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LOCAL DIRECTIONAL NUMBER BASED CLASSIFICATION AND RECOGNITION OF EXPRESSIONS USING SUBSPACE METHODS

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Abstract—Facial expression is immediate means of non-verbal behavioral communication of internal emotions and intensions by human beings. Facial expression recognition is a challenging task in Biometrics and in Forensics. This paper proposes a robust and efficient subspace method for Facial Expression Recognition (FER) at different critical conditions like illumination, pose, age variations and different partial occlusions. In this paper we implement appearance based linear subspace methods like PCA and ICA for dimensionality reduction of images and LDN for extracting the features of image. These sub-space methods extracts the local features from face textures and encodes it in a compact code using directional and sign information and provides more discriminate information as compared to other existing systems. Finally different facial expressions due to human internal emotions are classified using classifiers like SVM. And for the testing of the image we use JAFFE databases and can create our own database.

Keywords—Local Directional Number Pattern(LDN); facial expression; JAFFE database; Principal Component Analysis; subspace method

I. INTRODUCTION

Facial expression is one of the challenging task to researchers. There are several situations in which human faces can change their expressions depending on the internal behavior effects. This change in facial and expression recognition helps in psychological studies with human-computer interaction and data-driven animations, machine Learning, Pattern Recognition and Computer Graphics communities, mind tempering, Medical Field etc. And also it is a challenging task in the presence of blurring effects, hazing effects, illumination variations, pose, age and gender variations.

Facial expressions are determined by obtaining different features of the face. These features are holistic features, geometric features, color segmentation and template features. Holistic features are also known as appearance-based features. This appearance based methods use image filters either on the whole face to create holistic features, or some specific regions to create local features to extract appearance change in the face image. Geometric features are the features which indicate the distance between different parts of the face such as distance between both the eyes, eyes and the nose, and finally it should form a geometric shape. Color segmentation is nothing but based on the different color patches of the face. Template feature, is nothing but an eclipse is formed between the different parts of the face.

Local Directional Number Pattern (LDN)acts as a face descriptor for recognizing robust faces and encodes the information related to structural and intensity variations of face texture. LDN encodes the structure of a neighborhood by analyzing its directional information. Consequently, we compute the edge responses in the neighborhood, in eight different directions with a compass mask. Then, from all the directions, we choose the top positive and negative directions to produce a meaningful descriptor for different textures with similar structural patterns. This approach allows us to distinguish intensity changes from bright to dark. Further, this descriptor uses the information about the entire neighborhood. Hence by using this approach more information can be extracted into code.

This paper represents a method for face and facial expression recognition more efficiently and robust as compared to the existing methods. It is a novel encoding scheme, named as, Local Directional number pattern i.e., LDN encodes efficiently into a compact code by taking advantage of different structural face textures.

II LITERATURE SURVEY

In [1], a new method is proposed on the basis of novel encoding scheme named as Local Directional Number Pattern. It extracts local information from image and encodes it using coding scheme in a compact form to distinguish between similar structure patterns indicating different intensity variations. The local-feature methods compute the descriptor from parts of the face, and then gather the information into one descriptor. Among these methods are Local Features Analysis [2], Gabor features [3], Elastic Bunch Graph Matching [4], and Local Binary Pattern (LBP) [5]. The last one is an extension of the LBP feature, that was originally designed for texture description, applied to face recognition. LBP achieved better performance than previous methods, thus it gained popularity, and was studied extensively. Newer methods tried to overcome the shortcomings of LBP, like Local Ternary Pattern (LTP) [6], and Local Directional Pattern (LDiP) [7].Local Directional Pattern (LDiP) proposes a method which represents a pattern which encodes the directional information in the neighborhood, instead of the intensity. It uses an eight bit binary code which can be assigned to each and every pixel of an input image. LDiP is calculated by comparing a pixel values in different directions and produces pattern with more stability even in the presence of noise. Gabor features [8], is a method uses Gabor wavelet which is a sinusoidal plane with particular frequency and orientation modulated by a Gaussian envelope. Linear Discriminate Analysis [9] and most recent 2D PCA [10] are the examples considered under holistic methods. These methods have been widely studied because of local descriptors as they had gained attention because of their robust nature against illumination and pose variations. Heiseleet al. showed that component based methods are more valid as compare to holistic methods. The methods using local feature computes the descriptor from different areas of the face, and then collects the information into one descriptor. Among these different methods is a Local Features Analysis (LFA) which is a purely second order derivative method. The methods for holistic class are Eigenfaces and Fisherfaces [11], which are actually based on Principal Component Analysis (PCA); it uses PCA for dimensionality reduction and also yields projection directions for maximization of total scattering over each and every class i.e., across all of the facial images. An unwanted variation due to lighting and facial expression is actually retained by PCA. To overcome noise and illumination variation problems, other information have been used by duo methods. Facial expressions uses Support Vector Machine (SVM) classifier. It is mainly used for the purpose of classifying data as per the requirement of the proposed technique. SVM Classifier generally uses support vectors which are separated by a hyperplane, a maximal margin mainly classifies different pixel values that represents top directional information of local features.

III PROPOSED FRAMEWORK

The first stage of our proposed system is the training phase and the test phase. The images used for the face and expression recognition can be acquired from the standard database like JAFF database is used. This database have many images which depict various facial expressions like happy, anger, disgust, fear, surprise and sad. After this various features of the image is extracted by using different coding schemes. The features are then normalized and classified using support vector classifier(SVM) Classifier. Finally the obtained results are analyzed and compared with other existing methods.

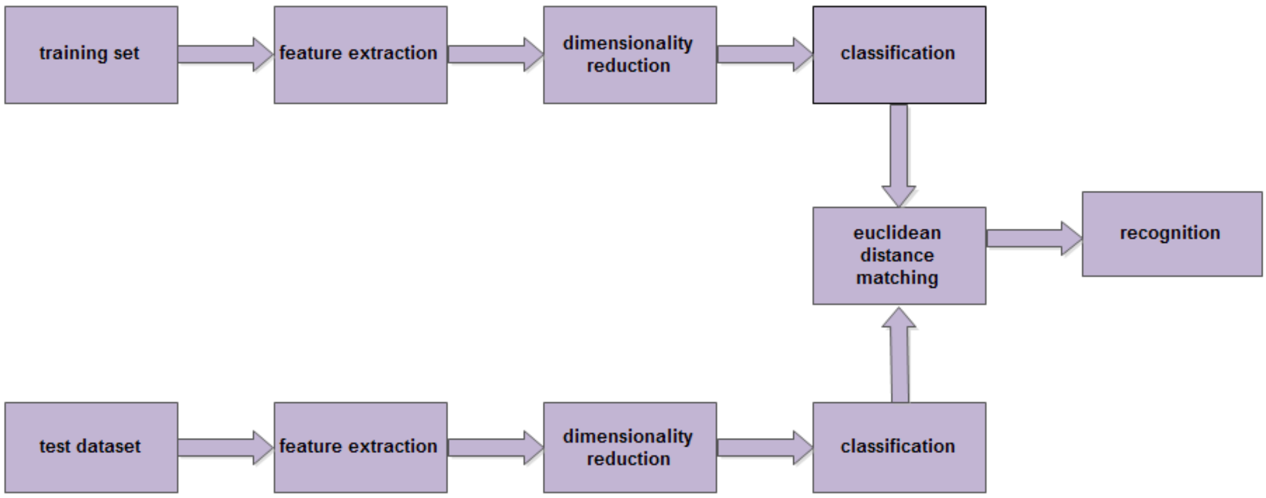

Figure 1: System Architecture

3.1 Image Acquisition

The JAFFE dataset images are used as input for processing. This dataset includes 100 images of various expressions like happy, anger, sad, surprise and disgust. the first stage contains the training dataset and the testing dataset. The training dataset will have 100 images of the database and the testing dataset will have only one input image.

Figure 2: JAFFE Dataset

3.2 Feature Extraction

Local Directional Number Pattern is used for feature extraction. from pre-processed images. Local Directional Number Pattern(LDN) is a six bit binary code assigned to each pixel of an input image. This code represents the structure of the texture and intensity transitions. Consequently, we create our pattern by computing the edge response of the neighborhood using a compass mask, and by taking the top directional numbers, that is, the most positive and negative directions of the edge responses. The method is actually more robust against the illumination changes and noise due to the use of gradient information.

LDN code is generated by analyzing the edge responses of each mask, M0…M7, t hat represents the edge significance in its respective directions, and by combining the dominant directional numbers. To produce LDN code, we need a compass mask to compute the edge responses. In this paper we use Kirsch Masking. Kirsch masking is basically used to extract edge responses and is rotated 45 apart to obtain mask in eight different directions. Further, Gaussian smoothing is used to stabilize the code using derivative Gaussian mask. This mask overcomes noise and illumination changes resulting into strong edge responses. Input images are decomposed resulting into directional templates.

Therefore, the code is defined as,

LDN(x, y) = 8ix,y+ jx,y(1)

Where, (x, y) = the central pixel of the neighborhood being coded,
ix,y = directional number of the maximum positive response,
ix,y=directional number of the minimum negative response.
Figure below shows an LDN code result.

Figure 3: LDN Code Result

3.3 Dimensional Reduction

In this paper, for dimensional reduction we are using different subspace methods. Usually the images will be in two dimensional, so in order to reduce this 2D images into 1D images subspace methods are used. Principal component Analysis(PCA) and Independent Component Analysis(ICA) are used for dimension reduction. PCA is a component based statistical subspace method used in facial expression recognition system to transform high dimensionality image data into low dimensionality image data to save memory space and to increase the speed of face recognition.PCA is used to project the spaces that give significant variations among known face images. The significant features variants are called eigenfaces. Basically these eigenvectors and eigenvalues are of the covariance matrix. To reconstruct the images largest eigenvectors and eigenvalues are used. Eigenvectors are the coordinate values that defines directions of the axes whose length are given by the eigenvalues. PCA method is useful in feature extraction at constant illumination conditions.

ICA is a generalization of PCA algorithm which also extracts the information contained in the higher-order relationship among pixels. Input pixel data is decorrelated by PCA method using secondorder statistics and there by produces lower dimension or compressed data with minimum mean squared re-projection error, Independent Component Analysis (ICA) subspace method minimizes both second-order and higher-order dependencies in the input signal. Both the training dataset and test dataset undergoes this dimensionality reduction.

3.4 Classification

In the trained dataset the images are classified using SVM classifier. We perform the facial expression recognition by using a to evaluate the performance of the proposed method. SVM is a supervised machine learning technique that implicitly maps the data into a higher dimensional feature space. Consequently, it finds a linear hyperplane, with a maximal margin, to separate the data in different classes in this higher dimensional space.

3.5 Euclidean Distance Matching

Next, we are giving one image for testing. For test image also the feature extraction and dimensional reduction is done by the system. The Euclidean distance is calculated for the test image and then the image with maximum Euclidean distance is matched . And further the recognition of the image takes place.

3.6 Face Recognition

LDN acts as a face descriptor and every face is represented by an LDN histogram (LH) which contains information of an image including edges, spots, corners, etc. and other local textures. The location information is aggregated to the descriptor by dividing the face image into small regions R1,...,RN and a histogram Hi is extracted from each region Ri. Finally, all the histograms obtained for different spots, edges, corners and other local textures due to different intensity variations are concatenated for the purpose of face recognition.

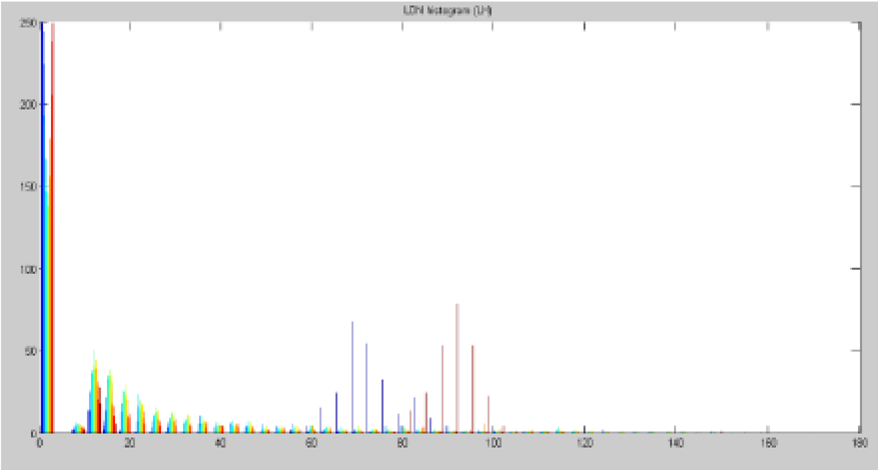

Figure 4: LDN Histogram Result

3.7 Expression Recognition

Facial Expressions can be recognized using Support Vector Machines (SVM).By using SVM, for facial expression recognition the accuracy of object can be maximized. The images are classified into different expressions in the training dataset. In the test phase the image gets matched with the image with the maximum Euclidean distance in the training dataset.

Figure 5: Resultant Recognized Face

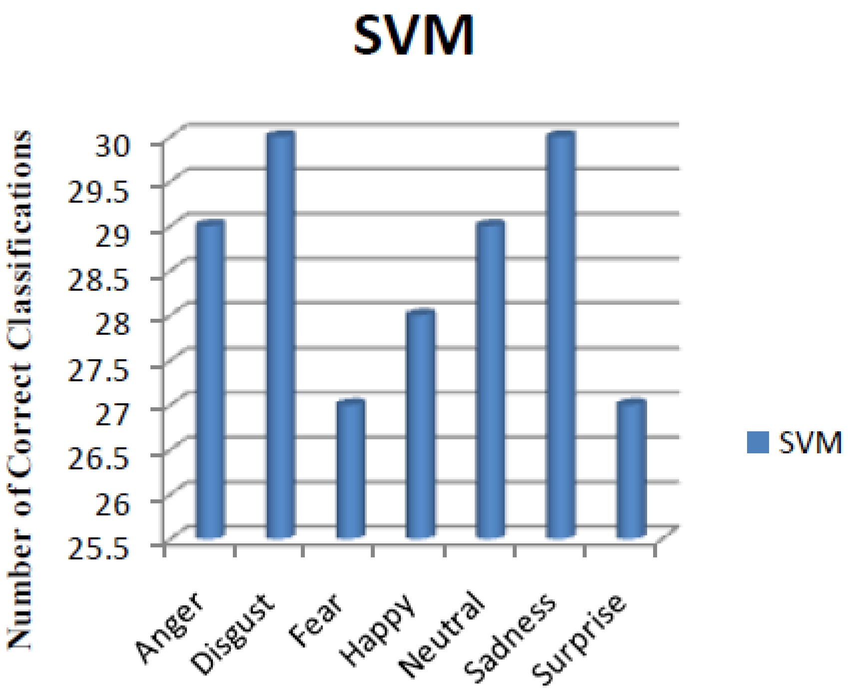

Figure 6: Face Expressions

IV CONCLUSION

LDN, that takes advantage of the structure of the faces textures and that encodes it efficiently into a compact code. LDN uses directional information that is more stable against noise than intensity, to code the different patterns from the faces textures.LDN uses the sign information of the directional numbers which allows it to distinguish similar textures structures with different intensity transitions e.g., from dark to bright and vice versa. It also uses Support Vector Machine (SVM) mainly used to classify data for the purpose of expression recognition. LDN is a good face descriptor which effectively performs per pixel computation. It overcomes noise and illumination problems and produces better results than other existing methods.

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