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Recognition of Heterogeneous Faces using Kernel Principal Component Analysis

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***Abstract*— Heterogeneous face recognition (HFR) involves matching two face images from alternate imaging modalities, such as an infrared image to a photograph or a sketch to a photograph. Accurate HFR systems are of great value in various applications (e.g., forensics and surveillance), where the gallery databases are populated with photographs (e.g., mug shot or passport photographs) but the probe images are often limited to some alternate modality. The prototype subjects (i.e., the training set) have an image in each modality (probe and gallery), and the similarity of an image is measured against the prototype images from the corresponding modality. The accuracy of this nonlinear prototype representation is improved by projecting the features into a nonlinear principal component subspace. Four different heterogeneous scenarios are: 1) near infrared (NIR) to photograph, 2) thermal to photograph, 3) viewed sketch to photograph, and 4) forensic sketch to photograph.**

***Index Terms*— Heterogeneous face recognition, kernel principal component analysis, infrared image, thermal image, forensic image, viewed sketch image**

I. INTRODUCTION

Face recognition is the process of recognizing/verifying a face from the given image. Detect a face in the image, Recognize/verify the face using database are the two steps used for face recognition. There are scores of algorithms that can be applied on an image to achieve these two steps. But each has its own down side. For one, many of these algorithms are computationally expensive and take a lot of time. The human face poses more problems than any normal object. This is primarily because; the human face comes in many forms, textures, features and colors. If we design an algorithm to detect a face, it has to be generic. It essentially needs to be one which is not constrained by the features of a human face.

The motivation behind heterogeneous face recognition is that circumstances exist in which only a particular modality of a face image is available for querying a large database of mug shots (visible band face images). For example, when a subject's face can only be acquired in nighttime environments, the use of infrared imaging may be the only modality for acquiring a useful face image of the subject. Another example is situations in which no imaging system was available to capture the face image of a suspect during a criminal act. In this case a forensic sketch, drawn by a police artist based on a verbal description provided by a witness or the victim, is likely to be the only available source of a face image. The main purpose of this paper is to recognize face images by using kernel principal component analysis algorithm when heterogeneous faces like infrared images, thermal images, viewed sketch images, forensic sketch images are given as an input image.

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II. Procedure for HETEROGENEOUS FACE RECOGNITION

A. Preliminary Process of an Image (or) Image Preprocessing

Preprocessing images commonly involves removing low-frequency background noise, normalizing the intensity of individual particle images, removing reflections, and masking portions of images. Image processing is the technique of enhancing data images prior to computational processing. Preprocessing is done by converting RGB true color images to grayscale images by eliminating hue and saturation information while retaining the luminance. Grayscale images are used to reduce undesired distortions and performance for the next process like, segmentation, feature extraction.

B. Canny Edge Detection Algorithm is used for Edge Detection

Canny edge detector have advanced algorithm. It is an optimal edge detection technique as provide good detection, clear response and good localization. It is widely used in current image processing techniques with further improvements.

Flow chart of canny edge detection algorithm

SMOOTHING: remove noise by convolving with Gaussian filter

↓

COMPUTE GRADIENTS: edges should be marked where the gradients of the image has large

↓

NON-MAXIMUM SUPPRESSION: only local maxima should be marked as edges

↓

HYSTERESIS THRESHOLDING: final edges are determined by suppressing all edges that are not connected to a very strong edge

Canny Edge Detection Algorithm

1) SMOOTHING: Noise Reduction by Smoothing

Noise contained in image is smoothed by convolving the input image I (i, j) with Gaussian filter mathematically, the smooth resultant image is given by

$$F(i,j) = G * I(i,j) \qquad (1)$$

Prewitt operators are simpler to operator as compared to sobel operator but more sensitive to noise in comparison with sobel operator.

2) COMPUTE GRADIENTS: Finding gradients

In this step we detect the edges where the change in grayscale intensity is maximum. Required areas are determined with the help of gradient of images. Sobel operator is used to determine the gradient at each pixel of smoothened image. Sobel operators in i and j directions are given as

$$D_i = \begin{bmatrix} -1 & 0 & +1 \\ -2 & 0 & +2 \\ -1 & 0 & +1 \end{bmatrix} \qquad D_j = \begin{bmatrix} +1 & +2 & +1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix}$$

These sobel masks are convolved with smoothed image and giving gradients in i and j directions.

$$G_i = D_i * F(i,j) \qquad (2)$$

$$G_j = D_j * F(i,j) \qquad (3)$$

Therefore edge strength or magnitude of gradient of a pixel is given by

$$G = \sqrt{G_i^2 + G_j^2} \qquad (4)$$

The direction of gradient is given by

$$\theta = \tan^{-1}\left(\frac{G_j}{G_i}\right) \qquad (5)$$

G_i and G_j are the gradients in the i- and j-directions respectively.

3) Non maximum suppressions: to preserve thin edges

Non maximum suppression is carried out to preserves all local maxima in the gradient image, and deleting everything else this results in thin edges.

For a pixel M (i , j): Firstly round the gradient direction nearest 45°,then compare the gradient magnitude of the pixels in positive and negative gradient directions i.e. If gradient direction is east then compare with gradient of the pixels in east and west directions say E (i , j) and W (i, j) respectively. If the edge strength of pixel M (i, j) is largest than that of E (i, j) and W (i, j), then preserve the value of gradient and mark M (i, j) as edge pixel, if not then suppress or remove.

4) Hysteresis Thresholding: for final edges

The output of non-maxima suppression still contains the local maxima created by noise. Instead choosing a single threshold, for avoiding the problem of streaking two thresholds t_{low} and t_{high} are used.

For a pixel M (i, j) having gradient magnitude G following conditions exists to detect pixel as edge:

If G < t_{low} then discard the edge.

If G > than t_{high} keep the edge.

If t_{low} < G < t_{high} and any of its neighbors in a 3 ×3 region around it have gradient magnitudes greater than t_{high}, keep the edge. If none of pixel (x, y)'s neighbors have high gradient magnitudes but at least one fall between t_{low} and t_{high}, search the 5 × 5 region to see if any of these pixels have a magnitude greater than t_{high}. If so, keep the edge.
Else, discard the edge.

C. MODULARISATION

Modularization means dividing the image into small number of modules. In this method, local variations in face images are recognized. But, there is a conflict that whether dividing the image into small modules or large modules. If the image is divided in two very smaller modules, a large amount of sub region information is lost because of dependencies among various neighboring pixels are ignored .this problem can be overcome by increasing module size i.e. making the modules larger. But, due to this modularization the local variations in face images are not perfectly recognized. So, in order to overcome these problems, a new modularization technique called neighborhood defined modularization technique is implemented.

1) NEIGHBORHOOD MODULARIZATION

Dividing the images into smaller or larger modules create some problems in recognition. Here, advantages of both modularizations are implemented. First, Divide the image into large modules called sub regions. Then, divide the each sub region into small number of modules. Then, by merging neighborhood small Modules in a sub region, large numbers of modules are created in a sub region. So, by using this region based modularization feature extraction approach local facial Variations caused by expression variations in image can be dealt more effectively.

In general, face images are captured by webcam and the face images are of size 1024 x1024. So, in order to process this image it takes a lot of time. So, to minimize the processing speed, the face images are normalized to a size of 64×64 in our experiments. Normalizing the image in terms of even powers of 2 also helps in dividing an image into modules of same size in a modular approach for face recognition. Modular PCA technique divides the image into non overlapping sub images. Then PCA is applied to each module. Several experimental results have been observed with different modules of size of 4x4, 8×8 and 16×16 on face images of size 64 ×64.

Finally, it is observed that, recognition accuracy is maximum when the image is divided into sub-regions of size 8× 8. With Large module size (16×16), the local variations of image are poorly recognized. In case of small module size (4×4), the dependencies among neighboring pixels are ignored. So, the sub-region information content is lost. Finally, it is concluded

that sub-region information must be considered because it occupies some facial feature information.
Hence, in the implemented neighborhood defined modularization approach, several 8 ×8 modules are created by combining neighborhood modules of size 4×8 modules in a large region of size 16 ×16 in a 64 ×64 face image.

Steps followed for the implementation of Neighborhood defined modularization technique for an image of size M×M dimensions are given below:

1. Divide each image into non overlapping large modules of (M/m) × (M/m) size to get (m×m) number of large modules.

2. Divide each large module of size (M/m)×(M/m) into modules of size(M/(m×i))×(M/(m×j)), where (i×j) is the number of small modules within a neighborhood.

3. Then, by merging (i×j) number of small modules in neighborhood, a total of R modules are created according to the relation= (i×j) !/ (k ! (i×j-k)) ! where k is the number of small modules to be merged.

D. FACE RECOGNITION USING KERNEL PRINCIPAL COMPONENT ANALYSIS

Initially, PCA technique is used in order to extract features of an image. PCA is a linear subspace approach, which cannot capture the relation among more than two variables. Because PCA is directly applied to image. So PCA cannot capture the variations caused by expressions and other variables. In order to deal with this problem nonlinear space method is used. The non linear relationship among pixels is captured using kernel PCA by projecting the data into higher dimensional spaces.

KERNEL PCA

Input: Data $X = \{X_1, X_2, \ldots \ldots X_l\}$ in n-dimensional space.
Process: Mean of the data is given by

$$m = \frac{1}{l}\sum_{k=1}^{l} x_k \qquad (6)$$

But mean not only enough to extract features. So, covariance matrix C is given by

$$C = \sum_{j=1}^{l} x_j x_j^T \qquad (7)$$

The Eigen vectors corresponding to covariance matrix is given by

$$CV = \lambda V \qquad (8)$$

Here data is projected in to higher dimensional spaces

$$\phi : X \rightarrow H \qquad (9)$$

Then Eigen values and Eigen vectors of covariance matrix is

$$C_\phi V_\phi = \lambda_\phi V_\phi \qquad (10)$$

So feature extraction can be done by finding Eigen values and Eigen vectors and weights to each module as follows

1. Kernel matrix

$$K_{ij} = K(X_i, X_j); \qquad i,j = (1,2,\ldots.l) \qquad (11)$$

$$K(x_i, x_j) = \exp\left(\frac{-\|x_i - x_j\|^2}{\sigma}\right)$$

2. Then, find kernel centered matrix .here i , j are unity matrices of module size

$$K' = K - \frac{1}{l}K.j.j' - \frac{1}{l}K.j.j' + \frac{1}{l^2}(K.j.j').j.j' \qquad (12)$$

3.Eigen values,eigen vectors computed for kernel centre Matrix

$$[W, \lambda] = eigK' \qquad (13)$$

4. Normalize the Eigen vectors

$$\alpha^{(j)} = \frac{1}{\sqrt{\lambda_j}} W_j \qquad (14)$$

5. Multiply normalized Eigen vectors with kernel centre matrix to get weight

$$x_j = \left(\sum_{i=1}^{l} \alpha_i^{(j)} K(x_i, x)\right)_{j=1}^{k} \qquad (15)$$

Apply KPCA to each module and calculate the weights for each individual module using Eigen vectors and kernel matrix. By using a minimum distance classifier classify each module based on the generated weights from the training and the testing phase for recognizing a face.

II. SIMULATION RESULTS

A. Input Image

Take four different modalities like figures a. infrared image, b. thermal image, c. forensic image, d. viewed sketch image as input for matching.

Fig .a
Infrared image

Fig. b
Thermal image

Fig. c
Forensic sketch image

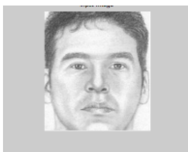

Fig. d
Viewed sketch image

B. Edge Detection four above four images

Fig.
Infrared image edge detection

Fig.
Thermal image edge detection

Fig.
Forensic image
edge detection

Fig.
Viewed sketch image
edge detection

After preprocessing commonly involves removing low-frequency background noise, normalizing the intensity of individual particle images, removing reflections, and masking portions of images. Image processing is the technique of enhancing data images prior to computational processing an image. Canny edge detector algorithm is used for edge detection to good detection, clear response and good localization as shown in the above figures for four modalities.

C. Face Recognition for above four images

After modularization, in pattern recognition feature extraction is the most difficult problem; its reason is that we want to obtain the best features with minimum classification error and low running time. Initially, PCA technique is used in order to extract features of an image. PCA is a linear subspace approach, which cannot capture the relation among more than two variables. Because PCA is directly applied to image. So PCA cannot capture the variations caused by expressions and other variables. In order to deal with this problem nonlinear space method is used. The non linear relationship among pixels is captured using kernel PCA by projecting the data into higher dimensional spaces. So apply kernel PCA to each module to extract features of each module and finally calculate the weights of each module by using kernel matrix and algorithm. By using a minimum distance classifier classify each module based on the generated weights from the training and the testing phase for recognizing a face. The image which is matched based on generated weights gives us an output of image matched else it gives face not in database.

Fig. a

Fig. b

Fig. c

Fig. d

The above fig. a, fig. b, fig. c, fig. d are corresponding gallery photographs i.e. visible band face image, called VIS of above given input images.

III. CONCLUSION

In this paper four different heterogeneous scenarios like infrared images, thermal images, viewed sketch images, forensic sketch images are given as an input image. First preprocessing is done for given image to reduce undesired distortions and enhance the data for further process .Then sobel operator is used for edge detection to make the recognition system independent to the illumination. Apply modularization to get local variations in an image. So feature extraction can be done by finding Eigen values and Eigen vectors and weights to each module by applying kernel principal component analysis (kpca) method. To recognize a face minimum distance classifier is used to classify each module based on the generated weights from the training and the testing phase. Therefore by using kernel pca algorithm for recognition rate is improved. In particular, the KPCA method will be useful for identification Systems subjected to large variations in illumination and facial expressions and also for different modalities.

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