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Face Recognition using Symbolic Data with Texture Features

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Abstract— Face recognition is a type of biometric identification method, it is challenging and one of the active research area in the field of Computer Vision. Variations in face image is due to changes in expression, presence of occlusion, geographical variations and illumination along with aging are some of the challenges to face recognition technique. In this paper, we attempt to solve illumination challenge for face recognition. Here, we propose a novel symbolic face recognition technique using Logarithm Gradient Histogram (LGH). Experimental results are carried out on standard benchmark databases like Extended YaleB, ORL. The performance of the proposed face recognition technique turns out to be 94.35 to 100% for the mentioned databases.

Keywords— Face recognition, Illumination invariant feature, Logarithm Gradient Histogram (LGH)

I. INTRODUCTION

In recent years, biometrics for identifying human features has increased significantly in large populations. Humans are recognized based on their physiological and behavioral characteristics such as face, fingerprint, hand geometry, IRIS, retina, gait, palm veins, voice etc. Among biometrics, face recognition is an active research area with noteworthy contributions in the field of artificial intelligence, pattern classification, computer and machine vision. Biometric authentication, human computer interaction, surveillance, forensics, and crime investigation are major applications of face recognition. In state-of-art method many face recognition methods have been proposed and developed. However, the performance of such face recognition methods is severely impacted in the presence of illumination occlusion and expression changes.

In a face recognition system, representing a face in the form of a face descriptor is an important step. A face descriptor can be able to recognize a suitable representation for every face, moreover, the efficacy of a descriptor can be determined by its ability to extract features from input images. In addition, an efficient descriptor must have the ability to differentiate between interclass and intra class structures with minimum time complexity. Lately, several researchers have proposed successful methods to extract the representation of a face, and computed efficient face descriptors. However, these methods fail to recognize faces under adverse conditions of illumination, pose, partial occlusions, ageing, lighting conditions, expression, etc.

Feature descriptor is a key factor in the performance of many computer vision and pattern recognition applications. Large number of feature descriptors has been developed to improve the performance for these computer vision and pattern recognition applications.

In such a case, the representation of face images as symbolic faces accounts for image variations of human faces under different orientation, facial expression, and lighting conditions. Some of the state-of-art methods such as symbolic PCA[1], symbolic kernel PCA[2], and symbolic LDA[3] approach for face recognition are reported. In which training face images are represented by symbolic face and which are further projected into compressed subspace i.e. face symbolic objects are represented by interval valued variables. Euclidian, City block and Cosine similarity measures are used for similarity analysis between trained symbolic faces and testing face.

Face recognition is increasingly being used in intelligent surveillance systems, identity authentication for security systems, face database matching and other identification systems. However, uncontrolled and various lighting conditions can cause unpredictable illumination effects on faces such as atypical shadow regions, which can make robust face recognition quite difficult.

The rest of the paper is organized as follows: in Section II, we present a brief review on face recognition and symbolic face representation techniques. In Section III we propose face recognition techniques using Symbolic Data with Texture Features. Section IV provides experimental results and analysis of proposed approach and conclusion is given in Section V.

II. Related Work

In literature, face recognition methods such as geometric based, holistic (The holistic methods involve a single vector which represents the entire facial features in a high dimensional space), and statistical-based, and appearance-based methods are used in various algorithms such as, principal component analysis (PCA)[4]. PCA is one of traditional methods used for lower dimensional representation of the face features. The PCA based methods involve converting original face image matrices into a high dimensional covariance matrix and it is difficult to evaluate accurately due to its large size. Hence PCA based methods require high computation time and suffer from poor discriminatory power for large set of training samples. In order to overcome these issues, other techniques such as, Locally Linear Embedding (LLE)[5], linear discriminate analysis (LDA)[6], independent component analysis (ICA)[7], locally preserving projections (LPP)[8], trace transforms (TT)[9], hidden Markov model (HMM)[10], and Kernel PCA and so on are proposed by many researchers. However, defining a novel descriptor for face recognition remains a challenging task.

The low complexity face image recognition system has been proposed to work in an unconstrained spatial resolution. However, local pattern descriptors are gaining more awareness for face recognition in resend years. A popular local texture descriptor technique called local binary pattern (LBP) is proposed by Ojala et al. [11]. LBP texture descriptor encodes every pixel in an image based on the deference between the center pixel and neighboring pixels. In addition, LBP extracts a higher order texture micro pattern from the locally encoded image. Ojala et al. [12] proposed to boost the efficiency of LBP descriptor by varying the sizes of the neighborhood. Furthermore, bi-linear interpolation technique was considered for different neighborhood sizes. However, a major demerit of LBP was the loss of brightness information due to the relation between the center pixel and neighboring pixels. To solve the demerit of LBP, complete modeling of the LBP (CLBP) was developed by Guo et al. [13], and it represents the local descriptor based upon the symbol, and magnitude differences between the pair wise pixels. A variation of LBP called the uniform LBP (ULBP) [4] uses descriptor patterns with only two transitions from 1 to 0 or vice-versa. The next variation of LBP is called the local phase quantization (LPQ) [14], in the LPQ method, patterns are generated by quantizing the LBP encoded image. The LPQ method outperforms the LBP in blurred images. Liao et al. [15] presents a multi-Block LBP, which captures both macro and micro patterns. Three/Four path LBP was extended from LBP, it generates the micro pattern descriptor by encoding the patch type of texture information. Afterward, LBP was extended to neighborhood intensity-based LBP (NI-LBP), center intensity based LBP (CI-LBP), angular difference based LBP (AD-LBP), and radial difference based LBP (RD-LBP) [15]. These methods generate the micro pattern descriptors for the complete image representation, consequently, they are more robust, and efficient than the LBP descriptor.

The appearance-based face recognition systems use face image pixel intensity values directly as the feature values for representation and recognition using single valued variable. But such single valued variable may not be able to capture the variation of feature values of the images of the same subject and will also have high dimensional features data. One of the methods adapted by researchers to develop efficient system with reduced number of features in methodology of feature learning.

III. Methodology

In face recognition system, light illumination is still challenging problem. In this field, many researchers only consider the variations caused by lighting direction (homogeneous lighting), but the effect of spectral wavelength is always ignored, and thus existing illumination invariant descriptors have its limitation on processing face images under different spectral wavelengths (heterogeneous lighting). Jun-Yong Zhu [16] et al., have proposed gradient based descriptor, namely Logarithm Gradient Histogram (LGH), which takes the illumination direction, magnitude and spectral wavelength together into consideration, so that it can handle both homogeneous and heterogeneous lightings. And these methods is single-valued variables may not be able to capture variation of each feature in all the face image of same subject; this leads to missing of information. The proposed algorithm extracts most discriminating interval type features which optimally discriminate among the classes represented in the training set.

To obtain robust description, post processing in taken on the two components before generating the histogram representation. Since the gradient orientation is somehow sensitive to the quality of image, a local smoothing operation is implemented on LGO in order to alleviate direction changes smoothly.

Then we quantify the values in LGO into several bins to achieve fault-toleration. Since the Lambertian assumption does not strictly hold everywhere, there are cast shadows in face images. As a result, the pixels with dominating values in LGM may belong to the boundaries of shadows, and meanwhile the edge of facial objects like eyes and mouths may become less significant especially when the lighting condition becomes severe. In this case, taking a local normalization operation may help extracting illumination invariant features. On one hand, it enhances the weak edges lying in dark are as which belongs to the facial objects and on the other hand it also alleviates the global domination caused by the strong edges of shadows. More importantly, the multiplicative constant coefficient can be eliminated in the local normalized LGM. As a result, the sub-histogram generated in each scale can be treated equally.

Finally, we obtain the quantified gradient orientation and normalized gradient magnitude for each pixel in face image. Since conducting pixel-wise matching on these two components between different face images in quite unreliable, we integrate LGO and LGM to form a unified histogram-based feature representation. The histogram is generated in a block-wise form; that is the post-processed gradient magnitudes of all pixels in the block will accumulate according to the orientation bines they belong to. At last, we concatenate histograms of all blocks into a long vector to form our histogram-based feature representation.

After extracting feature for face image, it fails to detect different face features in lighting conditions. Then we represent the face images as symbolic object or symbolic face of interval type at different lighting conditions. The symbolic face summarizes the variation of feature values through the different images of the same subject. The symbolic face reduces the dimension of the image space without losing a significant amount of information.

A. Construction of Symbolic Face

Let $F= \{f_1,\ldots, f_n\}$ be the collection of face images of the database, each of size $N\times M$. An image set is a collection of face images of m different subjects denoted by $D= \{d_1,\ldots, d_m\}$. We have assumed that images belonging to a face class are arranged from right side view to left side view. The view range of each face class is partitioned into q sub face classes and each sub face class contains r number of images. The feature vector of k^{th} sub face class d_i^k of i^{th} face class d_1,

where $1,2,\ldots,q$, is described by a vector of p interval variables $Y_1,\ldots,Yp$, and is of length $P=NM$. The interval variable Yj of k^{th} sub face class d_i^k of i^{th} face class is

described as $Y_j\left(d_i^k\right) = \left[\underline{x}_{ij}^k, \overline{x}_{ij}^k\right]$, where $\underline{x}_{ij}^k$ and $\overline{x}_{ij}^k$ are

minimum and maximum intensity values, respectively, among j^{th} pixels of all the images of sub face class d_i^k .The

vector X_i^k of interval variables is recorded k^{th} sub face class

d_i^k of i^{th} face class. This vector is called as symbolic face.

We denoted

$$X_i^k = \left(Y_1\left(d_i^k\right),\ldots,Y_p\left(d_i^k\right)\right)$$

$$i = 1,2,\ldots,m,\ k = 1,2,\ldots,q\ \ j = 1,2,\ldots,p \quad (1)$$

We represent the qm symbolic faces by a matrix X of size $(p \times qm)$, consisting of column vectors X_i^k, $i = 1,2,\ldots,m$, $k = 1,2,\ldots,q$.

B. Face recognition

The proposed method is used for the face recognition process. The primary aim of face recognition is to compare the extracted encoded feature vector from the given query image with all other stored data base candidates feature vector using dissimilarity measure. Many dissimilarity measures are presented such as Euclidean distance, city block distance, Minkowski distance, Chebyshev distance, Quadratic distance, Canberra distance, Angular separation, non-linear distance, Log-likelihood, Histogram intersection and Chi square. From literature, it is evident that the chi square attains the better accuracy when compared to other dissimilarity measure. Chi square measure between two vectors $f_1$and f_2, of length L is defines as:

$$X^2(f_1,f_2) = \sum_{i=1}^{L} \frac{\left(f_1(i) - f_2(i)\right)^2}{f_1(i) - f_2(i)}. \quad (2)$$

The corresponding face of the feature vector with the minimum distance value indicates the match found.

IV. EXPERIMENTAL RESULT AND ANALYSIS

In this section, we conducted to evaluate the proposed illumination invariant descriptor for single image-based face recognition. Further we have considered, the case when images were approximately captured under controlled homogeneous lighting, like with different lighting directions and magnitudes but with the same spectral wavelength, in our experiment.

The experimental results are represented using recognition rate and accuracy. The recognition rate and accuracy are defined as:

$$RecognitionRate = \left(\frac{TP}{TP+FN}\right)\times 100, \quad (3)$$

$$Accuracy = \left(\frac{True\ Positive + True\ Negative}{Total\ nunber\ of\ images}\right)\times 100. \quad (4)$$

A. Performance analysis on Extended YaleB database

Extended YaleB, face images from 38 individuals of nine posed were captured under 64 different lighting conditions, and we only used 64 x 38 = 2432 frontal face imaged here. All images were simply aligned according to eyes coordinates and resized to 128 x 128. The Extended YaleB database were captured in more challenging and complex environments. Some of examples can be found in figure 1. The whole database has been divided into 5 sets based on the angle between direction of lighting source and the direction of frontal face. To better explore the performance of our proposed illumination invariant descriptor, represent by symbolic face descriptor, we conducted experiments using all front lighting images as gallery and the rest to form the analysis set. Recognition accuracies were reported on set 1 to set 5 respectively.

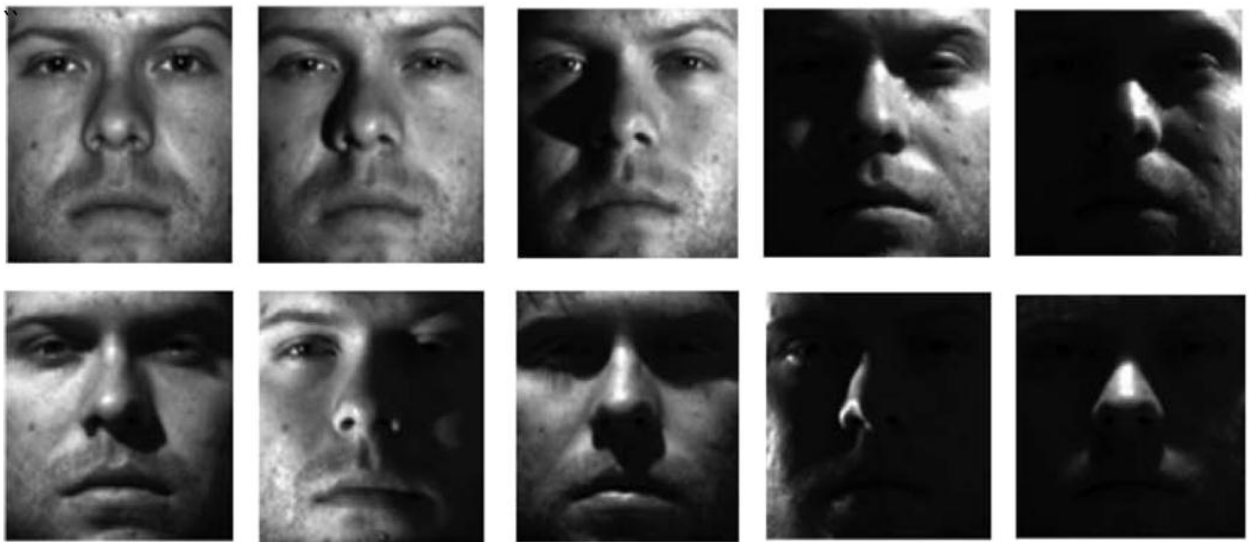

Figure 1. Images samples in Extended YaleB database in the upper row come from the controlled subset, and in the bottom row come from the uncontrolled subset.

Figure 2. Images samples from ORL database.

We observe that our proposed illumination invariant descriptor, represent by symbolic face descriptor, set1 records 100%, set2 records 99.12%, set3 records 100%, set4 records 98.85, set5 records 98.45% accuracy respectively.

B. Performance analysis on ORL database

Additionally, the performance of our propose illumination invariant descriptor, represent by symbolic face descriptor was evaluated on the ORL database which contains 10 different images of 40 subjects in different light conditions, different expressions and facial details. Further, all the images have changes in orientation and poses which have full front exposures.

Figure 2. shows the sample images of ORL database. The difficulty level of ORL database increases due to varying face expressions such as eyes open, eyes closed, smiling, non-smiling, glasses, no-glasses, changes in poses and orientation. We observed that our proposed approach recognition rate is 94.35% accuracy.

V. CONCLUSION

In this paper, we proposed a novel symbolic face recognition technique using Logarithm Gradient Histogram (LGH), we have considered variations caused by the lighting direction, so that the new proposed descriptor is able to handle face recognition under the homogeneous lighting condition. Experimental results verify the effectiveness of our proposed method on tackling single image based face recognition under illumination problem from the homogeneous lighting. Recognition rate for YaleB database, Set1. records 100%, set2 records 99.12%, set3 records 100%, set4 records 98.85, set5 records 98.45% respectively and for ORL database the recognition rate is 94.35%.

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