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FACE RECOGNITION IN NON-UNIFORM HUMAN FACE

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ABSTRACT

In this paper, generally a camera may capture a face, the raw biometric information is acquired and also sent to the biometric characteristic extractor. The extractor is normally software that extracts the features important for shaping identity from the raw information. This extracted feature information is called a template. The template is then sent near the matcher. The matcher links the newly-presented biometric information to earlier than submitted template information to make a decision.The future line presents a very low degree of complexity, which makes it suitable for real-time applications, using 17 general image eminence features extracted from one image to distinguish between legitimate and impostor samples. The new results, obtained on publicly available data set Labeled Face in the Wild, show that the proposed way is very competitive compared with other state-of-the-art approaches and that the analysis of the common image quality of actual biometric models tells highly valuable information that may be very resourcefully used to discriminate them from fake traits.

Indexed term: Face recognition, non-uniform blur, illumination, pose.

INTRODUCTION

Image is defined as a 2D function,f(x,y) and processing is application,pixels are small individual elements of adigital image,each and every pixel has a particular location and brightness or intensity value.

Image processing is defined as the process of analyzing and manipulation images using a computer.image processing has 2 types one is analog image processing and another one is digital image processing.The important needs for DIP are to improve the pictorial information for human interpretation and to process image data for storage,transmission and representation.

Identify face from space-varying motion, blur by arbitrarily-shaped kernels and Model the blurred face as a convex combination.Non-uniform blur-robust algorithm to construct an energy function with L1-norm constraint on the camera motion and Form a bi-convex set , the set of all images found from a face image by non-uniform blurring and changing the illumination and Obtain variations in pose.

Drawbacks are using space Varying method face will be recognized at any camera directions,Modeling the blurred face easy to recognize at any blurring effects without the lose of source and Large changes in facial expressions cannot be handled,It get less accuracy for recognize human faces.

Advantage: It will obtain high accuracy because of adding different feature,I also perform an iris and fingerprint dataset.

RELATED WORK

K.-C. Lee, J. Ho, and D. Kriegman. The linear subspace spanned by the corresponding images is a good approximation to the light shaft and the provides face recognition results in a wide range of difficult light settings.

Rob Fergus, Barun Singh,aron Hertzmann, Sam T. Roweis, William T. Freeman. The method assumes a uniform camera blur overall the copy and small inplane camera spin in to estimate the blur from the camera tremble the operator must specify an image region without saturation effects.

Sunghyun Cho, Yasuyuki Matsushita, Seungyong Lee In this paper aim to restore images blurred by unknown space varying movement blur kernels caused by different relative motions between the cameras then the act.

Qi Shan, Jiaya Jia, Aseem Agarwala In this paper, proposed a novel image deconvolution method for remove camera motion blur from a single image in minimize errors caused by inaccurate blur kernel estimation and image noise. S. Biswas, G. Aggarwal, and R. Chellappa established Shape-from-Shading (SFS) approaches often assume constant/piecewise.

SYSTEM DESCRIPTION

Surface respect is software applications that can be identify a specific individual in a digital image by analyzing and comparing patterns.

1. Preprocessing
2. segmentation
3. Feature extraction
4. Classification

Main focus of the work is forlarge changes in facial expressions can be handled during recognition process. The afterstagesmust be followed.1)Pixel Difference actions 2)Correlation-based measures 3)Edge-based measures 4)Spectral space measures 5)Gradient-based measures.

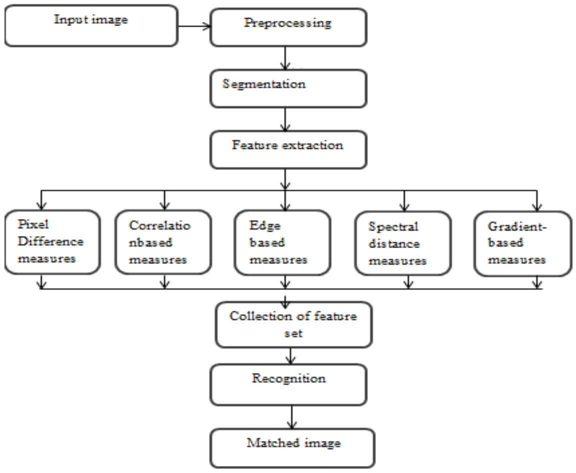

Fig1: system description.

IMPLEMENTATION

This unit defines the implementation of the proposed work. The proposed work consists of the following methods implementation.

- Preprocessing
- segmentation
- Feature extraction
- Recognition

A. Preprocessing :

To collectblur, illumination, different poses in the images of the same person and Input face image is splitted into direct input and gaussian filtered input the gaussian filter is used for blur images and noise is removed.

After read an image, apply gaussian Filte**r** to filter the image than the original face image and once the filter takes existed usefull, change the response image into gray scale image.

$$g(x) = \sqrt{a/\Pi}.e^{-a.x^2}$$

Gaussian filter is a filter whose impulse response is a gaussian function,Gaussian filter is more effective at smoothing images. It has its basis in the human visual perception system.

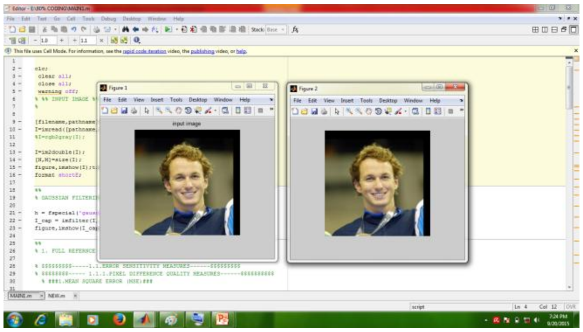

Fig2:Screen shot for preprocessing.

B. Segmentation:

Image segmentation is the processing of partitioning a input image into multiple segments.

Binary images is produced to color images by segmentation.Segmentation is the process of assigning each pixel in the source image from two or more classes. If there are more than two classes then the usual result is several binary images.

The unassuming type of segmentation is probably Otsu's method which assigns pixels to foreground or background created on grayscale intensity. Another method is the watershed algorithm. We use gray threshold level binarization of an image.

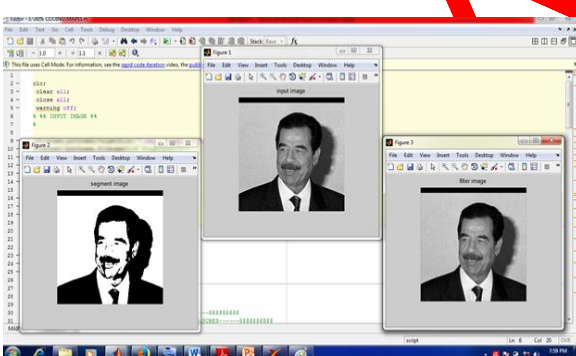

Fig3:Screen shot for segmentation.

C. Feature extraction:

The collected dataset, we needed to extract the feature to identify the identity of each face because from the dataset we could not identify the individuality of the face.the following 5 category in the 17 feature.

1.Pixel difference quality measures:-

1. Mean Square Error:

It is an estimator measures the average of the squares of the errors.MSE is a risk function, consistent to the expected value of the squared.

$$MSE = \frac{1}{NxM}\sum_{i=0}^{N-1}\sum_{j=0}^{M-1}[X(i,j) - Y(i,j)]^2$$

2. Peak signal to noise ratio:

The ratio of themaximum possible power of a signal and power of a corrupting noise that affects the fidelity of its representation.

Because of many signals contain a very wide dynamic range, PSNR is usually expressed in terms of the logarithmic decibel scale.

$$\mathbf{PSNR} = 10\log_{10}\left(\frac{I_{\max}^2}{\mathbf{MSE}}\right)$$

3. signal to noise ratio:

The level of a desired signal to the level of background noise ofSignal-to-noise is a measure used in science and engineering.

Signal to noise ratio is defined by way of the relationbetween the signal power to the noise power and is often expressed in decibels, indicates more signal than noise. The SNR is commonly represents the electrical signals, it can be applied to any form of signal.

$$SNR = \frac{\mu}{\sigma}$$

4. Structural content:

Structural content is defined inresources ofthe ratio between the square of amound of original image to the square of sum of reference image. In the form of calculation is known as,

$$SNR(\mathbf{I}, \hat{\mathbf{I}}) = 10\log\left(\frac{\sum_{i=1}^{N}\sum_{j=1}^{M}(\mathbf{I}_{i,j})^2}{N\cdot M\cdot MSE(\mathbf{I}, \hat{\mathbf{I}})}\right)$$

5. Maximum difference:

The full value is absolute difference image and original image is withdrawn to the reference image.Now the usage of equality is given by,

$$MD(I,\hat{I}) = \max\left|I_{i,j} - \hat{I}_{i,j}\right|$$

6. Average difference:

The average value per pixel is absolute difference images and original image subtracted is to the reference images. In the form of equation is given by,

$$AD(\mathbf{I},\hat{\mathbf{I}}) = \frac{1}{NM}\sum_{i=1}^{N}\sum_{j=1}^{M}(\mathbf{I}_{i,j} - \hat{\mathbf{I}}_{i,j})$$

7. Normalized absolute error:

Normalized absolute error is the sum of absolute of difference images is divided to the sum of absolute of original images. In the form of equation is given by,

$$NAE(\mathbf{I},\hat{\mathbf{I}}) = \frac{\sum_{i=1}^{N}\sum_{j=1}^{M}|\mathbf{I}_{i,j} - \hat{\mathbf{I}}_{i,j}|}{\sum_{i=1}^{N}\sum_{j=1}^{M}|\mathbf{I}_{i,j}|}$$

8. R-average MD:

The sum of maximum of R numbers value is summed and divided by R towardestimate average maximum differences. In the form of equation is given by,

$$RAMD(\mathbf{I},\hat{\mathbf{I}},R) = \frac{1}{R}\sum_{r=1}^{R}\max_r|\mathbf{I}_{i,j} - \hat{\mathbf{I}}_{i,j}|$$

9. Laplacian MSE:

Based on this h(image) = Ii+1, j +Ii−1, j +Ii, j+1 + Ii, j−1 − 4Ii, j equation the h(Ii, j) and h(I^i, j) could be calculated.

The ratio between the square of difference of these two values to the sum of original image h(Ii, j)value. In the form of equation is given by,

$$LMSE(\mathbf{I},\hat{\mathbf{I}}) = \frac{\sum_{i=1}^{N-1}\sum_{j=2}^{M-1}(h(\mathbf{I}_{i,j}) - h(\hat{\mathbf{I}}_{i,j}))^2}{\sum_{i=1}^{N-1}\sum_{j=2}^{M-1}h(\mathbf{I}_{i,j})^2}$$

2.Correlation based quality measures

1. Normalized cross-correlation:

The image-processing applications are the brightness of the copy thenshape can vary due to lighting and exposure conditions, the images can be normalized.

The typically done at every step by sum the mean and dividing by the standarddeviation. In the form of equation is given by,

$$NXC(I,\hat{I}) = \sum_{i=1}^{N}\sum_{j=1}^{M}(I_{i,j},\hat{I}_{i,j}) / \sum_{i=1}^{N}\sum_{j=1}^{M}(I_{i,j})^2$$

2. Mean angle similarity:

The mean direction similarity is the measure of similarity whichmean anglesimilaritybetween the original copy and reference image. In the form of equality is given by,

$$MAS(I,\hat{I}) = 1 - 1/NM\sum_{i=1}^{N}\sum_{j=1}^{M}(\propto_{i,j})$$

3. Mean angle magnitude similarity:

The mean direction magnitude similarity is the measure of similarity which mean angle's magnitude similarity between the original image and reference image. In the form of equation is given by,

$$MAMS(\mathrm{I},\hat{\mathrm{I}}) = \frac{1}{NM}\sum_{i=1}^{N}\sum_{j=1}^{M}(1-[1-\alpha_{i,j}][1-\frac{\|\mathrm{I}_{i,j}-\hat{\mathrm{I}}_{i,j}\|}{255}])$$

3.Edge based quality measures:

1. Total edge difference:

The ratio between the changes of total number of edges between the two images to the total number of pixels. In the form of equation is given by,

$$TED(\mathrm{I},\hat{\mathrm{I}}) = \frac{1}{NM}\sum_{i=1}^{N}\sum_{j=1}^{M}\left|\mathrm{I}_{\mathrm{E}i,j} - \hat{\mathrm{I}}_{\mathrm{E}i,j}\right|$$

2. Total corner difference:

The ratio between the differences of total number of corners between the two images to the total number of pixels. In the form of equation is given by,

$$TCD(I,\hat{I}) = \left|N_{cr} - \hat{N}_{cr}\right| / \max(N_{cr},\hat{N}_{cr})$$

4. Spectral distance quality measures:

1. Spectral magnitude error:

The difference between the Fourier transform of original image to the Fourier transform of reference image is averaged by total number of pixel. In the form of equation is given by,

$$SME(\mathbf{I},\hat{\mathbf{I}}) = \frac{1}{NM}\sum_{i=1}^{N}\sum_{j=1}^{M}(|\mathbf{F}_{i,j}| - |\hat{\mathbf{F}}_{i,j}|)^2$$

2. Spectral phase error:

The difference between the angles of Fourier transformed original image to the angle of Fourier transformed reference image is averaged by total number of pixel. In the form of equation is given by,

$$SPE(\mathbf{I},\hat{\mathbf{I}}) = \frac{1}{NM}\sum_{i=1}^{N}\sum_{j=1}^{M}|\arg(\mathbf{F}_{i,j}) - \arg(\hat{\mathbf{F}}_{i,j})|^2$$

5. Gradient based quality measures

Gradient magnitude error:

The between the gradient of original copy to the gradient of reference image is averaged by total number of pixel. In the form of equation is given by**,**

$$GME(I,\hat{I}) = 1/NM\sum_{i=1}^{N}\sum_{j=1}^{M}(|G_{i,j}| - |\hat{G}_{i,j}|)^2$$

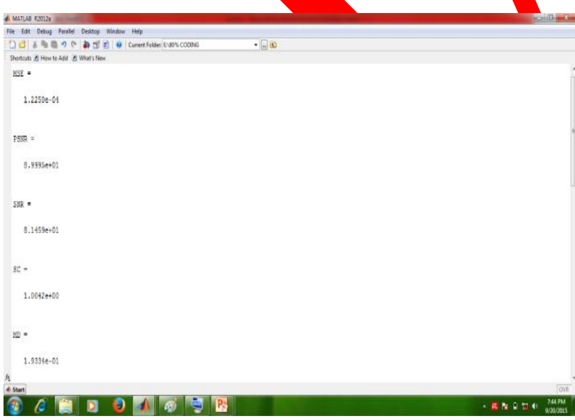

Fig4: Screen shot for feature extraction.

D. Recognition:

Direct discriminant studyis also closely related to principal component analysis (PCA) and factor analysis in that they together look for linear combinations of variables which best explain the data. LDA explicitly attempts to classical the change between the classes of data.

PCA on the other hand does not take into account any difference now class, then factor analysis builds the feature combinations based on differences rather than similarities. Discriminant study remains moreover different from factor analysis in that it is not an interdependent technique: a distinction between free variables then needy variables (also called criterion variables) must be made.

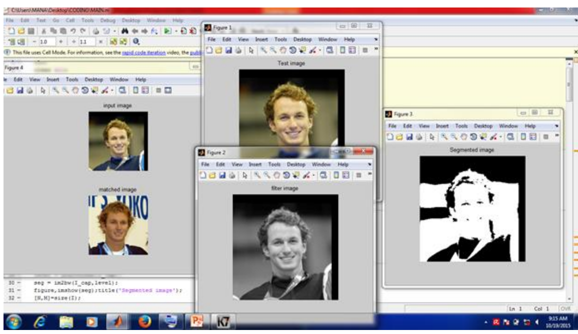

Fig5: Screen shot for recognition.

CONCLUSION

Image-based face recognition is static a exact challenging topic after decades of exploration. A number of typical algorithms stand accessible, being categorized into appearance-based and model-based schemes. It provides the experts and ploys of these two types of face recognition methods. Sensitivity to variation in pose and different lighting conditions is still a challenging problem. Extensively explored the illumination modify and synthesis for facial analysis using appearance-based approaches to achieve an illumination-invariant face recognition system. It proved that the set of all reflectance functions (The charting from surface normals to intensities) produced by Lambertian objects below cold, isotropic lighting lies close to a 9D linear subspace. The proposed algorithm was utilize used for face recognition across illumination changes. Although a number of efforts have been made on pose-invariant face recognition, the performance recognition system is satisfactory.

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