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An Efficient and Enhanced Unique Biometric Authentication System Using Optimized SVD

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ABSTRACT

Biometrics is an enhanced and automatic method of recognizing a person based on his/her physiological internal or external characteristic. Making recognition more consistent under hysterical lighting conditions, multi variant environmental conditions is one of the most important challenges for realistic face recognition systems. This concept introduces a novel unified and unique face recognition process using modified Singular Value Decomposition Technique. The human face is full of huge information, but operating with all the information is time consuming process and less accuracy. It is little bit better get unique and significant data regarding face and discards other ineffectual information in order to make system reliable, efficient. . This procedure involves retrieving of its facial features and then recognizes it, regardless of occlusion, ageing, illumination, expression, lighting and pose. Optimized SVD is used for an efficient recognition of facial biometric process.

Keywords: *Singular Value Decomposition (SVD), Biometrics, Optimization, Occlusion, Illumination*

I. INTRODUCTION

Face recognition is a main curtail and challenging issue in biometric applications. Since, face parameters changes from hour to hour depending on climate conditions; it is too tough task to calibrate the accurate yields from human being. Face recognition is very much useful in human computer communication, virtual reality, database recovery, multimedia, computer amusement, information safety e.g. operating system, medical records, online banking., biometric e.g. personal identification - passports, driver licenses , automated identity verification – border controls , law enforcement e.g. video surveillances , investigation , personal security – driver monitoring system, home video surveillance system. A face recognition system includes two steps, Face detection and face recognition. Feature extraction plays an important role in face recognition. More authors have come across regarding Feature extraction phase in multi aspects. Feature-based face recognition techniques [3], [2] have established the capability of invariance to facial changes caused by occlusion, illumination and have attained more successful rates. To make the recognition process illumination invariant, phase congruency feature maps are used instead of intensity values as the input to the face recognition system. The feature selection process presented in this paper is derived from the concept of modular spaces [3]–[5]. Local binary patterns (LBP) is a type of feature used for classification in computer vision. LBP is the particular case of the Texture Spectrum model proposed in 1990.LBP was first described in 1994. It has since been found to be a powerful feature for texture classification; it has further been determined that when LBP is combined with the Histogram of oriented gradients (HOG) classifier, it improves the detection performance considerably on some datasets. Local Binary Pattern (LBP) is a simple yet very efficient texture operator which labels the pixels of an image by thresholding the neighborhood of each pixel with the value of the center pixel and considers the result as a binary number. Due to its discriminative power and computational simplicity, LBP texture operator has become a popular approach in various applications. It can be seen as a unifying approach to the traditionally divergent statistical and structural models of texture analysis. Perhaps the most important property of the LBP operator in real-world applications is its robustness to monotonic gray-scale changes caused, for example, by illumination variations. Another important property is its computational simplicity, which makes it possible to analyze images in challenging real-time settings.

A. Face description using LBP

In the LBP approach for texture classification, the occurrences of the LBP codes in an image are collected into a histogram. The classification is then performed by computing simple histogram similarities. However, considering a similar approach for facial image representation results in a loss of spatial information and therefore one should codify the texture information while retaining also their locations. One way to achieve this goal is to use the LBP texture descriptors to build several local descriptions of the face and combine them into a global description. Such local descriptions have been gaining interest lately which is understandable given the limitations of the holistic representations. These local feature based methods are more robust against variations in pose or illumination than holistic methods. The basic methodology for LBP based face description proposed by Ahonen et al. (2006) is as follows: The facial image is divided into local regions and LBP texture descriptors are extracted from each region independently. The descriptors are then concatenated to form a global description of the face, as shown in below figure.

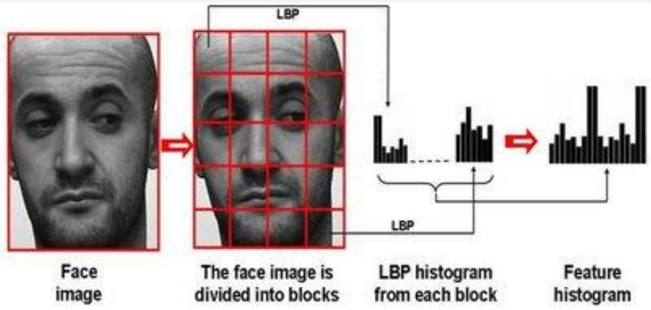
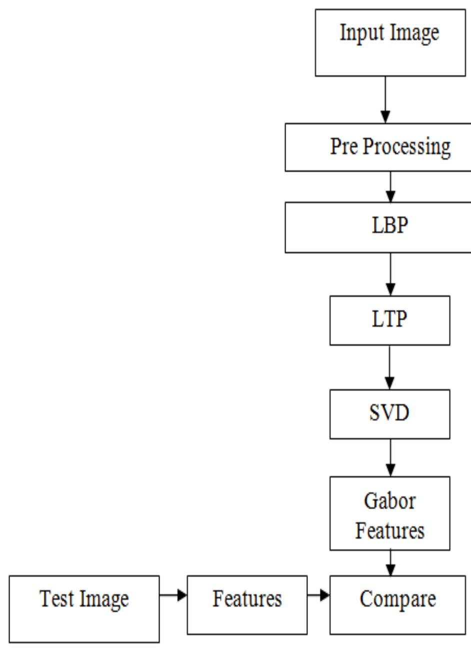


***Figure**: Face description with local binary patterns*

This histogram effectively has a description of the face on three different levels of locality: the LBP labels for the histogram contain information about the patterns on a pixel-level, the labels are summed over a small region to produce information on a regional level and the regional histograms are concatenated to build a global description of the face. It should be noted that when using the histogram based methods the regions do not need to be rectangular. Neither do they need to be of the same size or shape, and they do not necessarily have to cover the whole image. It is also possible to have partially overlapping regions.



B. Local ternary patterns (LTP):

Local ternary patterns (LTP) are an extension of Local binary patterns (LBP).[1] Unlike LBP, it does not threshold the pixels into 0 and 1, rather it uses a threshold constant to threshold pixels into three values. Considering k as the threshold constant, c as the value of the center pixel, a neighboring pixel p, the result of threshold is:

$$\begin{cases} 1, & \text{if } p > c + k \\ 0, & \text{if } p > c - k \text{ and } p < c + k \\ -1 & \text{if } p < c - k \end{cases}$$

In this way, each thresholded pixel has one of the three values. Neighboring pixels are combined after thresholding into a ternary pattern. Computing a histogram of these ternary values will result in a large range, so the ternary pattern is split into two binary patterns. Histograms are concatenated to generate a descriptor double the size of LBP.

II. Singular Value Decomposition

Singular value decomposition takes a rectangular matrix of gene expression data (defined as A, where A is a n x p matrix) in which the n rows represents the genes, and the p columns represents the experimental conditions. The SVD theorem states:

$\mathbf{A_{nxp}} = \mathbf{U_{nxn}}\ \mathbf{S_{nxp}}\ \mathbf{V^T_{pxp}}$

Where

$\mathbf{U^T U} = \mathbf{I}_{nxn}$

$\mathbf{V^T V} = \mathbf{I}_{pxp}$ (i.e. U and V are orthogonal)

Where the columns of U are the left singular vectors (gene coefficient vectors); S (the same dimensions as A) has singular values and is diagonal (mode amplitudes); and V^T has rows that are the right singular vectors (expression level vectors). The SVD represents an expansion of the original data in a coordinate system where the covariance matrix is diagonal.

Calculating the SVD consists of finding the eigenvalues and eigenvectors of AA^T and A^TA. The eigenvectors of A^TA make up the columns of V , the eigenvectors of AA^T make up the columns of U. Also, the singular values in **S** are square roots of eigenvalues from AA^T or A^TA. The singular values are the diagonal entries of the S matrix and are arranged in descending order. The singular values are always real numbers. If the matrix A is a real matrix, then U and V are also real.

To understand how to solve for SVD, let's take the example of the matrix that was provided in Kuruvilla et al:

$$A = \begin{bmatrix} 2 & 4 \\ 1 & 3 \\ 0 & 0 \\ 0 & 0 \end{bmatrix}$$

In this example the matrix is a 4x2 matrix. We know that for an n x n matrix W, then a nonzero vector **x** is the eigenvector of W if:

W **x** = delt **x**

For some scalar delt. Then the scalar delt is called an eigenvalue of A, and **x** is said to be an eigenvector of A corresponding to delt.

So to find the eigenvalues of the above entity we compute matrices AA^T and A^TA. As previously stated , the eigenvectors of AA^T make up the columns of U so we can do the following analysis to find U.

$$AA^T = \begin{bmatrix} 2 & 4 \\ 1 & 3 \\ 0 & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} 2 & 4 & 0 & 0 \\ 1 & 3 & 0 & 0 \end{bmatrix} = \begin{bmatrix} 20 & 14 & 0 & 0 \\ 14 & 10 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix} = W$$

Now that we have a n x n matrix we can determine the eigenvalues of the matrix W.

Since W **x** = □ **x** then (W- □ I)**x** = 0

III. Processing Steps

1. Get a dataset in S with N images.
2. Calculate the mean of S and store into imgm

$$imgm = \frac{1}{N}\sum_{i=1}^{N} Si \qquad (1)$$

3. Subtract imgm from the original faces Si gives A=Si-imgm where i=1,2,3,4…..N
4.Calculate the Singular Value Decomposition of A as shown in (1), obtain U,S and V. that is U is m x m right side matrix of singular value decomposition of matrix A m x n, S is an m x n diagonal matrix with singular values on the diagonal and V is n x n left side matrix of singular value decomposition of matrix A m x n.
5. Choose Singular Value range that is SV
6. Usv is m x SV matrix that are form from U.
7. Multiply A with transpose of Usv and assign to X, X=Usv' *A
8. Get the query image
9. Subtract query image from imgm and assign to qimgm.
10.Multiply qimgm with transpose of Usv and assign to X=Usv' * qimgm
11.Subtract x from X (D=X-x*ones(1,N))
12.Multiply D with transpose of D, Select diagonal of multiplied matrix and calculate square root of diagonal.

13.Select minimum of square root and compare with threshold value, if selected minimum value is less than threshold then query image is face otherwise query image is an unknown face image. In the above algorithm variables imgm, qimgm used to stored image mean and query image mean

IV. Results

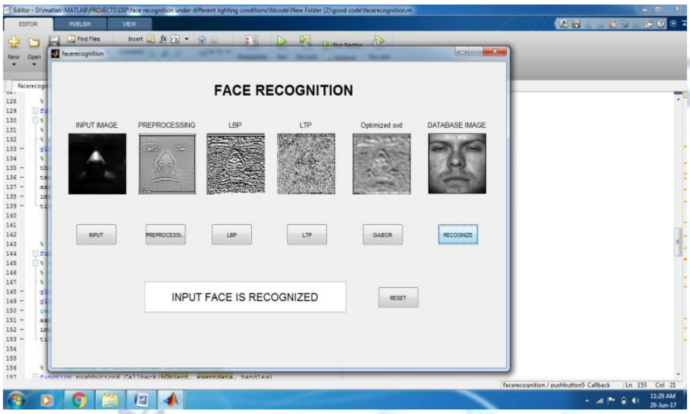


Fig: Face recognition with data base image

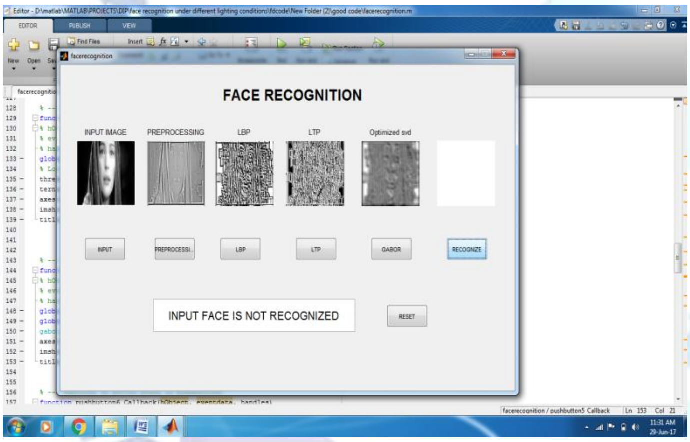


Fig: Face recognition with no data base image

V. Conclusion

A unique Face Recognition Using optimized Singular Value Decomposition of Facial Colour Image Database is designed and implemented in MATLAB2013B. Proposed Singular Value Decomposition is very useful methodology in Comparison, filtering data analysis and visualization. This paper yields unique and more accurate results for f ace recognition process. Almost thousand s of image are compared and tested in multi variant environments using the proposed technique. The best recognition rate achieved is 98.4 % percent for unified SVD. This is obtained by optimizing system parameters chosen after a in depth analysis of their influence on recognition rate and execution latency. Better results can be obtained with higher number of training images and original size of the image.

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