ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

TRACKING OBJECT USING EXPONENTIAL FORGETTING FACTOR IN THE LBP CODE

[1] HANANE. RAMI, [2] MOHAMMED. HAMRI, [3] LHOUSSINE. MASMOUDI
[1,2,3] LETS/Géomat Laboratory, Physics Department, Mohamed V University, Faculty of Science,
Rabat, MORROCCO
E-mail: [1] ramihanane@gmail.com , [2] hamri@fsr.ac.ma , [3] masmoudi@fsr.ac.ma

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 use the Exponential Forgetting Factor in the calculation of Local Binary Pattern to tracking the motif in a sequence of images. In the second one, we perform the algorithm by the pattern selected based on a distance measure to find similarity between two histograms, for this goal we work with The Chi-Square distance. For evaluation the algorithm tracking results we use the cumulative Euclidean distance from the pixel position for each images. The proposed approach has been tested on synthetic and real sequence images and the results are satisfactory.

Keywords: *Computer vision, Sequence image, Tracking, LBP, Exponential Forgetting Factor (EFF), Chi-Square distance.*

1. INTRODUCTION

Tracking of moving objects is important for video surveillance while future frame prediction is used in video coding. The goal of this paper was to design, implement on computer, and test on real images a variety of computer vision algorithms for region tracking over sequences of images. The region to be tracked is specified only in the First frame, and the algorithm proceeds to track the region through subsequent frames. Two different types of algorithms were tested using certain image characteristics.

The First, local tracking, is concerned with comparing local structures of the region between two frames. 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, global tracking is concerned with comparing the distributions of certain image characteristics in the region between two frames. Some very promising theoretical results have been demonstrated by viewing the image a 3-D surface and using functions of the principal curvatures as image characteristics for tracking. 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 disadvantage of this category is sensitive to changes in global illumination between two images, for remedied this problem we introduce the LBP operator in the frame of sequences images.

The Basic Local Binary Pattern operator LBP, introduced by Ojala et al. [10,11], is a well known texture feature which has been successfully applied to many applications, e.g., texture classification, texture segmentation, face recognition. The LBP operator has several interesting properties. First of all, it is simple and fast to compute. Moreover, it offers strong discriminative power for the description of texture structure while staying robust to monotonic lighting changes. All these advantages make LBP a good candidate for describing local image regions.

However, the drawback of the LBP feature lies in the high dimensionality of histograms produced by the LBP codes. Another disadvantage of LBP is the weighting of pixels which is far from center when we work with P=24, R=2 compared to P=8, R=2. Thus, a method to solve these problems is needed. In this way we propose to use the Exponential Forgetting Factor for tracking object in a sequence of images. Our aim is to build a more efficient local descriptor by introduce an exponentially decreasing weights old data in calculating the sum of pixel intensity value in a given window. In order to show the feasibility of the proposed method, it is tested and applied to both real and synthesized image sequences.

Journal of Theoretical and Applied Information Technology
31st May 2014. Vol. 63 No.3

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

This paper is organized as follows: The LBP operator is explained in Section 2 and the proposed approach are described in Section 3. In Section 4 presented the Chi-distance square, Experimental results are presented in Section 5 and Section 6 concludes this paper.

2. LOCAL BINARY PATTERNS (LBP)

The Basic Local Binary Pattern operator 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 [13,14,28] to describe the local textural patterns.

The LBP operator describes each pixel by the relative gray levels of its neighboring pixels. Precisely, for each neighboring pixel, the result will be set to one if its value is no less than the value of the central pixel, otherwise the result will be set to zero. The LBP code of the central pixel is then obtained by multiplying the results with weights given by powers of two, and summing them up together. Formally, the LBP code of the pixel at (xc, yc) is calculated as:

$$LBP_{P,R}(x_c, y_c) = \sum_{P=0}^{P-1} S(g_g - g_g) \times 2^P \qquad (1)$$

$$S(x) = \begin{cases} 1 & x \geq 0 \\ 0 & x \prec 0 \end{cases}$$

The original version of the local binary pattern operator works in a 3 × 3 pixel block of an image. The pixels in this block were 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 28 = 256 different labels can be obtained depending on the relative gray values of the center and the pixels in the neighborhood.

However, the drawback of the LBP feature lies in the high dimensionality of histograms produced by the LBP codes. Let P be the total number of neighboring pixels, then the LBP feature will have 2P distinct values, resulting in a 2P-dimensional histogram. For example, the size of the LBP histogram will be 256 (65536, respectively) if 8 (16, respectively) neighboring pixels are considered. It will rapidly increase to a huge number if more neighboring pixels are taken into consideration. Another disadvantage of LBP is the weighting of pixels which is far from center when working on a P=8, R=2, compared to the P=24, R=2. Thus, a method to solve these problems is needed.

3. PROPOSED METHOD

To reduce the dimensionality of the LBP histogram, a new strategy is the introducing the Exponential Forgetting Factor in the algorithm local measurement of the intensity (EFF) and for calculates the LBP code, namely LBP–EFF. The Exponential Forgetting Factor was used in several works [16,17,29]. The principle of the Exponential Forgetting Factor is to introduce an exponentially decreasing weights old data in calculating the sum of pixel intensity value in a given window.

Firstly, we propose to describe the EFF operator for each pixel by gray levels of its neighboring pixels. The EFF code of the central pixel is obtained by multiplying the results with weights Exponential Forgetting Factor, and summing them up together. Therefore, the weight of the latest data will be capped on the one hand, and learning results will focus on the old data on the other. Formally, the EFF code of the pixel at (xc, yc) is calculated as:

$$EFF(x_c, y_c) = \sum_{P=0}^{P-1} S(g_p - g_c) \times n(p) \times e^{-\lambda P} \qquad (2)$$

$$S(x) = \begin{cases} 1 & x \succ 0 \\ 0 & x \leq 0 \end{cases}$$

Where n(p) are classified in order ascending. The scalar is the Forgetting Factor. We use the Exponential Forgetting Factor (EFF) the old information is discounted according to an Exponential function. In EFF, pixel values are compared to the center pixel. See Fig. 1 for an illustration with eight neighbors.

9	2	11
14	10	20
6	13	8

Martice original

0	0	11
14	0	20
0	13	0

Threshold

$$EFF = 11 \times e^{-\lambda \times 1} + 13 \times e^{-\lambda \times 2} + 14 \times e^{-\lambda \times 3} + 20 \times e^{-\lambda \times 4}$$

Fig .1: EFF features for a neighborhood of 8 pixels

Secondly, we propose to introduce the Exponential Forgetting Factor in the calculation of Local Binary Pattern. The idea is to introduce an exponentially decreasing weighting recent data. Formally, the LBP-EFF code of the pixel at (xc, yc) is calculated as:

Journal of Theoretical and Applied Information Technology
31st May 2014. Vol. 63 No.3

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

$$LBP\_EFF_{P,R}(x_c, y_c) = \sum_{P=0}^{P-1} S(g_p - g_c) \times 2^P \; e^{-\lambda P} \qquad (3)$$

$$S(x) = \begin{cases} 1 & x \geq 0 \\ 0 & x \prec 0 \end{cases}$$

$\lambda \in [0.1[$ is the forgetting factor.

4. CHI-SQUARE DISTANCE

In this section, we perform the algorithm by the pattern selected based on a distance measure to find similarity between two histograms, for this goal we work with The Chi-Square distance.

The Chi-Squared ($x2$) was successfully used for texture and object categories classification [19, 20, 21], near duplicate image identification [22], local descriptors matching [23], shape classification [24, 25] and boundary detection [26].

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:

$$\chi^2(P,Q) = \frac{1}{2}\sum_i \frac{(P_i - Q_i)^2}{(P_i + Q_i)} \qquad (4)$$

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.

5. EXPERIMENTAL RESULT

The proposed method is achieved in two main steps. In the first one, we constructed the LBP-EFF code and EFF 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 The Chi-Square distance measures to find similarity between two histograms. For evaluation the algorithm tracking results we use the cumulative Euclidean distance from the pixel position for each images. The flowing we present the algorithm used in this stud.

Algorithm

First step

1. Extract reference pattern
2. Calcul LBP-EFF histogram of reference pattern: H(i,j) = Histogram Pattern(i,j)
3. Extract pattern of each image in the ce
4. Calcul LBP-EFF histogram pattern of each image in the sequence :
   Hn(i,j)= Histogram NewImage(i,j)

End

Second step

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

(x,y)=Min(chi2(H(i,j), Hn(i,j)) //(x,y): position min of the patterns of sequence image

End

In the flowing we present the experimentation results of the tracking image sequences. Real and synthesized image sequences are considered. For evaluation the algorithm tracking results we use cumulative Euclidean distance. The smaller the distance value is the better the tracking image method.

5.1. Synthesized Sequence Image

To evaluate the proposed descriptor, we used a sequence of grayscale image containing a moving ball. This database gives returns to Strauss [18]. There are two parameters to be fixed for the proposed LBP-EFF descriptors, including the number of neighboring pixels for the LBP-EFF operator (P), and the radius of neighboring circle for the LBP-EFF operator (R). Table 1 shows the cumulative Euclidean distance from the pixel position for each images i and (i +1) for the similarity measure using chi-square distance. Figure 3, we present examples of image sequence using the chi-square distance from the object tracking, it can be seen that its performance is acceptable for the synthetic sequence images.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Sequence N°	1	10	12	30	40	50	60	70	80	90	100	110	120	130	140	150
LBP-EFF (P=24, R=2)	8	233	588	842	938	1205	1498	1724	1941	2423	2682	2886	3163	3542	3911	4198
LBP-EFF (P=8, R=2)	17	285	638	891	1008	1301	1620	1829	2051	2572	2860	3109	3471	3883	4323	4540
LBP	16	337	678	928	1029	1333	1658	1891	2126	2579	2865	3139	3476	3799	4221	4327
EFF	16	211	553	804	906	1128	1461	1673	1869	2084	2383	2660	2845	3197	3504	4131

Table 1: Cumulative Euclidean distance for different methods

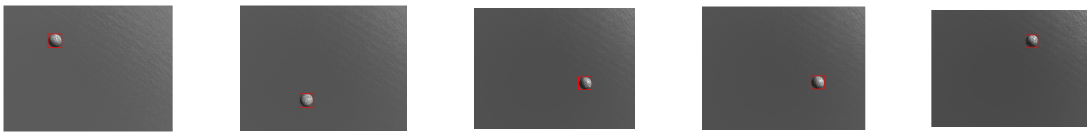

Image 1 *Image 30* *Image 90* *Image 125* *Image 160*

Fig.2 : Sequence Image Using The Proposed Method For Tracking The Ball

In order to compare the performances of the new method with some existing ones, we plotted the curves relating to Tables 1. The results are shown in Fig.2. Form the figure 4 presented the result for LBP-EFF operator, it can be seen that (P = 24,R = 2) obtain the best results than the (P=8, R=2). We thus compared this parameter (P=24, R=2) with EFF and LBP methods. The Figure 3 presented the Results for EFF and LBP-EFF (P=24, R=2) methods. The best performance is achieved when P = 24, R = 2. Figure 5, presented the Results for LBP and LBP-EFF (P=24, R=2) methods, this last gives the best result as the first one.

Figure 3: Results For EFF And LBP Methods

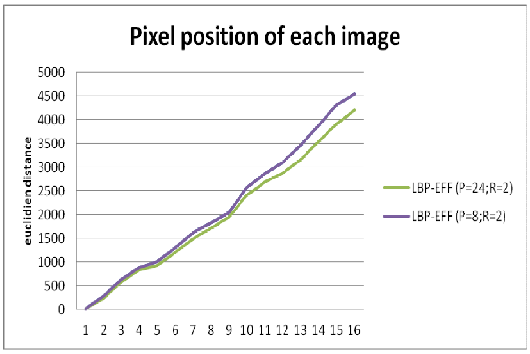

Figure 4 : Results For LBP-EFF Descriptor In Different Parameter

Journal of Theoretical and Applied Information Technology
31st May 2014. Vol. 63 No.3

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

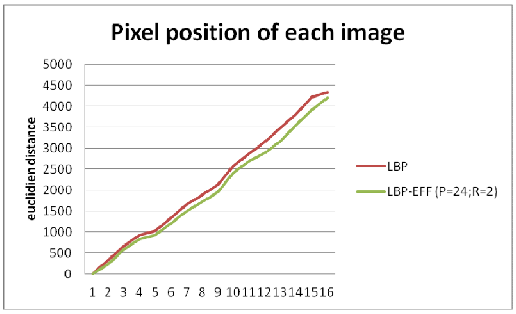

Figure 5: Results For LBP And LBP-EFF(P=24, R=2) Methods

5.2. Real sequence image

We also evaluated the proposed descriptors for the real sequence image. We have used the video realized by Sargi [27] for tracking the face. The Fig. 6 presented the result of the various images using the proposed method 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.

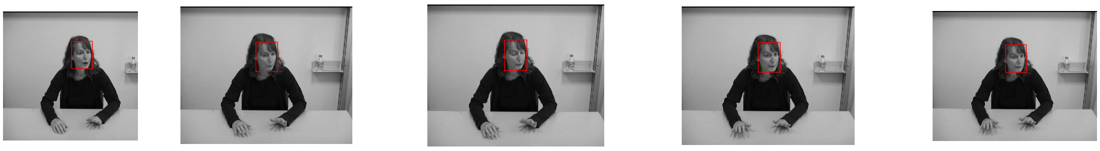

Image1 Image5 Image 10 Image15 Image 17

Fig. 6 : Sequence Image Using The Proposed Method For Tracking The Face

Sequence N°	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
LBP-EFF (P=24, R=2)	0	20	20	54	54	107	107	187	212	220	220	229	229	249	249	269
LBP-EFF (P=8, R=2)	0	10	10	27	27	92	141	266	367	495	559	639	752	761	761	802
LBP	0	50	50	100	149	262	303	392	392	445	445	449	449	478	478	546
EFF	0	89	154	167	167	220	324	473	498	503	503	556	556	560	560	628

***Table** 2: Cumulative Euclidean Distance For Different Method*

The image tracking results are shown in Fig. 6. Table.2 shows the comparisons of the proposed LBP-EFF descriptors with the popular LBP and EFF descriptors. Fig. 7 shows the comparisons of the best LBP-EFF (P = 24, R = 2) descriptors with the EFF descriptors. We can see from the results in Fig.9 that the EFF -LBP descriptor performs better than the popular LBP descriptor.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

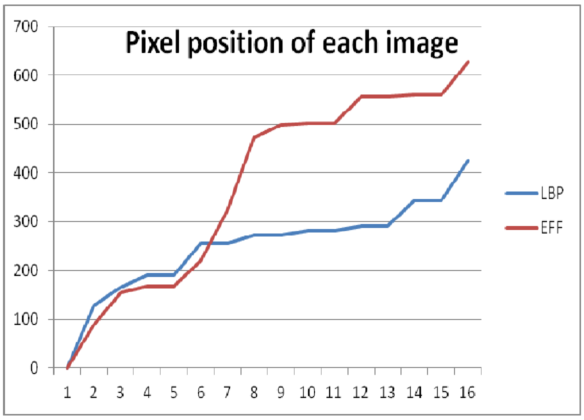

Fig 7: Results For EFF And LBP Methods

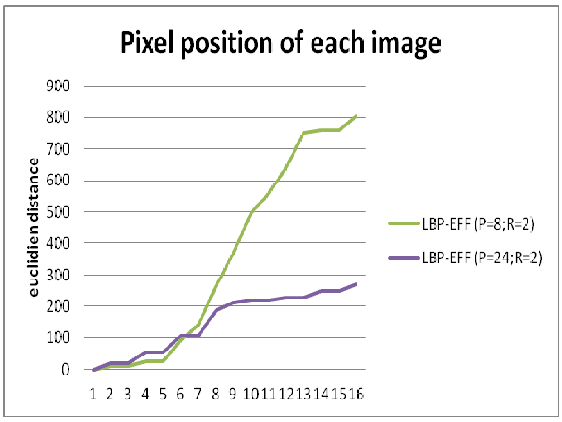

Fig 8: Results For LBP-EFF Descriptor In Different Parameter

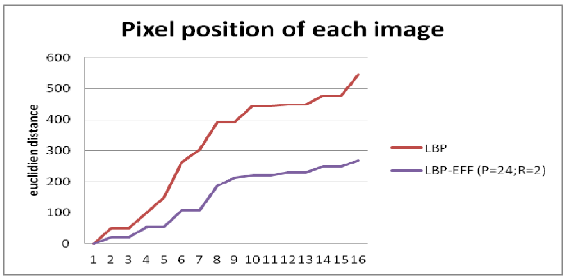

Fig. 9: Results For LBP And LBP-EFF(P=24, R=2) Methods

6. CONCLUSION

It is efficient to introduce an exponentially decreasing weights old data, in calculating the sum of pixel intensity value in a given window, for the tracking moving objects. For this purpose, we have introduced the Exponential Forgetting Factor in the algorithm local measurements of the intensity (EFF) and for calculate the LBP code (LBP–EFF).

For evaluation the algorithm tracking results we use the cumulative Euclidean distance from the pixel position for each images. The LBP-EFF (P= 24, R=2) descriptor gives best results than the LBP original and LBP-EFF (P=8, R=2) in the real and synthetique sequence images. In the future work, we will exploit the information color for constructed the LBP-EFF operator.

REFRENCES:

[1] Ghosh and Webb. 1994. Automated detection and tracking of individual and clustered cell surface low density lipoprotein receptor molecules.Biophys. J.66:1301–1318.

[2] Lee, and al. 1991. Direct observation of Brownian motion of lipids in a membrane.Proc. Nat. Acad. Sci. U.S.A.88:6274 – 6278.

[3] Smith, and al. 1999. A direct comparison of selectin-mediated transient, adhesive events using high temporal resolution.Biophys. J.77:3371–3383.

[4] Gelles, and al.1988. Tracking kinesin-driven movements with nanometre-scale precision.Nature.331:450 – 453.

[5] Kusumi, and al. 1993. Confined later diffusion of membrane receptors as studied by single particle tracking (nanovid microscopy). Effects of calcium-induced differentiation in cultured endothelial cells. Biophys. J.65:2021–2040.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

[6] Guilford and Gore, 1995. The mechanics of arteriole interstitium interaction. Microvas. Res.50:260 –287.
[7] Anderson and al. 1992. Tracking of cell surface desceptors by fluorescence digital imaging microscopy using a charge-coupled device camera.J. Cell ci.101:415–425.Tavel, P. 2007 Modeling and Simulation Design. AK Peters Ltd.
[8] Vanne, and al, 2006. "A High-Performance Sum of Absolute Difference Implementation for Motion Estimation," Circuits and Systems for Video Technology, IEEE Transactions on, vol.16, no.7, pp.876-883.
[9] Kanade and Okutomi.1994. A stereo matching algorithm with an adaptive window: theory and experiment. IEEE Transactions for Pattern Analysis and Machine Intelligence 16, 920-932.
[10] Ojala and al, 2002. Multiresolution gray-scale and rotation invariant texture classification with local binary patterns. IEEE Transactions on Pattern Analysis and Machine Intelligence, 24(7): 971-987
[11] Timo Ahonen and al, 2009. Rotation invariant image description with local binary pattern histogram
[12] Ojala T, Pietikäinen M & Harwood D (1996) A comparative study of texture measures with classification based on featured distribution. Pattern Recognition, 29(1):51-59.
[13] A. Hadid, M. Pietikainen and T. Ahonen. A Discriminative Feature Space for Detecting and Recognizing Faces. Proc of CVPR 2004.
[14] Jo Chang-yeon, "Face Detection using LBP features," Final Project Report, December 2008.
[15] Olivier STRAUSS Laboratoire d'Informatique, de Robotique et de Micro-électronique de Montpellier Département Robotique LIRMM 161, Rue ADA 34392 Montpellier CEDEX 5 France
[16] KulhavyH , R., & KaHrnyH , M. Tracking of slowly varying parameters by directional forgetting. In Proceedings of the ninth IFAC world congress, Budapest, Hungary, (pp. 687}692). (1984).
[17] KulhavyH , RRestricted. Exponential forgetting in real-time identification. Automatica, 23, 589}600. (1987).
[18] Snedecor, G., Cochran, W.: Statistical Methods, ed 6. Ames, Iowa (1967)
[19] Cula, O., Dana, K.: 3D texture recognition using bidirectional feature histograms. IJCV (2004)
[20] Zhang, J., Marszalek, M., Lazebnik, S., Schmid, C.: Local features and kernels for classification of texture and object categories: A comprehensive study. IJCV (2007) 3
[21] Varma,M., Zisserman, A.: A statistical approach to material classification using image patch exemplars. PAMI (2009) 3
[22] Xu, D., Cham, T., Yan, S., Duan, L., Chang, S.: Near Duplicate Identification with Spatially Aligned Pyramid Matching. CSVT (accepted) 3
[23] Forss´en, P., Lowe, D.: Shape Descriptors for Maximally Stable Extremal Regions. In: ICCV.(2007) 3
[24] Belongie, S., Malik, J., Puzicha, J.: Shape matching and object recognition using shape contexts. PAMI (2002) 3, 11
[25] Ling, H., Jacobs, D.: Shape classification using the inner-distance. PAMI (2007) 3, 11
[26] Martin, D., Fowlkes, C., Malik, J.: Learning to detect natural image boundaries using local brightness, color, and texture cues. PAMI (2004).
[27] Mehmet Emre Sargin and al.2005. Combined Gesture-Speech Analysis and Synthesis eNTERFACE05 Workshop in Mons, Belgium.
[28] Heikkilä, M., Pietikäinen, M., Schmid, C.: Description of interest regions with local binary patterns. Pattern Recognit. 42(3), 425–436 (2009)
[29] T. R. FORTESCUE, S. KERSHENBAUM : Implementation of Self-tuning Regulators with Variable Forgetting Factors* IMI International Federation of Automatic Control(1981)