International Journal of Scientific Engineering and Applied Science (IJSEAS) - Volume-1, Issue-4, July 2015
ISSN: 2395-3470
www.ijseas.com

A Common Feature Descriminant Analysis Approach For IR and Optical and Sketch Face Images

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Abstract *- The most challenging issue in heterogeneous face recognition is that face images associated with the same person but taken with different imaging devices may be mismatched due to the great discrepancy between the different image modalities (optical, infrared and sketch), which is referred to as modality gap. In biometrics research and industry, it is critical yet a challenge to match infrared face images, optical face images to sketches. The major difficulty lies in the fact that a great discrepancy exists between the infrared face image, corresponding optical face image and sketch image because they are captured by different imaging devices. In this paper our focus is on the approach which defines cross modality face reorganization problems such as sketch-photo and high-low resolution face matching. In this approach, a new learning-based face descriptor is first proposed to extract the common features from heterogeneous face images (infrared face images and optical face images and sketch images), and an effective matching method is hen applied to the resulting features to obtain the final decision.*

Keywords - Modality Gap, Sketches, Optical Face Image, Infrared Face Images, Heterogeneous Face Recognition

I. INTRODUCTION

Our proposed method is useful in identifying not only the sketch images with face sketches but also the suspects that deals with different image modalities. In biometrics research and industry, it is critical yet a challenge to match infrared face images and optical face images to sketches. The major difficulty lies in the fact that a great discrepancy exists between the infrared face image and corresponding optical face image because they are captured by different devices (optical imaging device and infrared imaging device).

Moreover, traditional optical imaging devices require appropriate illumination conditions to work properly, which is difficult to achieve satisfactorily in practical face recognition applications. To combat low illumination at nights or indoors, infrared imaging devices have been widely applied to many automatic face recognition (ARF) systems. The task of infrared-based ARF systems is to match a probe face image taken with the infrared imaging device to a gallery of face images taken with the optical imaging device, which is considered to be an important application of heterogeneous face recognition [1] (also known as *cross-modality face recognition*). The most challenging issue in heterogeneous face recognition is that face images associated with the same person but taken with different devices may be mismatched due to the great discrepancy between the different image modalities (optical, infrared and sketch), which is referred to as *modality gap*. The infrared photos are usually blurred, low contrast, and have significantly different gray distribution compared to the optical photos. In the discriminant analysis common feature (CFDA) approach, a new learning-based feature descriptor is first developed to learn a set of optimal hyper-planes to quantize continuous vector space into discrete partitions for common feature extraction, and an effective discriminant analysis technique is then applied for feature classification. We conduct extensive experiments on two large and challenging optical, infrared and face sketch datasets to investigate the effectiveness of our new approach.

II. PROPOSED APPROACH

In our new approach we are dealing with three different modalities infrared face image, optical face image and sketch image. To combat the modality gap we proposed a new approach called Common Feature Descriminant Analysis where a new learning based face descriptor is first developed where the vectors of continuous space is converted to discrete code representation in order to convert the image into an encoded image. Vectors of continuous space is converted to the decimal code with the help of pixel normalization techniques like K-min and Random Forest Algorithms where, center pixel value is normalized with respect the neighboring pixels.

Vector quantization is an effective technique that has been widely used to create discrete code representations for object recognition. An Image can be turned into an encoded image by converting each pixel into a specific code using vector quantization technique. We design a hyperplane based encoding method for effective feature representation for heterogeneous face images.

In feature extraction stage we use our CFDA approach for image encoding purpose. For image encoding purpose the image has to go through pipeline for feature extraction. For each pixel, we first sample its five d-neighbor (Radii = d) pixels for each direction (the figure shows one of four directions, with blue arrows), 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 hyper-planes (we only show one for illustration), 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 lies (i.e. 00 for the first partition, 01 for the second partition, and so forth). Finally, the four 2-bit values are concatenated to form an 8-bit value that will be converted into a decimal value (from 0 to 255) as the code. With the face image encoded the image we can use densely sampling technique in order to extract the features. For this the whole encoded image is divided into a set of overlapping patches with the size c x c pixels (the step between adjacent patches is s). Then compute the histogram over each patch of the frequency of each code occurring which gives a feature vector for each patch. Concatenate the outputs of each patch into a long vector to form the final face feature.

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 CFDA approach is proposed specifically for handling the optical-infrared face recognition problem. In the feature extraction stage, a learning-based feature descriptor is developed to maximize the correlations between the optical face images and corresponding infrared images. In this way, the modality gap between the two kinds of face images can be significantly reduced; hence, it is expected that the resulting features will be well-suited to the optical-infrared face recognition problem.

we propose a new approach called common feature discriminant analysis (CFDA) for optical-infrared face recognition. In the CFDA approach, a new learning-based feature descriptor is first developed to learn a set of optimal hyperplanes to quantize continuous vector space into discrete partitions for common feature extraction, and an effective discriminant analysis technique is then applied for feature classification. The experimental results are shown below for the controls points that are located from the detected face in order to perform futhur feature extraction processig.

Fig 1: Preprocessed Image

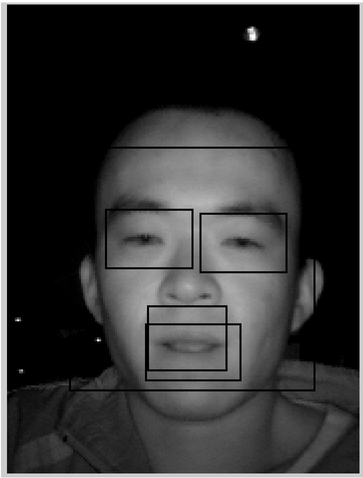


Fig 2 : Detected Face Parts

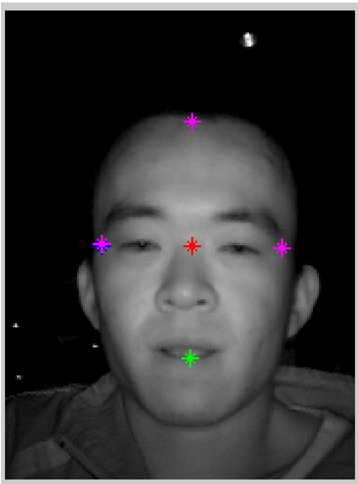


Fig 3: Control Points

In order to perform the matching between face images of different modalities, the different image modalities are taken to a common subspace where the modality difference is believed to be minimized. To encode the detected face vector quanization is the best choice. Vector quantization is an effective technique in mapping vectors of continuous space into discrete code representations, and has been widely used to create discrete image representations for object recognition. An image can be turned into an encoded image by converting each pixel into a specific code using the vector quantization technique. Various algorithms such as mean shift [20], k-means, random projection tree [21], [22], and random forest [23], [24] have been proposed to quantize a continuous space to form discrete partition cells for vector quantization. In this section, we design a hyperplane-based encoding method for effective feature representation for heterogeneous face images.

Fig 4: Encoded Face

With face images encoded, we can extract feature representations using a densely sampling technique as follows.

1. Divide the whole encoded image into a set of overlapping patches with size $c \times c$ pixels (the step between adjacent patches is s).
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.

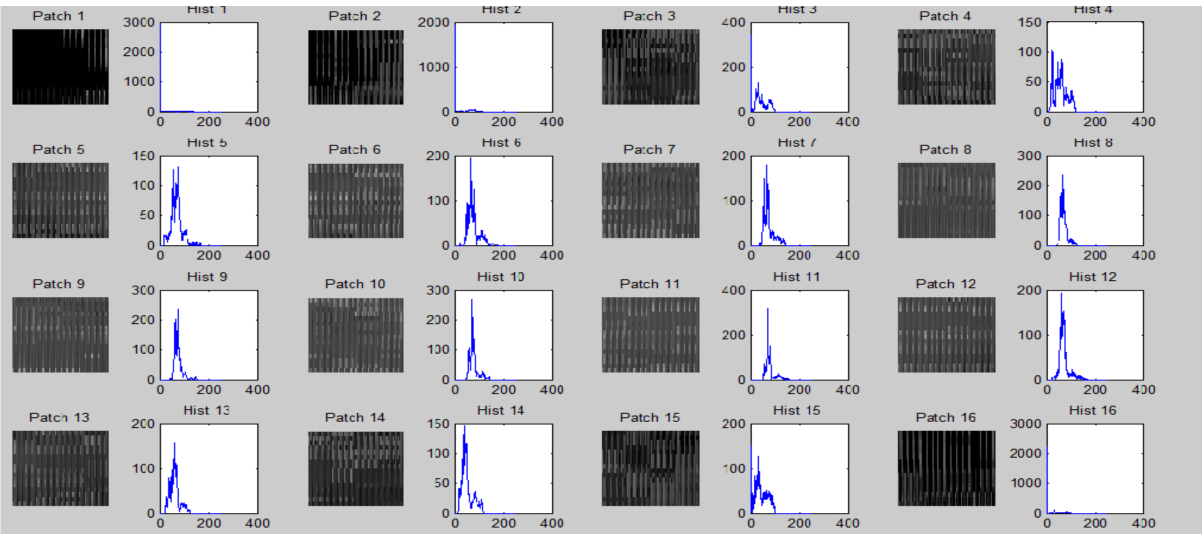
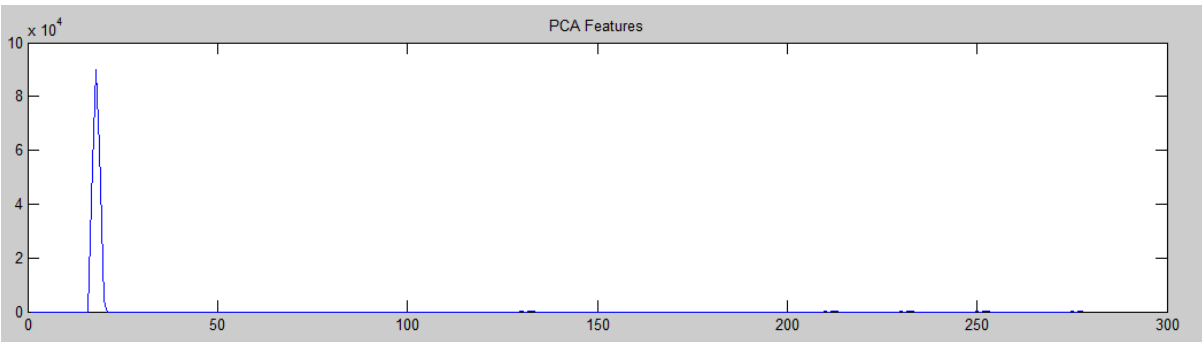


Fig 5: Histogram for 16 Patches



International Journal of Scientific Engineering and Applied Science (IJSEAS) - Volume-1, Issue-4, July 2015
ISSN: 2395-3470
www.ijseas.com

Fig 6: PCA Features for Detected Face

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.

III. EXPERIMETS

we conduct extensive experiments on one large and challenging optical and infrared face datasets to investigate the effectiveness of our new approach. The first dataset is collected CUHK, called CUHK Optical-IR and Sketch face dataset. It consists of 72 different persons with each one having one optical photo and one corresponding near infrared photo and sketch. Some examples from this dataset are shown in Figure 7(a)(b)(c). In our experiments, we divide the dataset into two parts: the images of 25 persons are used for training, and those of the remaining 47 persons are used for testing.

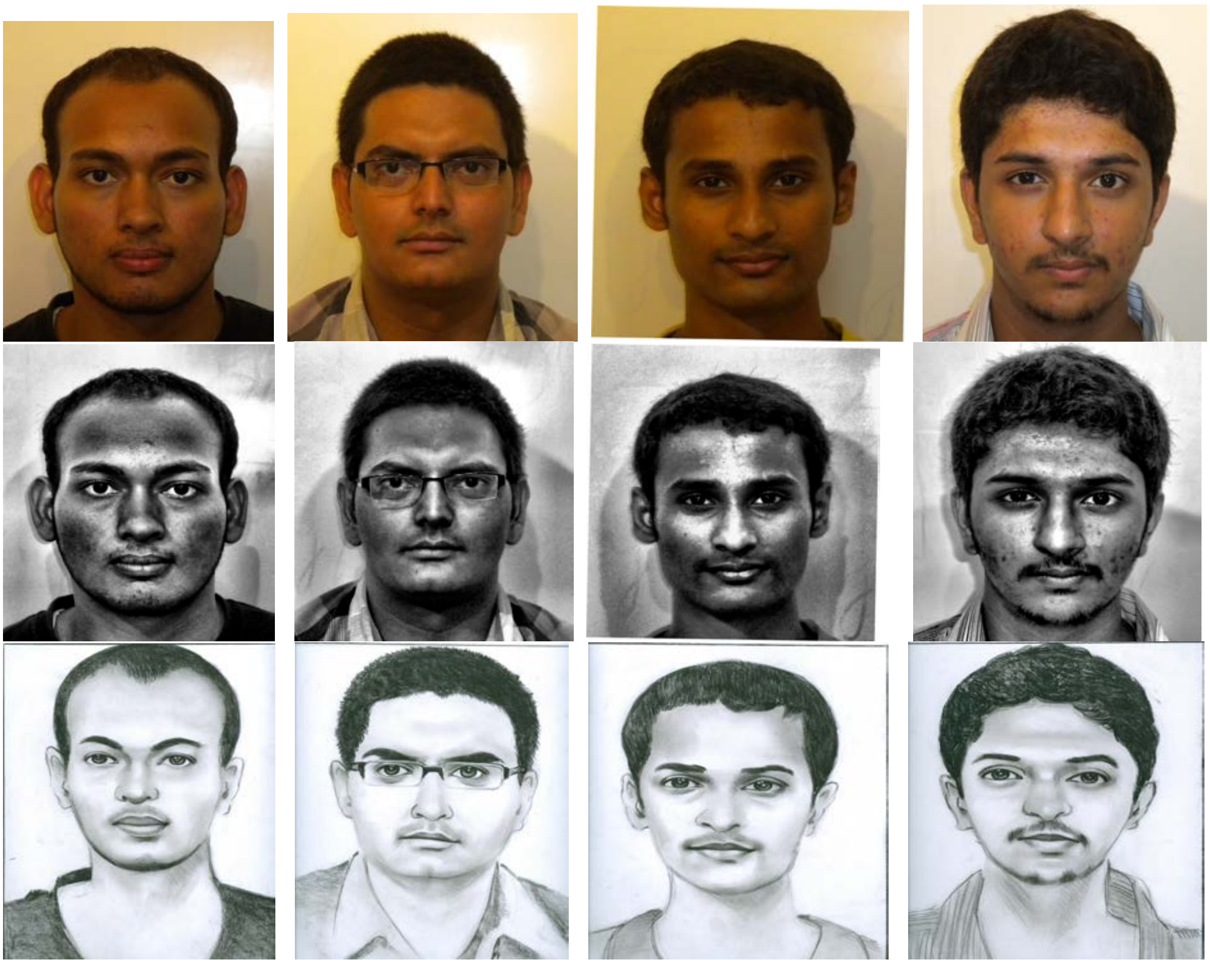


Fig. 7(a)(b)(c) Examples of Optical, Infrared and corresponding Sketch images from CHUNK VIS-IR-SKETCH dataset.

We first investigate the effectiveness of our descriptor and compare it with several state-of-the-art descriptors in heterogeneous face recognition. The comparative results are reported in Table IV. It is very clear that our approach achieves superior performance over the state-of-the-art methods in the literature. Finally, we evaluate the performance of our approach by gradually increasing the number of training samples and at the same time keeping the testing dataset unchanged. We compare our algorithm against the approach in [1][2] that is the best-performing method among the existing methods in Table I. The rank-1 recognition accuracies are reported in Figure 10, from which we can clearly see that our approach consistently outperforms the approach in [1] by a clear margin. This shows the robustness of our algorithm.

Algorithms	**Rank -1 Accuracies(%)**
Klare et al.[2] (2013)	87.80
Zhifeng Li.[1](2014)	90.45
Our approach	96.67

TABLE I: Comparison of our Approach with the state-of-the-art.

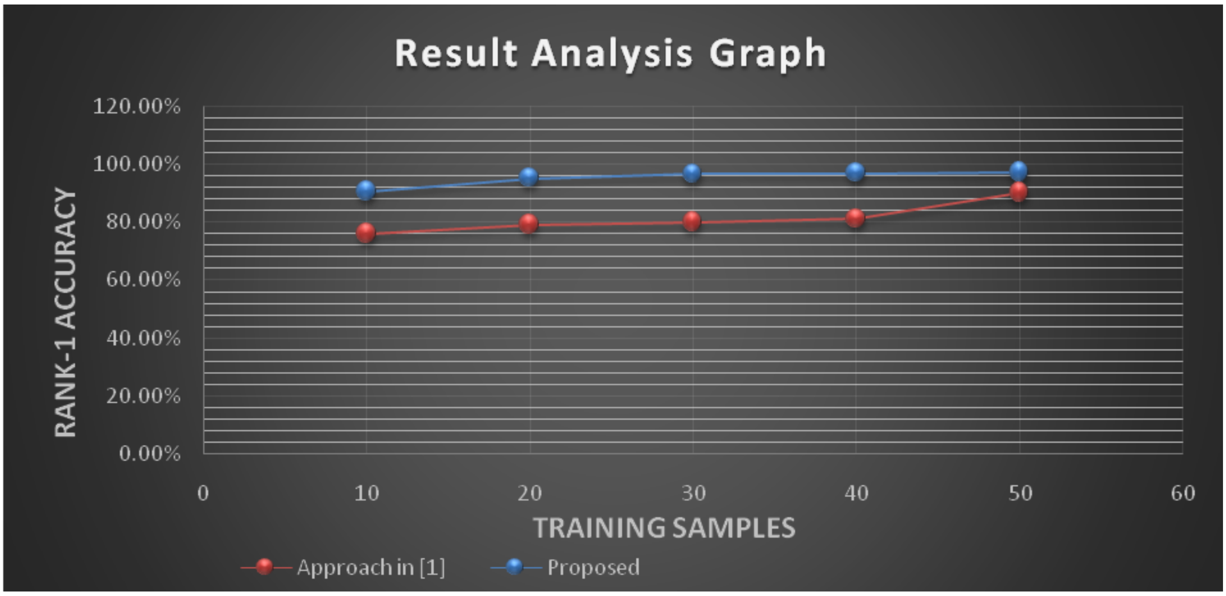


Fig 8: Illustration of rank-1 results by changing the size of training samples

IV. CONCLUSION

In this proposed paper we introduced a new approach called common feature discriminant analysis (CFDA), for matching infrared face images to optical face images and sketches. In CFDA, a new descriptor effectively represent optical, infrared face images and sketches to reduce the modality gap, and then a two-level matching method will be subsequently applied for fast and effective matching as a part of our proposed system. Extensive experiments on two large and challenging optical-infrared face datasets is used to find the significant improvement of our new approach over the state-of-the-art.

V. ACKNOWLEDGEMENTS

I sincerely acknowledge the teaching staffs of the department and authors of the corresponding references for their guidance and being an inevitable part of this review article.

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