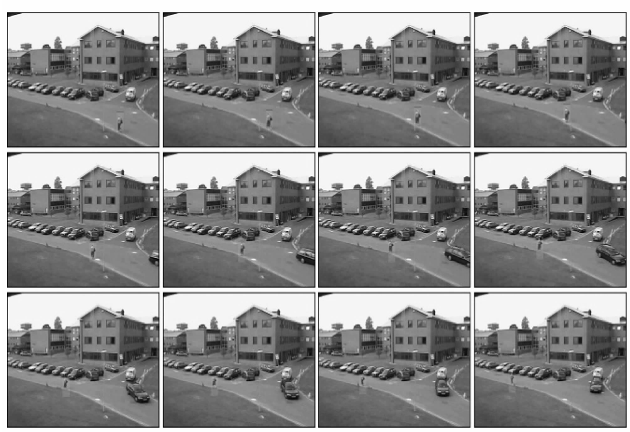

Fig. 10 Tracking Pedestrian _ 2 **result** (250 **frames, size:** 640×480) **using the proposed algorithm**

Fig. 11 Tracking girl _ fussy result (280 frames, size: 640×480) using the proposed algorithm

Table 1 Tracking time of serveral algorithms

Resources	*Algorithm*	*Bin num*	*Time cost*	*Distance gathering Time cost*
Man_passage	OPC	150	0.017s	<0.001s
	MS	4096	0.031s	
Pedestrain_1	OPC	60	0.015s	<0.001s
	MS	4096	0.031s	
Pedestrain_2	OPC	60	0.017s	<0.001s
	MS	4096	0.031s	
Girl_fussy	OPC	160	0.016s	<0.001s
	MS	4096	0.031s	

Window size:

Man_passage : 30*40----bin num=30*40/8

Pedestrain_1 : 30*30----bin num=30*30/15

Pedestrain_2 : 30*30----bin num=30*30/15

Girl_fussy : 80*80----bin num=80*80/40

OPC---Optimal color MS---Original Mean Shift

4 Conclusion

In this paper, we present an optimal color model method for tracking objects. Superior performance of the distance clustering and bin index mechanism is demonstrated on several examples. After the distance clustering, the construction of optimal color model can reduce the computation cost efficiently. Currently, we are working on adaptive window algorithm which can locate the target position more accurately under more complex environments. Bin classification will be further improved.

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