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Context-Aware Local Binary Feature Learning : An Approach For Face Recognition

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Abstract— This system uses Context-Aware Local Binary Feature Learning (CA-LBFL) Method for face recognition. Learning based methods such as DFD and CBFD learn features representation from raw pixel and they are more susceptible to noise where existing local feature descriptors are hand crafted and they require strong prior knowledge and heuristic. Proposed system uses contextual information for face recognition because context provides strong prior knowledge. It helps to enhance the robustness and stableness of various visual analysis tasks. to jointly learn multiple projections matrices for mapping we make use of context-aware local binary multi-scale feature learning (CA-LBMFL), where each projection matrix corresponds to a specific scale of pixel difference vector (PDV). PDVs are extracted from image and stored in a text file in the binary form. Face recognition is performed on the basis of this extracted features. For heterogeneous face matching we implement coupled learning methods based on CA-LBFL and CA-LBMFL. Experimental result is based on two widely used datasets LWF and YTF.

Keywords—Face representation,Face recognition,Heterogenous face,Context-Aware,Binary feature learning.

I. Introduction

A smart environment is one that is able to identify people, interpret their actions, and react appropriately. Thus, one of the most important building blocks of smart environments is a person identification system. Facial recognition systems are built on computer programs that analyze images of human faces for the purpose of identifying them. These systems are based on recognition algorithm such as eigenface or hidden Markov model. Also,some techniques are used in a face recognition system such as local binary patterns, robust face region descriptors, discriminant face descriptor. But these methods require strong prior knowledge and are heuristics. Also,this methods learn feature representations from raw pixels directly, they only learn each feature code individually and are more susceptible to noise.

Nowadays face recognition system is gaining significant importance and attention. Variety of face representation methods are proposed earlier [2][6] [19][11] [29][12].they are divided into two categories, holistic feature representation [6][30] and local feature representation [2][19][11][29].Principal Component analysis(PDA) [30] and linear discriminate analysis (LDA) [6] are types of representative holistic features. Whereas local binary pattern [2], gabor descriptor [11], discriminal face descriptor [19] and compact binary face descriptor [29] are types of representative local features.

Existing local feature descriptors [2][6][41][50] divide a facial image into small regions and compute a description of each region using local binary pattern, thus it requires prior knowledge and heuristics. Earlier binary descriptors include binary robust independent elementary feature (BRIEF), oriented FAST and rotated BRIEF (ORB), binary robust invariant scalable key point (BRISK) and fast retina key point (FREAK).However, the performance of these methods is not powerful enough because raw intensity comparisons are susceptible to scale and transformation.

Rest of the paper is organized as follows, Section I contains the introduction of System, Section II contain the literature survey of system. Section III explains the CA-LBFL methodology with a flow of system, Section IV describes results and discussion using graphs, and Section V concludes research work with future directions.

II. Related Work

A. *Face Representation*

Human have to be represented before recognition can take place. Representation plays the most important role and it probably exceeds that [3] played by recognition, known

As classification or identification. There are two main categories of face representation: homogeneous face recognition and heterogeneous face recognition. The aim of homogeneous face recognition is to recognize faces from the same modality and the aim of the heterogeneous face recognition system is to match faces from different sources like visible photos to near infrared images or sketches.

There are two categories of homogeneous face representation method: Holistic Feature Representation [6] [20] and local feature representation [2] [19] [12] [14].

In holistic feature representation all of the images of a lambertian surface taken from a fixed viewpoint but under variation in illumination. Also that lies in a 3D linear subspace of the high dimensional image space. Also the holistic feature representation is based on the information theory approach that break down face images into a small set of characteristic feature images called “eigenfaces” [6] which may be thought of as the principal component of the initial training set of face images. To perform face recognition first step is to project a new image into the subspace spanned by the eigenface(face space) and then classify the face by comparing its position in face space with the position of known individuals.

There are two methods of local feature representation method, i.e. hand-crafted and learning base LBP[2] and Gabor wavelets[12] are the type of the gradient or texture information within local regions first and then generate a concatenated feature for face representation.DFD[24] and CBFD [14] are types of learning-based methods which learn distinctive local features in a data-driven ways. Heterogeneous face recognition refers to matching a probe face image to a gallery of face images taken from alternate imaging modality. There are three heterogeneous face representation methods available: 1. image synthesis [17], this method uses the automatic sketch synthesis algorithm. This algorithm is based on an embedded hidden markov model (E-HMM) and selective ensemble strategy. The E-HMM firstly model the nonlinear relationship between a photo-sketch pair firstly and then a series of pseudo-sketch. 2. Modality: invariant feature extraction: it uses a face descriptor called Histogram of averaged oriented gradient (HAOG) [16]. 3. Common space projection: It uses an approach for cross modal matching, i.e the matching of patterns represented in different modalities when pairs of same or different data are available for training (e.g. faces of same or different people) in that case, standard approach, such as partial least squares (PLS) or canonical co-relation analysis (CCA) map the data into a common latent space that maximizes the covariance.

B. Face Learning

Previously varies feature learning methods have been proposed, i.e. greedy layer wise training of network [8] which include sparse auto encoder, a fast learning algorithm [22] for deep belief nets which include restricted boltzman machine, hierarchical representation includes convolution neural network [24], for unsupervised feature learning, construction independent component analysis [7] and its variants have been used. Standard ICA requires an orthonoramily constraint to be enforced; also, ICA is sensitive to whitening. Contractive auto-encoders [25] include denoising and training auto-encoders.

C. Binary Feature Descriptor

Recently binary feature descriptor includes binary robust independent elementary feature (BRIEF) [9] e.g. calonder et al propose binary strings as an efficient feature point descriptor which is called BRIEF, it shows that it is highly discriminative even when using relatively few bits and can be computed using simple intensity difference tests oriented FAST and rotated BRIEF (ORB) [26] e.g. Rublee et al proposed an alternative approach to SIFT or SURF key point descriptor called as ORB.

III. METHODOLOGY

Our system uses context aware local binary feature learning (CA-LBFL) method for face recognition and context aware local binary multi-scale feature learning (CA-LBMFL) to jointly learn multiple projection matrices for face representation.

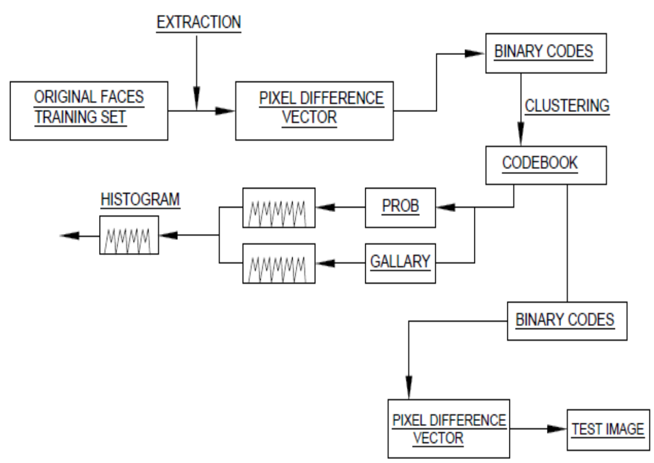

Figure 1.Architecture of the proposed system.

Figure 1 explains the architecture of the proposed system.
For training image in image annotation part of the system firstly we need to pass the folder which contains the facial images. Images are converted into grayscale image. Then Pixel difference vectors (PDV) are extracted from images.

Then these features are converted to local binary form using Local Binary Pattern (LBP) function using equation(1), and stored in a text file.

bitmap.GetPixel(x, y).R > bitmap.GetPixel (x_n,y_n).R) . . . (1)

For testing image, we first pass the feature file which contains the all features in LBP. Then we pass the image to be tested. Then the classification is done on the basis of LBP features.

IV. Results and Discussion

Proposed system uses two widely used datasets for experimental results YTF [30] and LFW [27].We compared our system with previous systems. Then, we summarize the observations of all the experiments.

A. Results on YTF.

The YTF [30] dataset contains 3425 videos with varying variations of pose, expression and illumination. We first added the faces in a database using the CA-LBFL method. Then features are extracted and converted into specified format. When we start a video the face is shown with a name of the. We have tested the system in terms of accuracy.

Following graph shows the average verification rate of our CALBFL and the state-of-the-art learning-based face descriptors on YTF with the image-restricted setting. According to the results our method gives a higher verification rate then commonly used descriptor.

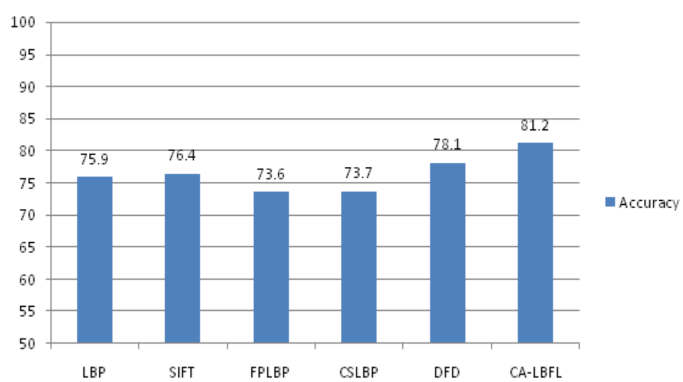

Figure 2. Recognition accuracy and the standard error (%) comparison with the commonly used face descriptors.

B. Results on LFW.

The LFW [27] dataset contains 13233 facial images. These images are captured in wild condition. These images are in large intra-class variations such as varying poses, expressions, illuminations and backgrounds.

Following graph shows a comparison with the state-of-art face descriptors using mean verification rate and area under ROC.

According to the results we see that CA-LBFL achieves better performance than existing state-of-art methods.

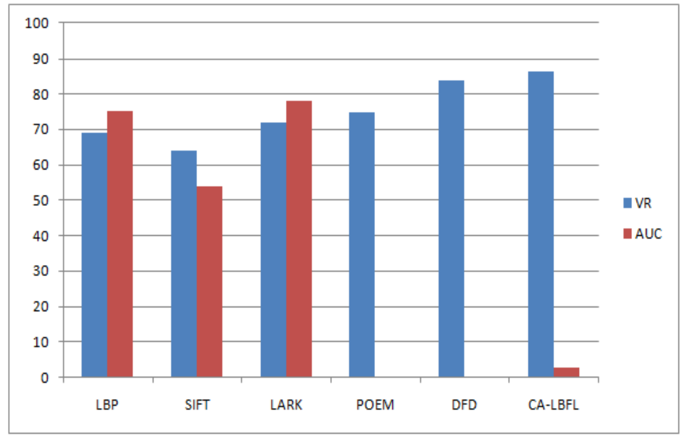

Figure 3. Mean verification rate (VR) (%) and area under ROC (AUC) (%) comparison with state-of-the-art face descriptors

V. Conclusion and Future Scope

This system uses context-aware local binary feature learning (CA-LBFL) method. We have also used context-aware local binary multi-scale feature learning (CA-LBMFL) method to jointly learn multiple projection matrices for mapping. For heterogeneous face matching we implemented coupled learning methods which are based on CA-LBFL and CA-LBMFL. We have performed an experimental analysis by using widely used datasets YTF and LFW.

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