A New Image Division for LBP Method to Improve Face Recognition under Varying Lighting Conditions

Heydi Méndez Vázquez, Edel García Reyes and Yadira Condes Molleda
Advanced Technologies Application Center. 7ma, No. 21812, Siboney, Playa, Cuba, 12200
{hmendez,egarcia,ycondes}@cenatav.co.cu

Abstract

Local Binary Patterns (LBP) is one of the most used methods in face recognition. This paper presents a different way of obtaining the regions that are used to construct the LBP histograms, in order to improve its performance in front of illumination problems. The proposed method takes into account the shape of the face to build a triangular mesh in which a better description of the face image through LBP is achieved. Experimental results conducted on Yale B database show that under varying lighting conditions, the proposal improves the performance of the traditional rectangular division of the LBP method.

1. Introduction

Automatic face recognition has been widely used in a variety of applications in the last years [1]. Although there are a number of face recognition algorithms which work well in constrained environments, face recognition is still an open and very challenging problem in real outdoor applications. Variations in lighting are among the most affecting performance of face recognition systems [2]. To attack the problem of face recognition under illumination variation, several algorithms have been proposed. Nevertheless, their performances are still far from ideal and many of them require a large number of training images.

Face recognition methods based in one single image per person can be classified into two categories taking into account the type of features that they use: geometric based methods and appearance based methods. Appearance based methods, have been the dominant techniques in the last years. Such an approach generally operates directly on the pixel intensities or other image-based representation and has greatly improved the effectiveness and efficiency of face recognition systems [3]. These kinds of methods can be used either in a holistic or in a local way. The holistic methods identify a face using as input a vector that represents the whole face image. The local ones use the information of the face image localities for the recognition purpose.

In [4] it is shown that local normalization methods are more invariant to illumination variations than global ones. Then, a variety of local appearance based methods for face recognition has been developed. Among them, Local Binary Patterns (LBP) [5] is one of the most used [6], showing promising results.

In this paper the sensitiveness of the LBP method to lighting variations is analyzed and a new sub-division of the images, taking into account the shape of the faces, is proposed in order to improve the performance of this method in front of illumination problems. Section 2 reviews the LBP method and makes an analysis of its sensitiveness to illumination variations. Section 3 presents the proposed method. Section 4 reports on the experimental results. Finally, Section 5 concludes the paper.

2. LBP method

The use of the LBP in face recognition was introduced in [5] and it has been applied in many face recognition applications afterwards [6].

The original LBP operator labels the pixels of an image by thresholding the 3x3- neighbourhood of each pixel with the centre value and considering the result as a binary number called the LBP code. Later the operator was extended to be applied in a circular neighbourhood of different radius size and was refined to represent the most important microstructures with the *uniform LBP* [7].

In any case, the image is divided into rectangular regions and histograms of LBP codes are calculated over each of them. Finally, the histograms of each region are concatenated into a single one that represents the face image and a dissimilarity measure is used to compare the histograms of different images.

978-1-4244-2175-6/08/$25.00 ©2008 IEEE

2.1 LBP as illumination invariant

The idea behind using LBP features is that face images can be seen as a composition of micro-patterns. Specifically, the *uniform LBP* describes those structures which contain at most two bitwise (0 to 1 or 1 to 0) transitions, then can represent import features such as edges, spots and flat areas, as can be seen in Fig. 1. With this operator, these patterns can be represented only taking into account if the surrounding pixel values are bigger or smaller than the center pixel value. Many papers declare that the LBP operator is robust to illumination variations [8] [9]; this means that the operator is able to describe the facial features independently from the variations of illumination that may be affecting the image.

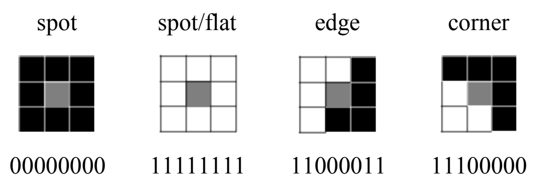


Fig. 1. Examples of micro-patterns represented by LBP operator

If we look at an image under the Lambertian model, the intensity of a pixel that represents a point on an object surface can be expressed as:

$$I(x, y) = \rho(x, y) n^T (x, y) \bullet s \qquad (1)$$

where ρ is the albedo, which depends on the physical properties of the surface, n^T is the normal vector to the surface and represents the shape of the object, and s represents the light source direction and intensity. From equation (1) can be inferred that the affectation caused by the lighting effects depends largely on the shape of the surface.

An illumination invariant descriptor must be able to represent the physical properties and shape of the object surface regardless of the incident light. With the traditional LBP division, the difference between two pixels intensities described by the LBP operator is affected by the incident light, since in a regular rectangular region the slope of the surface can change and the effect of the incident light in the pixel intensity depends on it. Only if the affectation causes a monotonic variation - it means, the change on the pixel intensity is in similar proportion and sign - the operator has an invariant behavior. In any other case, more usually presented in real life applications, the LBP is affected by the illumination, meaning that the operator is sensitive to this kind of variations.

3. New image division for LBP

If the face image is divided in regions taking into account its shape, in a way that each local region can be considered as a plane, characterized by a single normal vector for all points of the face image at that local neighbourhood, the combination of n^T and the light source s in each region remains constant, in a value that depends on the shape of the face of the person in that locality. Then the difference between the central pixel intensity I_C and the pixel intensity of its neighbour I_1 represents only the difference between their albedos, as it is expressed in equation (2):

$$I_1 - I_c = (\rho_1 - \rho_c) n^T \bullet s \qquad (2)$$

This way, the LBP operator will describe only the local changes on the physical properties of the face surface, which must be unique for every person in each region. The combination of all local characterizations leads to a global characterization of the face image that must be less sensitive to lighting variations than the one using the traditional regions division.

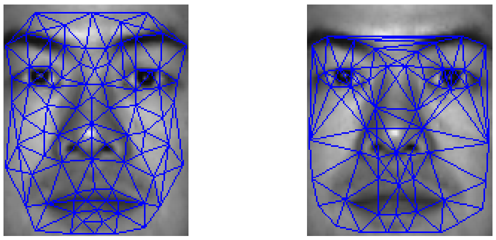
To obtain these wanted regions over the face images we decided to use a triangular mesh in which the vertices are placed in those points where the slope of the surface changes, as can be seen in Fig.3 (a). Then the LBP histograms will be calculated over the triangular regions of different size, instead of the traditional rectangular regions.

3.1 Construction of the triangular mesh

Since the general shape of all different human faces is very similar, we can construct first a base mesh and then adapt it to each particular face.

The base mesh was created marking manually 83 points in 10 face images of different subjects and obtaining a mean model. Our mesh is very similar to the CANDIDE-3 model [10], which is very used in computer graphics applications and considers the face image as a set of planar triangular facets, but we are only working with the inner region of the face, then we selected a subset of the vertices of the CANDIDE-3 model and added a few points, all of them carefully chosen in locations where the slope of the surface changes. A Delaunay triangulation was used to join the vertices and obtain the regions. All images were first geometric normalized by the centres of the two eyes.

Our mesh is different to the one used in the standard Active Appearance Models (AAM) method [11]. To construct an AAM, important points are also manually annotated, but the principal difference is that the landmarks are situated over the facial features: eyebrows, eyes, nose, mouth and jaw, in this case the triangular mesh is calculated to establish a reference coordinate system relative to these landmarks. In our case, the landmarks are located over the ridges of face's surface. In Fig. 2 can be compared our mesh with an AAM mesh over a face image. As can be appreciated, our mesh regions tend to have the same normal vector, which is not the case in the AAM mesh.



(a) (b)

Fig. 2. Comparison between a) our triangular mesh and b) the AAM mesh.

Once we have the base mesh, it can be adapted to each face image according to its own shape. To extract the shape information, the multi local level set extrinsic curvature (MLSEC) operator [12] was used. This operator allows obtaining the ridges and valleys of the face image, which have been pointed as a relevant face shape description less sensitive to illumination changes [13]. The following steps are executed to obtain the ridges and valleys with the MLSEC operator:

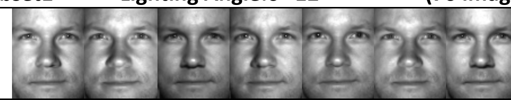
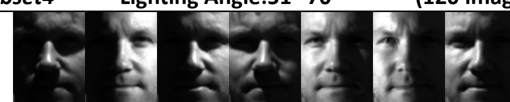
1) The image is smoothed with a Gaussian filter.
2) The normalized gradient vector field of the smoothed image is computed.
3) The divergence of the vector field is calculated, leading to a measure of valleyness and ridgeness.
4) The response of the operator is thresholded: image pixels where the MLSEC response is smaller than -1 are considered ridges, and those larger than 1 are considered valleys.

The base mesh is then loaded in each input image and each one of its vertices is automatically moved to the nearest pixel in its neighbourhood which corresponds to a ridge.

4. Experimental results

The Yale B Face Database [14] was used to evaluate the proposed triangular division. This face database contains images of 10 subjects seen under 576 viewing conditions (9 poses and 64 illumination conditions). Since we are concerned with the illumination problem in this paper, only the frontal face images were used, including the corrupted images of the database. The 64 frontal images of each subject were divided into 5 subsets according to the angle between the light source direction and the camera axis (the larger the angle the more unfavourable the lighting conditions are). In Table 1 are shown some example images in each subset:

Table 1. Yale B Face Database division according to the lighting variations.

Subset1	**Lighting Angle:0^{0}-12^{0}**	**(70 images)**
		
Subset2	**Lighting Angle:13^{0}-25^{0}**	**(120 images)**
		
Subset3	**Lighting Angle:26^{0}-50^{0}**	**(140 images)**
		
Subset4	**Lighting Angle:51^{0}-70^{0}**	**(120 images)**
		
Subset5	**Lighting Angle:71^{0}-130^{0}**	**(190 images)**
		

In our experiments, all face images were closely cropped to include only the face region, the extracted face images were geometric normalized by the centres of the two eyes to be 64 × 80 pixels in size.

The *Subset 1* was used as gallery set and each one of the rest subsets were tested. We compare the traditional rectangular region division with our triangular division, in both cases the *uniform LBP* was used as descriptor. The obtained results are shown in Table 2 and Table 3.

Table 2. Equal Error Rate (EER) using different divisions in each subset.

	Subset2	Subset3	Subset4	Subset5
rectangular region division	5.95%	23.46%	33.28%	37.16%
our triangular division	4.88%	20.81%	26.55%	29.90%

Table 3. Recognition rate at the first position.

	Subset2	Subset3	Subset4	Subset5
rectangular region division	99.17%	97.14%	65.83%	22.10%
our triangular division	100%	97.86%	78.33%	45.79%

The EER is the point where the false acceptance rate equals to the false rejection rate. The lower the EER the better the performance of the method. In

Table 2 it can be seen that the proposed method has lower EER than the traditional region division in all subsets.

Table 3 shows that in all subsets, from the first position, the recognition rate was higher when the proposed division was used. This can be verified in Fig. 3 in which the cumulative match score vs. rank curve was used to illustrate the performance of the two divisions in *Subset 5*, the most difficult one.

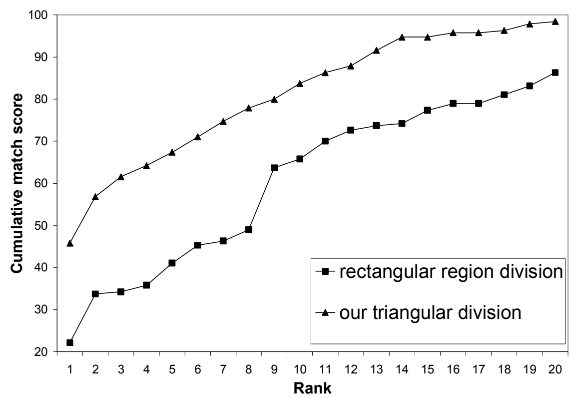


Fig. 3. Cumulative match score vs. rank curve

In general, for the LBP method, the proposed triangular division shows better results than the traditional rectangular division, reaching the 100% of recognition rate in a lower rank.

5. Conclusions

In this paper the sensitiveness of the LBP method to lighting variations was analyzed and a new sub-division of the images, taking into account the shape of the faces, was proposed in order to improve the performance of this method in front of illumination problems. The experimental results conducted on Yale B Face Database confirmed that the proposed division improves the performance of the uniform LBP method in front of illumination variations. Nevertheless the method can be used with other extensions of the LBP descriptor [6] which have proven to be superior.

Finally, it is necessary to say that our method requires a previous geometric normalization of the face images, but this is also the case of the original LBP method. Furthermore, the geometric normalization used in this paper is only based on the eyes coordinates, and there are some eyes detectors which have shown very good performance even when there are illumination variations [15].

References

[1] S.Z. Li and A.K. Jain, “Handbook of face recognition”, *Springer*, 2005.

[2] P.J. Phillips, W.T. Scruggs, A.J. O’Toole, P.J. Flynn, K.W. Bowyer, C.L. Schott and M. Sharpe, “FRVT 2006 and ICE 2006 Large-Scale Results”, National Institute of Standards and Technology, MD 20899, March 2007.

[3] X. Tan, S. Chen, Z.H. Zhou and F. Zhang, “Face recognition from a single image per person: A survey”, *Pattern Recognition*, Vol.39 No.9, pp.1725-1745, September 2006.

[4] M. Villegas and R. Paredes, "Comparison of Illumination Normalization Methods for Face Recognition", *Third COST 275 Workshop*, 2005.

[5] T. Ahonen, A. Hadid and M. Pietikäinen, “Face recognition with local binary patterns. Computer Vision”, *ECCV 2004 Proceedings, Lecture Notes in Computer Science 3021*, Springer, pp. 469-481, 2004.

[6] S. Marcel, Y. Rodriguez and G. Heusch: “On the Recent Use of Local Binary Patterns for Face Authentication”, *International Journal on Image and Video Processing Special Issue on Facial Image Processing*, 2007.

[7] T. Ojala, M. Pietikäinen and T. Maenpaa, “Multiresolution gray-scale and rotation invariant texture classification with local binary patterns”, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Volume 24, pp. 971–987, 2002.

[8] G. Heusch, Y. Rodriguez and S. Marcel, “Local Binary Patterns as an Image Preprocessing for Face Authentication”, *IEEE International Conference on Automatic Face and Gesture Recognition*, 2006.

[9] S. Marcel, J. Keomany and Y. Rodriguez, “Robust-to-illumination face localisation using Active Shape Models and Local Binary Patterns”, *IDIAP Research Report*, July 2006.

[10] J. Ahlberg, “CANDIDE-3—an updated parameterised face”, Report No. LiTH-ISY-R-2326, Sweden, January 2001.

[11] T. Cootes, G. Edwards and C. Taylor, “Active appearance models”, *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol.23 No.6, June 2001.

[12] A. M. López, F. Lumbreras, J. Serrat and J.J. Villanueva, “Evaluation of Methods for Ridge and Valley Detection”. *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol.21 No.4, April 1999.

[13] A. Pujol, A. Lopez, J.L. Alba, and J.J Villanueva, “Ridges, Valleys and Hausdorff Based Similarity Measures for Face Description and Matching”. *Proc. International Workshop on Pattern Recognition and Information Systems*, pp. 80-90, Portugal, July 2001.

[14] A.S. Georghiades, P.N. Belhumeur and D.J. Kriegman, “From few to many: illumination cone models for face recognition under variable lighting and pose”. *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol.23, No.6, June 2001.

[15] Z. Xingming, Z. Huangyuan, "An Illumination Independent Eye Detection Algorithm". International Conference on Pattern Recognition (ICPR'06) Vol. 1, pp. 392-395, 2006.