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EFFICIENT OBJECT TRACKING METHOD USING LBP BASED TEXTURE FEATURE AND OHTA COLOUR MOMENT

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ABSTRACT

This paper addresses a real time object tracking considering LBP based texture and Ohta based color moments as features for covariance tracking algorithm. The performance of the proposed algorithm is compared with other techniques such as the covariance object tracking with RGB features and color histograms based method interms of detection rate and computational time. The comparisons of the performance include detection rate and computational time.These methods have been applied to four different challenging situations and the resulting experimental results show the robustness of the proposed technique against occlusion, camera motion, appearance and illumination change.

KEY WORDS: Object Tracking, Covariance Matrix, Local Binary Pattern, Ohta Colour Model, Riemannian Geometry

INTRODUCTION

Object tracking is the process of following an object through successive image frames to determine its relative movement with respect to another object. Real time object tracking is a challenging problem in the field of computer vision, motion-based recognition, automated surveillance, traffic monitoring, augmented reality and sports video. In this paper four different challenging situations of object tracking in sports video have been carried out. In the survey study of Alper Yilmaz et al. in [1], the object tracking methods are classified into different categories on the basis of object detection. For detecting object in scene different techniques such as point detection, background subtraction, segmentation or supervised learning are used. Usually, a connected component algorithm is applied to obtain the connected region corresponding to the object. This process is referred to as the background subtraction. Varity of background subtraction methods are explained in [2]. Dipti Patra et al. [3] used image segmentation and pattern matching for object tracking. The histogram matching technique is implemented by F. Porikli et al. [4] for object tracking. However when there is similarity in object colour with the background, the histogram matching gives poor performance. In [5] Oncel Tuzel et al. proposes a region covariance descriptor for object detection and classification. A covariance matrix is generated to represent the target by combining several low level image features such as colours, intensities, gradients and coordinates. The region covariance descriptor is having low dimensionality and good discriminability. Using the elements of Riemannian geometry, Faith Porikli et al. [6] develops an effective descriptor where RGB colour components have been taken as some components of feature vector. In [7] RGB as well as L*a*b colour components have been used as the components of feature vector. Due to correlation property of RGB colour component the misclassification of object can occur in tracking. To improve the performance of tracking in [8] ohta colour features are used in place of using RGB color components. When more number of features are used to describe an object, the tracking speed decreases. So for improving tracking efficiency the detection rate as well as the tracking speed should improved. The texture patterns [9, 15] reflects the spatial structure of the object. The texture feature introduces new information that color features don't convey. To overcome the short comings of the existing approaches we proposed a covariance matrix representation by using the Ohta colour moments and texture pattern.

This paper is organized as follows: in section 2 Local Binary Pattern (LBP) is briefly described. Ohta model is described in section 3.The tracking technique using ohta color moments and LBP based texture feature is represented in section 4. Section 5 includes the experiments and result followed by conclusion in section 6.

LOCAL BINARY PATTERN

The LBP operator was introduced in [13] for texture classification. For a centre pixel in an image, the LBP value is computed by comparing its gray value with its neighbours, as shown in Fig. 1, based on

$$LBP_{P,R} = \sum_{p=1}^{P} 2^{p-1} \times f_1(g_p - g_c) \tag{1}$$

$$f_1(x) = \begin{cases} 1 & x > 0 \\ 0 & else \end{cases} \tag{2}$$

where g_c correspond to the grey value of the centre pixel of a local neighborhood and g_p correspond to the grey value of the P equally spaced pixels on a circle of radius R (R>0).

This LBP model is grey scale invariance model. The grey scale and rotation invariance model [10] is obtained by the following equation.

$$\mathrm{LBP}_{\mathrm{P,R}}^{\mathrm{riu2}} = \begin{cases} \sum_{p=0}^{p-1} s(g_p - g_c) & \text{if } U(\mathrm{LBP}_{\mathrm{P,R}}) \le 2 \\ P+1 & \text{otherwise} \end{cases} \tag{3}$$

$$U(\mathrm{LBP}_{\mathrm{P,R}}) = \left| s(g_{p-1} - g_c) - s(g_0 - g_c) \right| + \sum_{p=1}^{p-1} \left| s(g_p - g_c) - s(g_{p-1} - g_c) \right| \tag{4}$$

By definition, the $P+1$ "uniform" binary patterns occur in a circularly symmetric neighbour set of P pixels. Equation ( ) assigns a unique label to each of them corresponding to the number of "1" bits in the pattern (0 to P), while the "nonuniform" patterns are grouped under the "miscellaneous" label $P+1$.

2	5	3	9	1
6	17	29	1	5
2	5	9	9	2
3	17	3	2	1
1	2	3	2	1

The $\mathrm{LBP}_{\mathrm{P,R}}^{\mathrm{riu2}}$ model has nine uniform texture patterns, which are shown in Fig. 2. Each of the uniform patterns is called as a micro-texton. The micro-texon include spots, flat areas, edges, line ends and corners, etc. In Fig. 2, the white circles represent "1" and the black circles represent "0".

Edge, line ends and corners are represents the main features of the target and named as “major uniform pattern”where as spot and flat areas are represented as “micro texon”. So for the object representation we have considered five major uniform patterns.these major patterns are extracted as ( ).

Where

17	29	1
5	9	9
17	3	2

1	1	0
0		1
1	0	0

8	4	2
16		1
32	64	128

	45	

Figure 1: Example of Calculating $LBP_{8,1}$ (LBP Pattern Is 10110100, Decimal Pattern is 45)

$$
\mathrm{LBP}_{8,1}^{\mathrm{riu2}} = \begin{cases} \sum_{p=0}^{7} s(g_p - g_c + a) & \text{if } U(\mathrm{LBP}_{\mathrm{P,R}}) \le 2 \text{and} \\ & \sum_{p=0}^{7} s(g_p - g_c + a) \in \{2,3,4,5,6\} \\ 0 & \text{otherwise} \end{cases} \tag{5}
$$

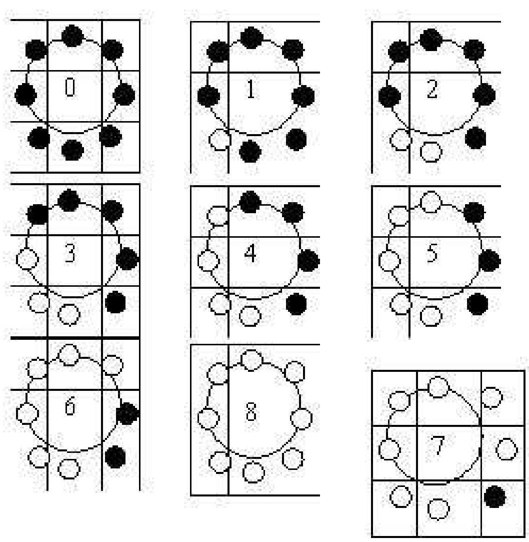


Figure 2: 0,1,7,8 are the Spots or Flat Area, 2, 6 are the Line End, 3,5 are the Corner, 4 is the Edge

OHTA COLOR MODEL

Ohta [7] had proposed a simple linear transformation from RGB to $I_1I_2I_3$ model conversion given by

$$
\begin{aligned} I_1 &= \frac{1}{3}(R+G+B) \\ I_2 &= \frac{1}{2}(R-B) \\ I_3 &= \frac{1}{4}(2G-R-B) \end{aligned} \tag{6}
$$

where I_1 is the achromatic and I_2 and I_3 are two chromatic components. By using this model statistical realization of inter channel correlations is realized. Hence the resulting colour channels are almost decorrelated.

STEPS OF OBJECT TRACKING

A. Object Representation

We represent the target object as the image I, which is a three dimensional colour image. Let F be the $W \times H \times d$ dimensional feature image extracted as

$$F(x,y) = \emptyset(I,x,y) \tag{7}$$

Where function $\emptyset$ can be any mapping such as colour. The image I is represented by a given rectangular window $R \subset F$. Let $\{f_k\}_{k=1,2....n}$ be the d-dimensional feature vectors inside R. We construct the feature vector f_k using two types of mappings such as spatial attributes and appearance attributes. The spatial attributes are obtained from pixel coordinates values, texture pattern and appearance attributes are obtained from colour.

$$f_k = \left\{ I_1, I_2, I_{3,}\ LBP_{P,R}^{riu2} \right\} \tag{8}$$

where I_1, I_2, I_3 are the Ohta colour components and $LBP_{P,R}^{riu2}$ is the rotation invariant LBP pattern.

B. Covariance Matrix

The covariance matrix for the M X N rectangular region R is calculated as follows

$$C_R = \frac{1}{MN}\sum_{k=1}^{MN}(f_k - \mu_R)(f_k - \mu_R)^T \tag{9}$$

The size of the covariance matrix is $d \times d$, where d is the number of features, μ_R the vector of the means of the corresponding features for the points within the region R.

The covariance matrix proposes a natural way of fusing multiple features which might be correlated. The covariance matrix is a symmetric matrix where its diagonal entries represent the variance of each feature and the non-diagonal entries represent their respective correlations. The noise corrupting each sampleis largely filtered out during the averaging step of covariance calculation. Also the covariance matrices are having low dimension as compared to other region descriptors.

There are several advantages of using covariance matrices as region descriptors. It embodies the information embedded within the histograms as well as the information that can be derived from the appearance models.

The covariance matrix of any region has the same size, thus it enables comparing any regions without being restricted to a constant window size. The upd ation of the model is required because the shape, size and position of non rigid objects undergo changes every time therefore the tracking process needs to adapt the changes. So we construct and update a temporal kernel of covariance matrices corresponding to the previously estimated regions $R_1, R_2 \dots . R_T$. We keep a set of T previous covariance matrices $[C_1, C_2 \dots . C_N]$, where C_1 is the current covariance matrix. The sample mean covariance matrix as given in [5] is:

$$C = \begin{bmatrix} \sigma_{1,1}^2 & \sigma_{1,2}^2 & \cdots \\ \sigma_{1,2}^2 & \sigma_{2,2}^2 & \\ \vdots & & \ddots \end{bmatrix}_{d\,Xd} \tag{10}$$

Where

(11)

μ is the mean computed over the regions and M X N is the window size.

C. Object Tracking

To obtain the most similar region to the given object, we need to compute distances between the covariance matrices corresponding to the target object window and the candidate regions. However, the space of covariance matrices is not a vector space. For example, the space is not closed under multiplication by negative scalars. Therefore an arithmetic subtraction of two matrices would not measure the distance of the corresponding regions. The distance metric uses the sum of the squared logarithms of the generalized eigenvalues to compute the dissimilarity between covariance matrices as

(12)

where) are the generalized eigenvalues of and , computed from

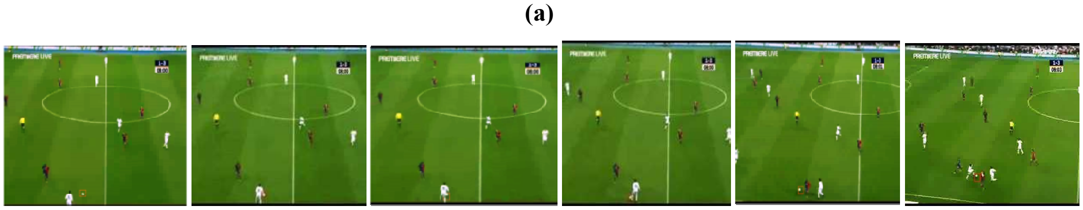
(13)

is the generalized eigenvectors. The distance measure satisfies the metric axioms, positivity, symmetry, triangle inequality, for positive definite symmetric matrices. At each frame we search the whole image to find the region which has the smallest distance from the current object model. The best matching region determines the location of the object in the current frame.

EXPERIMENTS AND RESULTS

In this section extensive experiments are performed to testify the proposed object tracking method using LBP based texture feature and ohta colour moment. The performance is compared with Covariance Tracking using Model Update Based on Means on Riemannian Manifolds and Ohta Based Covariance Technique for Tracking Object in Video Scene. Four different video scenes are used in evaluating the different methods. The algorithms are implemented in MATLAB and run on a PC with Intel Core 2 Duo 3.0 GHz with 4 GB RAM. The proposed algorithm has been tested on several video sequences for four different challenging situations. These include the most challenging one i.e. tracking of non rigid object in illumination varying condition. The detection rate (ratio of number of frames accurately tracked to the total number of frames) is calculated for each of four cases. Also the tracking speeds of different methods are compared. Fig.2 shows the tracking results of the proposed method in different conditions.

(a)



(b)

(c)

(d)

Figure 2: Tracking Results of the Proposed Method (A)Head Tracking in Tennis Player Sequence (B) Ball Tracking in Football Sequence1 (C) Player Tracking in Football Sequence1 (D) Player Tracking in Football Sequence2

In first experiment the face of the tennis player is the object. In this video the object color and the background color is distinct and also the background is still. All the three methods can track the object efficiently. Fig.2 (a) shows the tracking result of the proposed method.

In second experiment a moving camera football sequence is taken. Here the ball is the object of interest.

The size of the object is very small and in some frames it is being occluded by the players. Also the ball color is similar to the color of player's uniform. In this video the background is also moving. All the three methods are able to track the object but the detection rate and tracking speed of the proposed method is better as compare to others.

The third experiment is the tracking of player in the same video sequence of experiment-2.The player's shape and size is changing in different frames.

Table1: Detection Rate of Different Methods

Video Sequence	Ohta Based Covariance Tracker	RGB Based Covariance Tracker	Proposed Method
Exp A	97.5	97.5	73.4
Exp B	97.78	96.5	78.3
Exp C	98.32	95.67	79.1
Exp D	98.56	95.5	48.7

Table1: Tracking Speed of Different Methods

Video Sequence	Ohta Based Covariance Tracker	RGB Based Covariance Tracker	Proposed Method
	366 seconds	322 Seconds	255Seconds

Fourth experiment contains the tracking of the player in a more challenging situation. In this video sequence the object is the player which moves across the changing lighting condition. Also it is having complex changing background. In this condition the proposed method tracks the object more efficiently and accurately.

CONCLUSIONS

In this paper, we have proposed the use of Ohta colour features and texture feature for constructing the covariance matrix. For extracting the texture feature the LBP operator has been used. The LBP operator is an effective tool to measure the spatial structure of local image texture. Five major uniform $LBP_{8,1}^{riu2}$ texture patterns and colors are taken for target representation. The decorrelated Ohta colour moments and texture patterns effectively extracts the edges, corners and color information. The proposed method uses less number of features as compare to the previous methods which improves the computational efficiency of the method. Experimental results reveal that the proposed method is capable of handling occlusion, camera motion, complex background, appearance change and lighting changes. Also the detection rate of the proposed method is better as compared to other methods. In future work, we expect to improve our method in the case of multiple objects tracking with occlusion.

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