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Objects Tracking in Images Sequence Using Center-Symmetric Local Binary Pattern (CS-LBP)

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Abstract: In this paper we present a method for objects tracking in images sequence. This approach is achieved into two main steps. In the first one, we constructed the Center-Symmetric Local Binary Pattern (CS-LBP) histogram pattern of each image in the sequence and the reference pattern. In the second one, we perform the algorithm by the pattern selected based on a distance measures to find similarity between two histograms. The maximum CS-LBP histogram distance gives best results than the chi-square one. The proposed approach has been tested on synthetic and real sequence images and the results are satisfactory.

Keywords: Sequence image, Computer vision, Tracking, LBP, CS-LBP histogram, Chi-square distance..

1. INTRODUCTION

Tracking systems is important in computer vision. It is applied in different domain, for example in video surveillance and human computer interfaces (HCI). Various methods can be found in the literature and can be roughly classified into two basic categories:

- The first category is the algorithms that estimate the absolute positions of the pixel in each image independently. This category includes the center-of-mass, or centroid algorithm [1,2] and direct fits of Gaussian curves to the intensity profile [3,4].

- The second category includes algorithms that estimate the change in position of a pixel by comparing an image to one subsequent. This category includes cross-correlation method [5, 6, 7], and SAD algorithm method [8]. The use of the second category is well known and commonly used in tracking for sequence image. And it is commonly used in tracking vision for the visual matching problem [9].

- The SAD method suffers from the sensitivity to intensity scaling of the image and the template [11, 12, 13], but the ZNCC method presents an ambiguity in the area with similar brightness or similar texture. It is demonstrated that the CS-LBP is mainly characterized by the invariance to monotonic changes in gray-scale and fast computation, and it has proven performance background in texture Classification [10]. While operating in gray-scale color space, CS-LBP is also robust to illumination changes.

- Texture, which has not enjoyed major attention in tracking applications, provides a good option to enhance the power of color descriptors. In this way we propose to use the CS-LBP [31] histograms to tracking the motif in a sequence of images. In order to show the feasibility of the proposed method, it is tested and applied to both real image sequences and synthesized image sequences

2. LOCAL BINARY PATTERNS (LBP)

The basic local binary pattern operator, introduced by Ojala et al. [15,16], was based on the assumption that texture has locally two complementary aspects, a pattern and its strength. In that work, the LBP was proposed as a two-level version of the texture unit [17,14] to describe the local textural patterns. The original version of the local binary pattern operator works in a 3 × 3 pixel block of an image. The pixels in this block are thresholded by its center pixel value, multiplied by powers of two and then summed to obtain a label for the center pixel.

As the neighborhood consists of 8 pixels, a total of 2^8 = 256 different labels can be obtained depending on the relative gray values of the center and the pixels in the neighborhood. See Fig.1 for an illustration of the basic LBP operator.

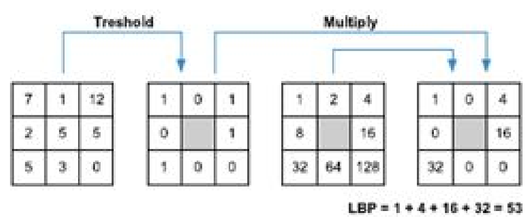

Fig. 1: The original LBP

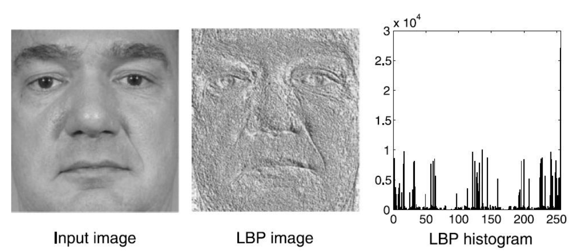

Fig.2 : Example of an input image, the corresponding LBP image and histogram

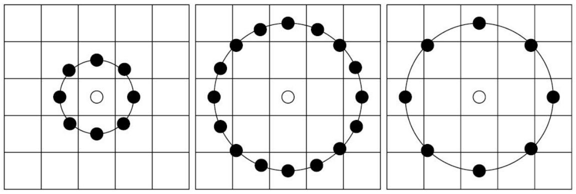

Fig.3 : The circular *(*8, 1*)*, *(*16, 2*)* and *(*8, 2*)* neighborhoods. The pixel values are bilinearly interpolated whenever the sampling point is not in the center of a pixel

Local binary pattern is a simple description operator of local texture. It can resist to the changes of illumination [10, 11]. And it has proven performance background in texture classification [10]. In recent years, the LBP operator has been used for texture classification, face recognition, image retrieval and other fields.

2.1 Center-Symmetric LBP

Center-Symmetric Local Binary Patterns (CS-LBP) [31] were developed for interest region description. CS-LBP aims for smaller number of LBP labels to produce shorter histograms that are better suited to be used in region descriptors. Also, CS-LBP was designed to have higher stability in flat image regions.

In CS-LBP, pixel values are not compared to the center pixel but to the opposing pixel symmetrically with respect to the center pixel. See Fig. 4 for an illustration with eight neighbors [31].

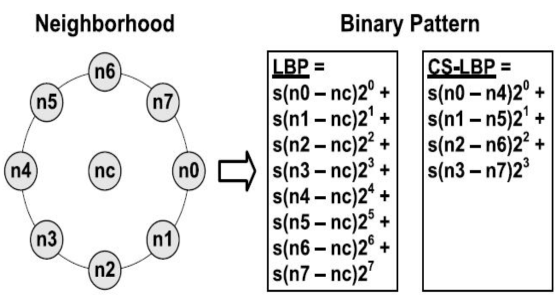

Fig 4 : LBP and CS-LBP features for a neighborhood of 8 pixels

3. HISTOGRAM DISTANCE

The use bin-to-bin distances for comparing histograms is very important. This practice assumes that the histogram domains are aligned. This distance depends on the number of bins. If it is low, the distance is robust, but not discriminative, if it is high, the distance is discriminative, but not robust. Distances that take into account cross-bin relationships (cross-bin distances) can be both robust and discriminative. There are two kinds of cross-bin distances. The first is the Quadratic-Form distance [19]. Let P and Q be two histograms and A the bin-similarity matrix. The Quadratic- Form distance is defined as:

$$QF^{A}(P,Q) = \sqrt{(P-Q)^{T}\ A(P-Q)}$$

When the bin-similarity matrix A is the inverse of the covariance matrix, the Quadratic-Form distance is called the Mahalanobis distance. The second type of distance that takes into account cross-bin relationships is the Earth Mover's Distance (EMD) [20].

In many natural histograms the difference between large bins is less important than the difference between small bins and should be reduced. The Chi-Squared (***X2***) is a histogram distance that takes this into account. It is defined as:

$$\chi^{2}(P,Q)=\frac{1}{2}\sum_{i}\frac{(P_i-Q_i)^2}{(P_i+Q_i)}$$

The ***X2*** histogram distance comes from the x2 test-statistic [21] where it is used to test the fit between a distribution and observed frequencies. Chi-square histogram distance is one of the distance measures that can be used to find dissimilarity between two histograms. ***X2*** was successfully used for texture and object categories classification [22, 23, 24], near duplicate image identification [25], local descriptors matching [26], shape classification [27, 28] and boundary detection [29].

4. PROPOSED METHOD

The proposed method is achieved in two main steps. In the first one, we constructed the Center-Symmetric Local Binary Patterns (CS-LBP) [31] histogram pattern of each image in the sequence and the reference pattern. In the second one, we perform the algorithm by the pattern selected based on a distance measures to find similarity between two histograms. The flowing we present the algorithm used in this stud.

Algorithm:

First step

1. Extract reference pattern

2. Calcul CS-LBP histogram of reference pattern:
H(i,j) = HistogramPattern(i,j)

3. Extract pattern of each image in the sequence

4. Calcul CS-LBP histogram pattern of each image in the sequence :
Hn(i,j)= Histogram NewImage(i,j)

End

Second step

Medd=Abs(max(H(i,j))- max(Hn(i,j)))

Min(Medd(I,j))

Or

Calcul the Chi-square distance between H(i,j) and Hn(i,j)
Min(chi2(H(i,j), Hn(i,j))

End

5. EXPERIMENTAL RESULT

In this section, we present the experimentation results of into tracking image sequences. Real image sequences and synthesized image sequences are considered. For evaluation the algorithm tracking results we use Euclidean distance.

5.1 Synthesized Sequence Image

We used a sequence of grayscale image containing a moving ball. This database gives returns to Strauss [18]. Table 1 shows the cumulative Euclidean distance r from the pixel position for each images i and (i +1) for the similarity measure using chi-square and maximum histogram.

Table 1: Cumulative Euclidean distance for the two method

Sequence N°	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
Chi-square	4	77	122	158	168	236	273	299	316	369	386	403	443	479	508	545	571	611	660
Max-histogram	1	54	91	100	101	166	192	205	250	299	316	336	373	409	435	472	512	537	586

Figure 5 presents the evolution of the position of pixels for each image using de cumulative Euclidean distance. The figure shows that the similarity measure uses the maximum histogram is below the chi-square. Therefore, the maximum CS-LBP histogram distance gives best results than the chi-square one. Finally, we present examples of image sequence using the max histogram. From the results, it can be seen that its performance is acceptable for the synthetic sequence images.

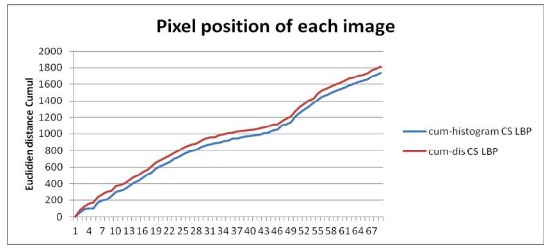

Figure 5 :Evolution of the position of pixels for each image using de cumulative Euclidean distance

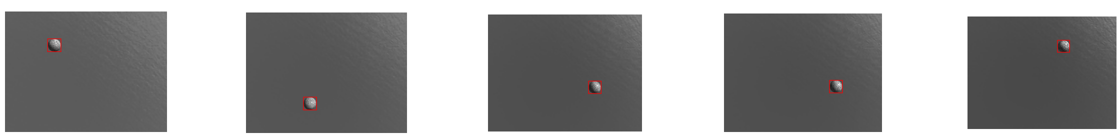

Image1 Image15 Image30 Image45 Image 60

Fig. 6 : same image using max-histogram for tracking the ball

5.2 Real Sequence Image

In order to compare the performances of the method we have considered a real sequence image. We have used the video realized by Sargi [30] for tracking the face. Table 2 present the cumulative Euclidean distance from the pixel position for each images i and (i +1) for the similarity measure using chi-square and maximum histogram. The table shows that the values relate to the measurement of Chi-square augment rapidly. In particular; the both methods are almost similar in images 4 and 5 as you can see in Fig.7.

Table 2: Cumulative Euclidean distance for the two method

Image Sequence N°	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Chi-square	0	100	100	105	105	157	207	211	211	279	352	501	502	502	502	520
Max-histogram	0	26	26	99	99	119	119	120	120	188	273	318	386	402	402	442

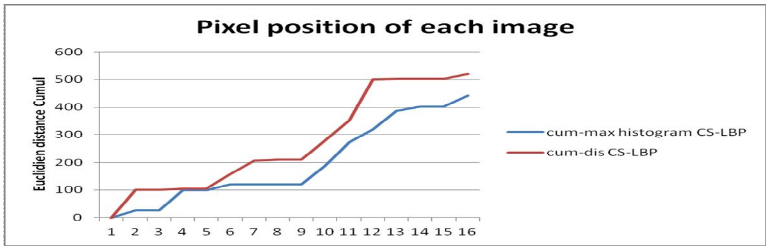

Fig. 7 :Evolution of the position of pixels for each image using de cumulative Euclidean distance

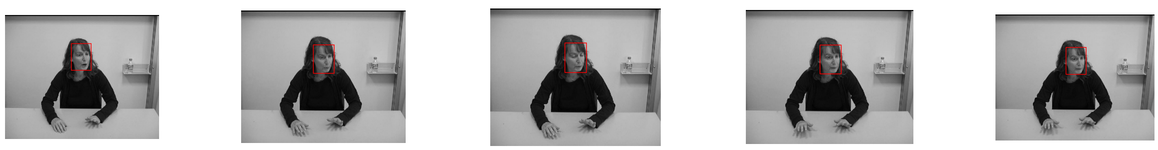

Image1 Image5 Image 10 Image15 Image 17

Fig. 8 : same image using max-histogram for tracking the face

6. CONCLUSION

In this paper a method for objects tracking in images sequence using Center-Symmetric Local Binary Patterns (CS-LBP). For evaluation the algorithm tracking results we use the cumulative Euclidean distance from the pixel position for each images. The maximum CS-LBP histogram distance gives best results than the chi-square one. From the results, it can be seen that its performance is acceptable for both the synthetic and real sequence images. In the future work, we will exploit the information color for constructed the CS-LBP operator.

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