IOSR Journal of Engineering (IOSRJEN) **www.iosrjen.org**
ISSN (e): 2250-3021, ISSN (p): 2278-8719
PP 10-14

Analysis and Recognition of Face using Local Binary Feature Learning

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Abstract: *In this paper, Facial expressions and gestures provide intuitional cues for the interpersonal communication. Imparting intelligence to the computer for identifying facial expressions is a crucial task. Facial expressions and the emotions are governed by identification of facial muscle movement by the visual cortex and training a machine to identify these highly movements is an our primary interest. This thesis presents robust facial expression analysis algorithms for the static images as well as an efficient extension to sequence of images. We present an efficient pre processing method of the feature which eliminates the effect of illumination on the detected face part images thus making them efficient for feature extraction. Robust Local Binary Patterns and Gabor filters are implemented for feature extraction which are known to provide efficient face representation and analysis. LBP facial features are represented inform of weighted histograms which are best classified using Kullback Leibler divergence measure .Artificial Neural Network classifier is also tested for the classification of fused Gabor and LBP features.*

Keywords**:** *Biometrics, Face recognition, Identification of person*

I. Introduction

Face recognition has attracted much attention in computer vision and numerous face recognition methods have been proposed over the past three decades [1], [7]]. As a representative pattern recognition problem, there are two main procedures in a practical face recognition system: face representation and face matching. Face representation aims to the extract discriminative features to separate face images of different persons, and the face matching is to design of effective classifiers to recognize different persons.

A variety of face representation methods have been proposed in recent years [1], [7] and they can be mainly classified into two categories: the holistic features of representation [7] and local feature representation [1]. Representative holistic features are principal component analysis (PCA), linear discriminant analysis (LDA) [7], and their variations [7]. Representative local features include local binary patterns (LBP) [1], Gabor descriptor, discriminant face descriptor (DFD) and compact binary face descriptor (CBFD) [43]. Generally, local features achieve the better performance than holistic features due to the new robustness to the local changes in feature description.

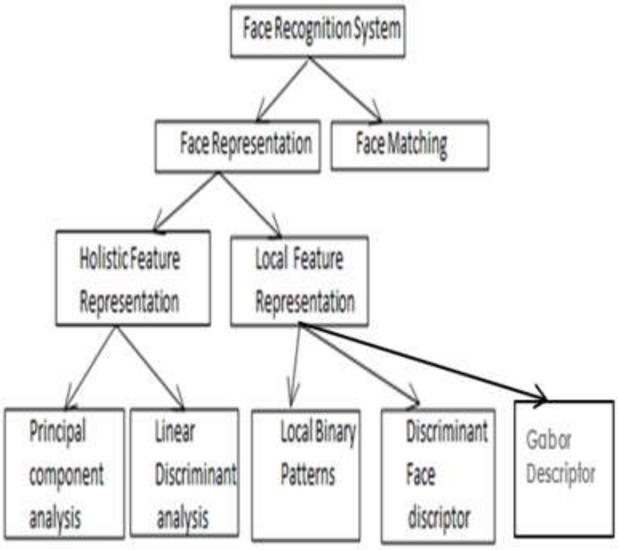


Figure1: Block Representation of Introduction

II. Proposed Work

Complete work is include in three basic topics, which is describes as follows.

2.1 Face Representation

Face In present day scenario computers have become more ubiquitous and indispensable part of our lives. For this same reason Human Computer Interaction (HCI) has become an emerging area of research and it is a prior necessity for imparting intelligence to computers to understand and act according to human behavior. Interpersonal communication is broadly classified into verbal communication and the nonverbal communication. The Verbal communication consists of the only new raw voice data input and nonverbal communication accounts for the tone and intensity of voice merged with facial expressions and gestures. The combined effect of these cognition to communicate. Recognizing facial expressions is the vital in human computer interfaces because it is a visible embodiment of a person's psychological state, intention and personality. Without any vocal data facial expression cues combined with gestures efficiently elicit the internal meaning of speaker which contains forms the basis of facial expression recognition. In the communication 55 percent of perception is through facial expression, 38 percent through gestures and voice data carries 7 percent of information. Facial expressions are considered to be uniform universally among different human races. Facial expression can be defined as a temporal deformation of facial features like eyes, nose, lips, cheeks, etc which is a result of muscular activity aroused by internal feelings or events occurring in the surroundings. Extent of Opening of eyes, frowning of eyebrows, the rise of eye brows, widening and shortening of mouth especially at the corners form an important aspect of expression classification as identified by the human visual cortex.

Hence our facial expression recognition system should be designed such that even the slightest change in the movement of facial organs can be efficiently identified and adhere to exact classification. The Heterogeneous face representation suffers from large object modal discrepancies and it is desirable to the design cross-modal models which are robust to the intra-modality differences. Existing heterogeneous face representation methods mainly contains three categories: image synthesis modality-invariant feature extraction and common space projection. Image synthesis approaches transform faces of one modality into another, so that heterogeneous facial images can be directly compared. Representative methods include face sketch synthesis with embedded hidden Markov model (E-HMM) and face identity-preserving (FIP) features [84]. Modality-invariant feature extraction approaches extract local features which are robust to modalities, such as histogram of averaged oriented gradients(HAOG) and graphical heterogeneous face recognition (GHFR) . However, both image synthesis and modality-invariant feature extraction approaches are modality-specific. Common space projection methods learn a common subspace to minimize the modal differences. For example, Yi et al. learned a canonical correlation analysis (CCA) based projection. Mignon and Jurie presented a cross modal metric learning (CMML) approach by learning a common subspace. Different from modality specific heterogeneous face recognition with the approaches, our C-CALBFL and C-CA-LBMFL learn a common subspace in an unsupervised manner, which are widely applicable to various heterogeneous face recognition tasks.

2.2 Feature Learning

There have extensive feature learning in recent years [8] and representative feature learning models include sparse auto-encoders detected auto encoders , restricted Boltzman machine, convolutional neural networks, independent subspace analysis and reconstruction of any independent component analysis

Recently, feature learning based methods have achieved reasonably good performance in the many face recognition systems. For example, new Sun et al. Proposed a deep hidden identity features (Deep ID) method through deep convolutional neural networks. Hussein et al. presented a local quantized pattern (LQP) method by modifying the LBP method with a learned coding strategy. Cao et al. [12] proposed having learning-based (LE) feature representation of the various method by applying the bag-of-word (Bow) framework. Lei et al. presented a discriminant face descriptor (DFD) method by the image of face learning an image filter using the LDA criterion to obtain LBP-like features. Lu et al. proposed a compact binary feature of descriptor (CBFD) by learning a hashing filter to project each image by having patch into a compact binary vector in an unsupervised manner. They also new presented a simultaneous local binary feature learning extraction of the image and encoding (SLBFLE) approach to simultaneous learn the projection matrix and the dictionary. However, both CBFD and SLBFLE only new exploit the relationship of binary bits at the same position, while the proposed CALBFL investigates the contextual information within each binary descriptor.

2.3 Binary Feature Descriptor

Recently, the binary feature descriptors have received increasing interest due to their any efficiency of storing and matching in computer vision. Earlier binary descriptors include binary robust independent elementary feature (BRIEF) [2], oriented FAST and rotated BRIEF (ORB) [5], binary robust invariant scalable keypoint (BRISK) [3] and fast retina keypoint (FREAK) [2]. BRIEF computes binary vectors directly by the simple binary tests between pixels in a smoothed image patch. New ORB improves BRIEF by first employing scale pyramids and orientation operators to the obtain scale and rotation invariance. BRISK shares the similar purpose as they show ORB by leveraging a circular sampling pattern. FREAK uses the retinal sampling grid for fast object computing and matching inspired by the human visual system, with retina having the object. However, the performance of these methods is not powerful enough because raw intensity comparisons are susceptible to scale and transformation. To address this, several learning-based methods having been proposed in recent years. For example, Trzcinski et al. [69] presented D-BRIEF method to learn discriminative projections by encoding similarity relationships. They also applied boosting to learn hash functions in Bin Boost [6]. Bantams et al. [4] proposed a binary online learned descriptor (BOLD) maximize the inter-class distances as well as minimize the intra-class distances of binary codes, respectively.

III. Working Of System

First proposed by the Ojalaet. al. [5] local binary pattern (LBP) operator is an image operator capable of transforming an image into an image of integer labels describing small-scale local characteristic preserving appearance of the image. The statistics of these integer labels, especially the histogram, is further used for image analysis.LBP was first introduced for texture analysis as in [1] with the new features basing on nonparametric recognition and classification of textures at the same time of taking rotation invariance into consideration. According to them texture is governed by a pattern and also by the new context extent of its intensity or strength. LBP operator has two main parameters (P_p, R_p) where P_p is representing the sampling points of the number and R_p is representing the radius. Figures 3.1 (a),(b),(c) represent LBP (8,1) (8,2) and (16,2) operators respectively where each cell represents a pixel value and radius pertains to number of blocks from the center of the pixel. If we consider a monochrome image where I(x,y) is the intensity value of center of the pixel then new image will be identified.

For facial expression analysis which is mainly based on feature texture of regions it is necessary that the features remain invariant to rotation because of the expression images are rarely static. Local patterns of new natural images have less variations hence considered uniform. They also give robustness to the statistical representations and hence mathematically very efficient in terms of the comparison and computational complexity. According to Ojala et. al. ULBP has efficiently represented flat regions, edges, spots, corners and line ends.

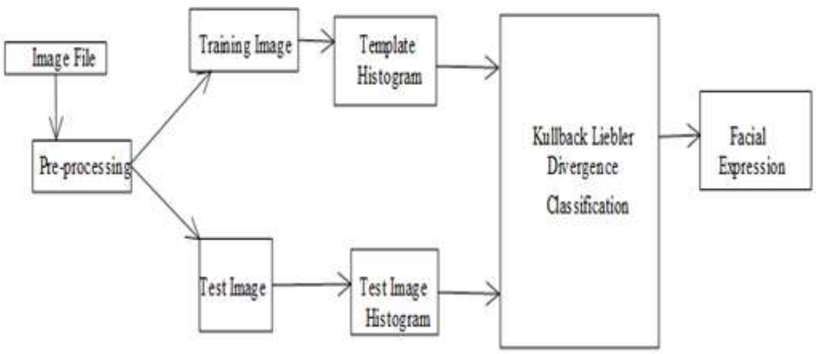


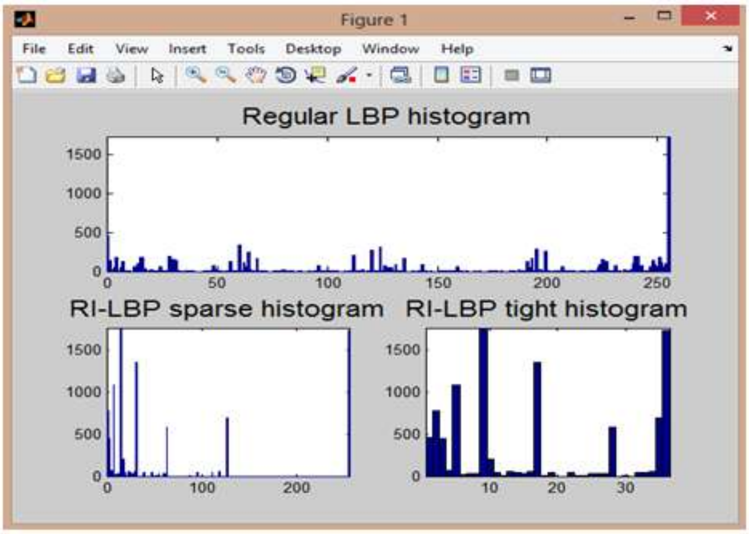
Figure3: Principle of Face Recognition.

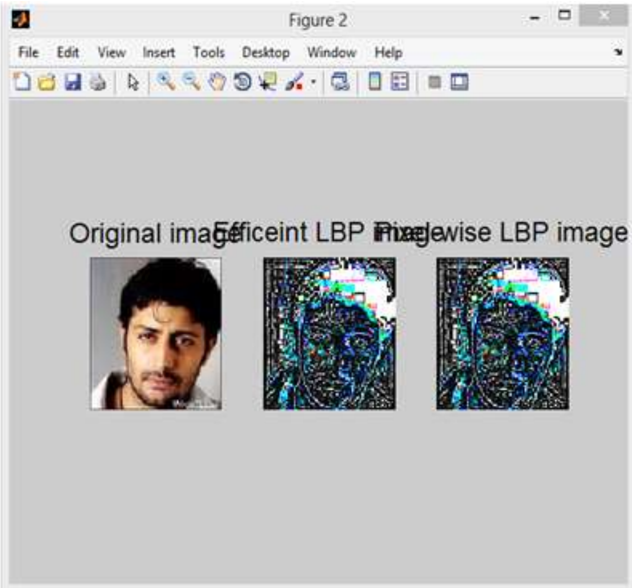
[4]. Modality-invariant feature extraction approaches extract local features which are robust to modalities, such as histogram of averaged oriented pixel calculated.

Gradients (HAOG) [1] and graphical heterogeneous face recognition (GHFR) [2]. However, both image synthesis and modality-invariant feature extraction approaches are modality specific . Common space projection methods learn a common subspace to minimize the modal differences. For example, Yi et al. [8] learned a canonical correlation analysis (CCA) based projection. Mignon and Juries [9] presented a cross modal metric learning (CMML) approach by the learning a common subspace. Different from modality specific heterogeneous face recognition approaches, our C-CALBFL and C-CA-LBMFL learn a common subspace in any unsupervised manner, which are the widely applicable to the various heterogeneous face recognition tasks.

IV. Result:

Following figure are the histogram of the project and the output image.





V. Conclusion:

This thesis presents two facial expression recognition algorithms which are efficient in the recognizing and differentiating seven expression classes of the objects. An efficient facial expression recognition method is proposed in algorithm 1 which uses robust Local Binary Patterns for the facial feature extraction and representation along with Kullback Leibler divergence for the classification. Pre processing of the new image improves the classification accuracy of KL divergence measures. Experimental results show that pre processing of the combined algorithm with KL divergence have less confusion for the correct emotion class recognition

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