Face Recognition Using Local Graph Structure (LGS)

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Abstract. In this paper, a novel algorithm for face recognition based on Local Graph Structure (LGS) has been proposed. The features of local graph structures are extracted from the texture in a local graph neighborhood then it's forwarded to the classifier for recognition. The idea of LGS comes from dominating set points for a graph of the image. The experiments results on ORL face database images demonstrated the effectiveness of the proposed method. The advantages of LGS, very simple, fast and can be easily applied in many fields, such as biometrics, pattern recognition, and robotics as preprocessing.

Keywords: Algorithm, Feature evaluation and selection, Pattern Recognition, Pattern Recognition.

1 Introduction

The question of whether face recognition is done holistically or using the local feature analysis has also been researched in the literature. Studies done by Bruce Bruce [1] suggested the possibility of global descriptions or holistic representations as a precursor or pre-process for finer feature recognition. Various approaches in face recognition have been proposed in the literature; these can be classified into three categories, namely feature-based, holistic (global), and hybrid methods. While feature-based approaches compare the salient facial features or components detected from the face, holistic approaches make use of the information derived from the whole face pattern. By combining both local and global features, the hybrid methods attempt to produce a more complete representation of facial images.

The main idea behind this feature-based technique is to discriminate among the different faces based on the measurement of structural attributes of the face. The method extracts and computes a set of geometrical features from faces such as the eyes, eyebrows, nose, and mouth and feeds them into a structural classifier. One of the earliest methods, included in this category, was proposed by Kelly [2]. In this method, Kelly used the width of the head, the distances between the eyes and from the eyes to the mouth, etc. Kanade [3] applied the distances and angles between eye corners, mouth extrema, nostrils, and chin top in his work on Computer Recognition of Human Faces. Cox, Ghosn and Yianios [4] introduced a mixture-distance technique, which used manually extracted distances, with each 30 manually extracted distances that represented face. Without finding the exact locations of the facial features, Hidden Markov Model (HMM) has been successfully applied to face recognition. The HMM

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based methods use strips of pixels that cover the forehead, eyes, nose, mouth, and chin [5-6]. [5]Nefian yielded a better performance than Samaria using the KL projection coefficients instead of the strips of raw pixels.

One of the most successful systems in the graph matching system reported by Wiskott et al. [7] employs the Gabor wavelet features at facial landmarks. A flexible face structure or elastic bunch graph match (based on the dynamic link architecture or DLA), presented in Buhmann, Lades & van der Malsburg [8] and Lades et al. [9], is combined with the local Gabor features description onto one system. Elastic Bunch Graph Matching, a topology graph was constructed for each face first, with each node attaching one or several Gabor jets. Each component of a jet is a filter response of a specific Gabor wavelet, extracted at a pre-defined critical feature point.

In the Elastic Bunch Graph Matching, a topology graph is first constructed for each face, with each node attaching one or several Gabor jets. Each component of a jet is a filter response of a specific Gabor wavelet, extracted at a pre-defined critical feature point. These locally estimated Gabor features are known as robust against illumination change, distortion and scaling [10], and this is the first key factor in the EBGM method. Another key point of this method lies in the graph matching, of which the first step is similar to that in Lee [10], i.e., both the local and global similarities are considered. The second step, where a deformable matching mechanism is employed, i.e., each node of the template graph is allowed to vary its scale and position according to the appearance variations on a specific face. To investigate the discriminative power of the Gabor features (nodes), a systematic way of selecting the nodes from a dense set is presented in Krüger [11] and Krüger et al.[12] . In their work, more nodes were found to yield better results, because more information was used. Nevertheless, this effect saturates if the nodes are too close and the corresponding Gabor coefficients become highly correlated due to the overlap between the kernels. On the other hand, the computational effort linearly increases with the number of nodes. The optimal number of nodes becomes a compromise between recognition performance and speed. The EBGM method has been proven to be very effective in face recognition and was one of the top performers in the FERET evaluation tests. Learning discriminative facial locations and obtaining optimal local feature extractor parameters are formulated as a feature subset selection problem. In feature selection, the aim is to select a subset from a given set such that the classification accuracy of the selected subset is maximized.

Baldi and Hornik [13] generates an optimal linear encoding using optimization methods in layered linear feed-forward neural networks to neutrally spanned subspace, average distortion is minimized by using the principal components of the examples. pairwise relationships between pixels of the image is computed by PCA and important information which contained in high-order relationship among pixels are discarded. Therefore, it reasonable to look for a method that considers this high-order statistic. One of these methods is Independent component analysis (ICA) uses sigmoidal neurons to derive the principle of optimal information transfer, Movellan & Sejnowski[14]. In 2007, Zou, Ji, & Nagy [15] have conducted comparative studies on local matching approaches. The general idea of local matching methods is to first locate several facial features and then classify the faces by comparing and combining the corresponding local statistics. Ruiz-del-Solar, Verschae, Correa, [16] have studied and analyzed four face recognition methods that are based on different representations of the image: (1) LBP Histograms, (2) Gabor Jet Descriptors (GJD), (3) SIFT Descriptors, and (4) ERCF (Extremely Randomized Clustering Forest) of SIFT Descriptors. These representations are used in different ways by the analyzed face recognition methods: (1) LBP Histograms are directly used as feature vectors together with distance metrics for comparing these histograms, (2) GJD are used together with Borda count, (3) SIFT Descriptors are used together with local and global matching methods, and (4) ERCF are used together with linear classifiers.

The studies mentioned above made use of some forms of local information in their systems. These local regions are either rigidly chosen or placed over facial landmarks. To some extent, the selection of these regions is based on an intuitive knowledge of facial structure and the importance of facial features. However, these features may not always be optimal in building a face representation for the task of recognition. Instead, it may be better to learn an optimal selection of the features directly from the data rather than using a manual selection.

2 Local Graph Structure (LGS)

The idea of Local Graph Structure (LGS) comes from a dominating set for a graph G = (V, E) is a subset D of V such that every vertex not in D is joined to at least one member of D by some edge. The domination number γ (G) is the number of vertices in a smallest dominating set for G.

LGS works with the six neighbors of a pixel, by choosing the target pixel C as a threshold, then we start by moving anti clockwise at the left region of the target pixel C, If a neighbor pixel has a higher gray value than the target pixel (or the same gray value) then assign a binary value equal to 1on the edge connecting the two vertices, else we assign a value equal to 0. After finish on the left region of graph we stop at the target pixel C and then we move in a horizontal way (clockwise) to the right region of the graph and we apply the same process till we get back to the target pixel C.

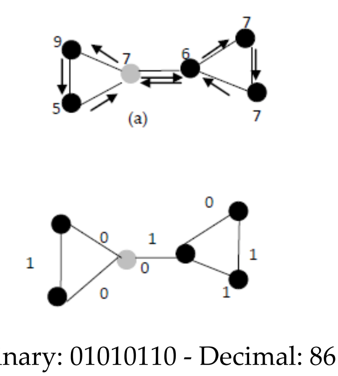

Fig. 1. Local graph structure (a. Direction, b. Binary)

To produce the LGS for pixel (x_d, y_d) a binomial weight 2^p is assigned to each sign $s(g_d - g_n)$. These binomial weights are summed:

$$LGS(x_d, y_d) = \sum_{K=0}^{7} s(g_d - g_n)2^p \tag{1}$$

$$\text{where} \quad s(x) = \begin{cases} 1 & x \geq 0 \\ 0 & x < 0 \end{cases}$$

Where $p = 7.\ \ p = 7, 6, \ldots 0.$

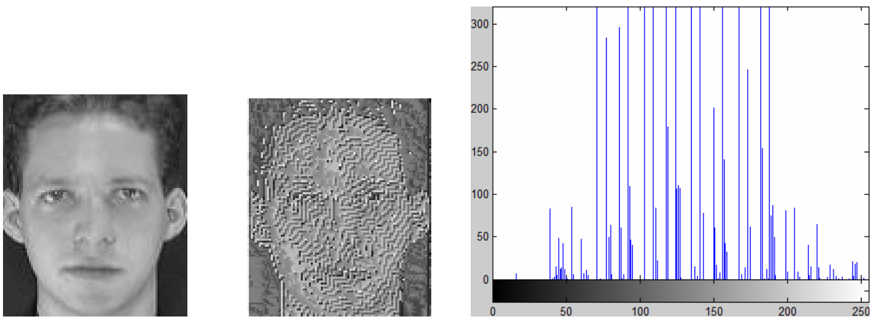

Fig. 2. LGS operator

3 Experiments and Results

Local Graph Structure (LGS) have proved to be useful because it contains information about the distribution of the local micropatterns, such as edges, spots and flat areas, over the whole image. A decimal representation is obtained by taking the binary sequence as a binary number between 0 and 255. For dominant pixel, not only accounts for its relative relationship with its neighbours but also the relationship between the pixels that form the local graph of the target pixel C (dominant pixel) , while discarding the information of amplitude, and this makes the resulting LGS values very insensitive to illumination intensities. The 8-bit binary series with binomial weights consequently result in 256 different patterns in total for the pixel representation.

In the initial work of face processing using LGS, can be seen in Fig 3, is an example of new generated image from original image using LGS, a histogram of the LGS representing the distribution of 256 patterns across the face image. The advantage of LGS; Firstly it is a local measure; some of the regions contain more useful information than others when face image been divided into regions, it can be expected to assist in terms of distinguishing between people. Secondly it is a relative measure, and is invariant to any monotonic transformation such as shifting, scaling, or logarithm of the pixel-values. Therefore it can be invariant to a certain range of illumination changes.

We test our method using the public ORL face database [17]. The database consists of 400 faces; Ten different images of each of 40 distinct subjects. The faces were captured with the subjects in a straight, frontal position against a dark identical background, and with acceptance for some sloping and regular change of up to 20 degrees. Image variations of five individuals in the database are illustrated in Fig3.

Fig. 3. Example of an original image of ORL face database

To assess the performance of LGS on face recognition, 40 subjects have been taken for our experiments, 8 images for training and the remaining 2 images for testing; LGS applied to find the histograms for the entire training and testing sets. The correlation is used to computes the correlation coefficient of histogram between two images recognition. For e.g. A and B are two different histogram of images, A and B are vectors of the same size. The correlation coefficient is computed as follows:

$$result=\frac{\sum_{m}\sum_{n}(A_{mn}-\bar{A})(B_{mn}-\bar{B})}{\left[\sum_{m}\sum_{n}(A_{mn}-A^{2})\right]\left[\sum_{m}\sum_{n}B_{mn}-\bar{B}^{2}\right]} \tag{2}$$

Table 1 illustrates the sample of result obtained by the proposed method.

Table 1. Similarity Rate

Subjects	Testing Image	Index of output	Similarity (with Training) ALG
Subject 1	1	1	99.22%
	2	5	98.01%
Subject 2	3	10	99.67%
	4	12	99.65%
Subject 3	5	17	99.63%
	6	17	99.53%
Subject 4	7	30	99.59%
	8	25	99.68%
Subject 5	9	35	99.66%
	10	40	99.67%
…….	…..	………	…….
Subject 40	79	315	99.70%
	80	319	99.53%

The overall detection rate of LBGS is shown in Table 2.

Table 2. Overall Recognition RATE

LGS	Recognition Rate
Overall	93.75%
Max Recognition	99.87%
Min Recognition	98.01%

4 Conclusion

The features of local binary graph structure are derived from a general definition of texture in a local graph neighborhood. The advantages of LGS over other local methods it's invariant to illumination changes, computational efficiency, and fast so that it can be easily applied in real-time system. LGS assigns weight for target pixels (dominant) by considering not only the direct relationship of target pixels to its neighbours but also the relationship between the pixels that form the local graph of the target pixel; this feature is unique to LGS and lead to improve the image appearance and subsequently the recognition performance. This is especially applicable for faces from which the photos are taken under different lighting conditions. Important regions for feature extraction are those with the eyes and the mouth as you can see in figure. ALG can easily be combined with other methods and can easily kernelized by using different kernels functions.

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