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EDA: Novel Technique for Image Matching

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Abstract

This paper recognizes the problem of matching images from different modalities. These different modality images are known as heterogeneous images. These type of images have large differences between them. These differences are known as modality gap. To reduce this gap, here proposed a new algorithm called EDA. It has wide applications like IR to optical image matching, Sketch to optical image matching etc. The main advantage of EDA approach is we can do matching of different modalities using the same feature descriptor. The key idea is to learn an encoding mechanism which will turn images in different modalities into their encoded images to reduce the modality gap between them. Here Sketch to optical image matching is done as an example.
Keywords: EDA, Encoded Images, Heterogeneous Images, IR, Modality Gap, Sketch

I. INTRODUCTION

Human face recognition plays an important role in application, such as criminal identification, credit card verification, security system, scene surveillance etc. Heterogeneous Face Recognition refers to the method of recognition of face images captured in different modalities.One of the most challenging tasks in AFR is the matching between face images acquired in heterogeneous environments. An example is photo to sketch matching. Automatic retrieval of face images from police mug-shot databases is critically important for police and law enforcement agencies. It can effectively help investigators to locate or narrow down potential suspects. However, in many cases, the photo image of a suspect is not available and the best substitute is often a sketch drawing based on the recollection of an eyewitness. Thus we can make a collection of sketch databases of criminals. Suppose a crime occured and assume that we take photos of several people in that place. Then we can compare that face photos with sketches stored in database. This helps the police in law enforcement. This EDA approach can be used to make a novel sketch retrieval system using face photos.

Fig. 1: Optical Image and corresponding Sketch Image

Face recognition is one of the biometric methods to identify peoples by the feature of face, which is very important for many applications such as retrieval of an identity from a database for banking system and criminal investigations, video surveillance, smart cards, virtual reality, entertainment, forensic applications.

II. RELATED WORKS

X. Wang et. al [4] proposed a novel face photo-sketch synthesis and recognition method using a multiscale MRF model. It has useful applications for both digital entertainment and law enforcement. They assume that faces to be studied are in a frontal pose, with normal lighting and neutral expression, and have no occlusions. To synthesize sketch or photo images, the face region is divided into overlapping patches for learning. The size of the patches decides the scale of local face structures to be learned. From a training set which contains photo -sketch pairs, the joint photo-sketch model is learned at multiple scales using a MRF model. By transforming a face photo to a sketch, the difference between photos and sketches is significantly reduced, thus allowing effective matching between the two in face sketch recognition. After the photo-sketch transformation, in principle, most of the proposed face photo recognition approaches can be applied to face sketch recognition in a straightforward way.B. Klare et. al [7] proposed a new method for Automatic retrieval of face images from police mug-shot databases. It is critically important for law enforcement agencies. It can effectively help investigators to locate or narrow down potential suspects. However, in many cases, the photo image of a suspect is not available and the best substitute is often a sketch drawing based on the recollection of an eyewitness. This paper present a novel photo retrieval system using face sketches. By transforming a photo image into a sketch, they reduce the difference between photo and sketch significantly, thus allowing effective matching between the two. Eigen face method is used here. The eigenface approach uses the KLT for the representation and recognition of face images.Sharma et. al proposed Partial Least Square analysis[12] which is a regression model that differs from Ordinary Least Square regression by first projecting the regressors and responses onto a low dimensional latent linear subspace. PLS chooses these linear projections such that the covariance between latent scores of regressors and responses is maximized and then it finds a linear mapping from the regressors latent score to response's latent score. They apply PLS by using images from one modality as regressors and using corresponding images from a different modality as responses. In this way, they learn a linear projection for each modality that maps images into a common space in which they can be compared.Z. Lei et. al proposed [13] coupled discriminant analysis. In this, two implementations of LCKS based coupled discriminant analysis methods, namely LCKS-CDA and LCKS-CSR, are presented This paper incorporates locality constraint in kernel space into coupled subspace learning to solve the heterogeneous face recognition problem. Both the coupled projections proposed here are supposed to be represented by all available samples from different modalities, so that the mutual information between different modalities is sufficiently explored. The locality information in kernel space is modeled and imposed onto the combination coefficients properly. In this way, structures of the data in the input space and transformed kernel space are utilized, resulting in more discriminative information for heterogeneous face recognition. A generic HFR framework was proposed in which both probe and gallery images are represented in terms of non-linear kernel similarities to a collection of prototype face images to enhance heterogeneous face recognition accuracy.

III. PROPOSED METHOD

A. Vector Quantization:

This approach is illustrated in Figure 2. For each pixel, first sample its five d-neighbor pixels for each direction, and then subtract the center pixel value. Finally the centered vector is normalized into the unit L2-norm to form the associated pixel vector of that direction. Each pixel is associated with four vectors, forming four sets of training vectors that are used to train four encoders. Each encoder consists of two sets of mutually orthogonal hyperplanes, which divide the vector space into four partitions. Vectors of each direction are encoded into a 2-bit value, according to the partition in which the vector lie. Finally, the four 2-bit values are concatenated to form an 8-bit value that will be converted into a decimal value as code.

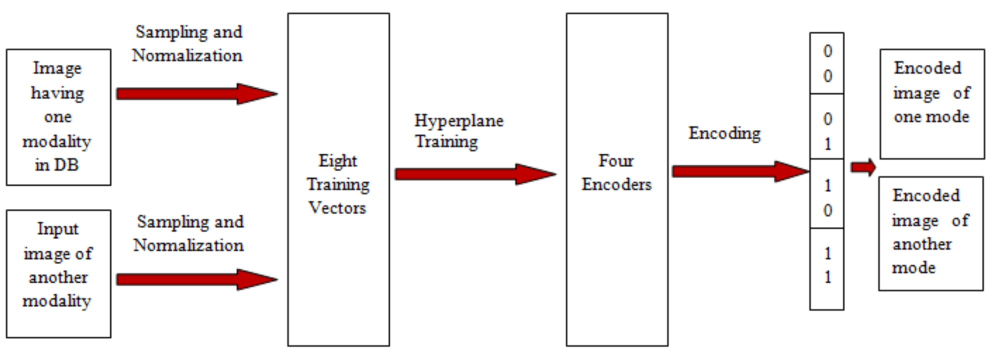

Fig. 2: Pipeline for Extracting the Feature Descriptor

B. Feature Extraction

1) Divide the whole encoded image into a set of overlapping patches with size cxc pixels.

2) Compute the histogram, over each patch, of the frequency of each code occurring which gives a feature vector for the patch.
3) Concatenate the outputs of each patch into a long vector to form the final face feature.

C. *Matching Framework:*

The matching framework involves two levels of subspace analysis. In the first level, the large feature vector is first divided into multiple segments of smaller feature vectors. Discriminant analysis is performed separately on each segment to extract the discriminant features. The goal for the first level is to generate more discriminative projections to reduce intraclass variations and avoid over-fitting. In the second level, projected features from all the segments are then combined, with PCA for efficient recognition. The two-level matching framework is based on the local feature-based discriminant analysis (LFDA) approach. Figure 3 presents an illustration of this algorithm.

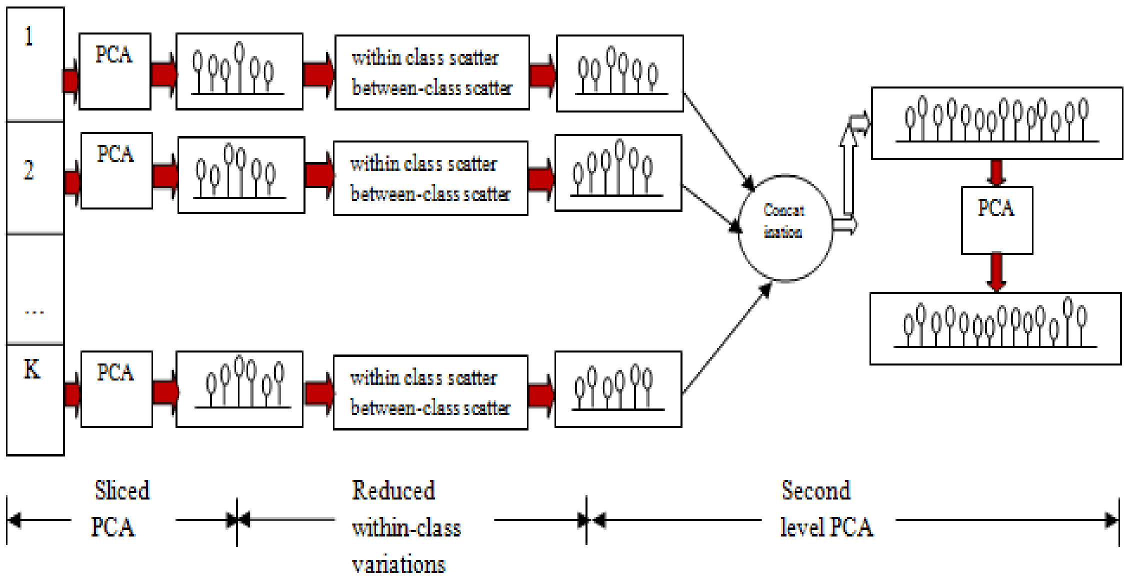

Fig. 3: Illustration of the Two-Level Matching Framework

IV. EXPERIMENTAL RESULTS

Fig. 4: Face Images and Respective Sketch Images Dataset

Block diagram of optical to sketch matching is given below in fig.5. Input optical image and sketch image undergo various pre processing steps. Preprocessing includes converting the input face image into gray and binary image. Then vector quantization method is done to convert continuous space into discrete code representation. Then patch conversion is done to divide the image into small patches. Then histogram of each small patch is computed. Then each small patch is concatenated to form a final face vector. Then common features are computed. Then these features are compared together to get final result.

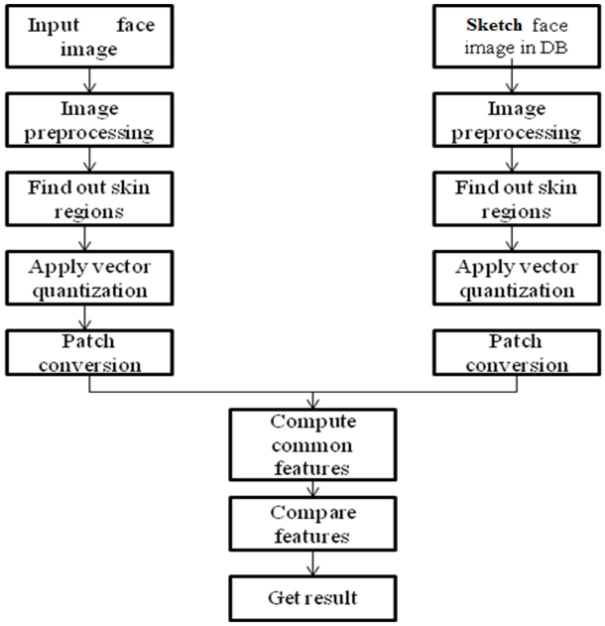

Fig. 5: Block Diagram of Optical To Sketch Image Matching

Fig. 6: Matching Optical Images To Sketch Images Result

Table - 1
Comparison Of EDA Descriptor With State-Of- The-Art Descriptors Using The PCA+LDA Matching Scheme

Descriptors	*Rank-1 Identification accuracies*
LBP	*63.72%*
HOG	*62.14%*
MLBP	*67.47%*
CITE	*72.53%*
EDA	*78.19%*

From above table, we can see that EDA is better than all other previous methods. It has higher identification accuracy than others. Moreover, EDA is a binary encoding method, So it is more better than CITE, HOG methods.

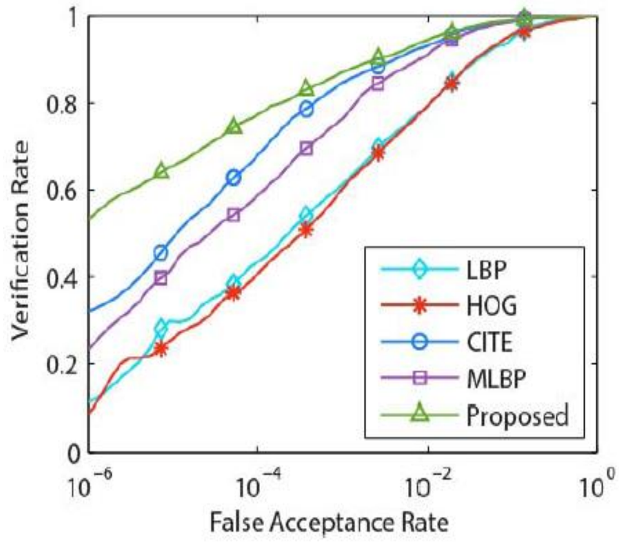

Fig. 7: Comparison of Our Descriptor with State-Of-The-Art Descriptors Using the PCA+LDA Matching Scheme

V. CONCLUSION

This paper proposes a new approach called Enhanced discriminant analysis (EDA) for image matching. The above mentioned approach ECFDA is a general heterogeneous feature descriptor. So it can be used for various heterogeneous matching applications. Here face photo to sketch matching is done which is useful for law enforcement applications. Extensive experiments on large and challenging datasets which show the significant improvement of this new approach over the state-of the- art. In the future, this approach can be extended to general cross-modality face recognition problems such as thermal-photo and high-low resolution face matching.

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