Region based Face Recognition underDifferent Illumination Using Effective Machine Learning

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Abstract

The idea of this work is to recognize face images under different illuminations. Image pre-processing has been done through wavelet decomposition, edge generation, region segmentation through edge intensity, image enhancement by histogram equalization on low frequency for contrast and adaptive region based Edge for detailed coefficient for edge enhancement and reconstruct the enhanced image through IDWT (Inverse Discrete Wavelet Transform). From this image pre-processing stages edge and contrast of the image has been normalised for further procedure. Feature extraction is done for extracting the texture feature through LBP(local binary pattern) and LTP(local ternary pattern).Using K-nn(Nearest neighbour) classifier in order to recognize the match between the trained image and the testing image. The data set that used for testing recognition under difficult illumination condition is Extended Yale –B, the above mention process are done for the given data set. Query image is given as input to the process where the above mentioned image pre-processing, Feature extraction, and finally classification done between the trained image and query image. Data set used Extended Yale-B, which contain 39 person images with 46 light illumination variation.

Keywords*:Image pre-processing, adaptive region based edge enhancement, local binary pattern, texture feature, k-nn classifier.*

1. Introduction

Face recognition is used to identifying efficient and discriminative facial appearance descriptors that can counter large variations in illumination, pose, facial expression, ageing, partial occlusions and other changes. There are two main approaches such as geometric feature-based descriptors and appearance- based descriptors. Geometric feature-based descriptors can be hard to extract reliably under variations in facial appearance, while appearance-based descriptor such as eigenfaces tend to blur out small details owing to residual spatial registration errors.

Recently, representations based on local pooling of local appearance descriptors have drawn increasing attention because they can capture small appearance details in the descriptors while remaining resistant to registration errors owing to local pooling. Another motivation is the observation that human visual perception is well-adapted to extracting and pooling local structural information ('micro-patterns') from images. Methods in this category include Gabor wavelets local autocorrelation filters, and Local Binary Patterns.

Many approaches have been proposed for face recognizing. For many practical applications, some of the current systems are sufficiently mature to be used. However, in some other applications, such as video surveillance scenarios, there is still work to be done in order to efficiently detect or recognize the faces. Among the factors challenging the ongoing research are poor quality images, different facial orientations and changes in illumination conditions. Face recognition has received a great deal of attention from the scientific and industrial communities over the past several decades owing to its wide range of applications in information security and access control, law enforcement, surveillance and more generally image understanding. Numerous approaches have been proposed, including eigen faces, fisher faces and laplacian faces, nearest feature line-based subspace analysis , neural networks, elastic bunch graph matching, wavelets, and kernel methods. Most of these methods were initially developed with face images collected under relatively well controlled conditions and in practice they have difficulty in dealing with the range of appearance variations that commonly occur in unconstrained

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natural images due to illumination, pose, facial expression, ageing, partial occlusions.

Accomplishing face detection from single images is a challenging task because of variability in scale, orientation, pose, facial expressions, lighting conditions, and camera calibrations. In recent years, many methods have been proposed to detect faces. Roughly, they can be divided into two categories: feature-based and image-based. In the first category, the apparent properties of the face, such as facial features, edges, etc, are exploited. Typically, the detection algorithms extract features from the image and then manipulate distances, angles and areas. Unlike the feature-based approaches, the image based techniques apply a window-scanning algorithm on the image and classify the extracted sub-window into face and non-face classes. Neural networks, PCA, and SVM are examples of image-based techniques.

Appearance-based methods have attracted a great deal of attention in computer vision. Traditional appearance-based image analysis and recognition employs principal components analysis (PCA) to parsimoniously model the variation apparent in training image ensembles, typically using the well-known matrix singular value decomposition (SVD) and dimensionality reduction through the omission of higher-order singular vectors. Conventional PCA, which is a linear method, models the apparent variation as if it had resulted from a single contributory factor. However, natural images result from the interaction of *multiple* factors or modes related to scene structure, illumination, and imaging. For example, facial images are the result of facial geometry (person, expression), the pose of the head relative to the camera, the lighting conditions, and the type of camera employed. This multifactor variation causes severe difficulties for conventional appearance-based face recognition methods. In particular, the PCA approach and its variants adequately address face recognition only under tightly constrained conditions e.g., frontal images, fixed light sources, fixed expression where person identity is the only factor that is allowed to vary.

Face Recognition Systems (FRS) have been receiving recently special attention. This can be evidenced by the emergence of Face Recognition conferences, systematic empirical evaluations of face recognition techniques, protocols, and many commercially available systems. This introductory section offers a general view of the applications, the configuration of a generic FRS, and finally a background on the different approaches related with FRS under varying illumination.

2.Framework of The Proposed Image Preprocessing Method

Before adaptive region based segmentation from the edge intensity values obtained from edge map generation the wavelet decomposition is applied over the original image to get the low level frequency(Approximation co-efficient) and high level frequency(Detailed co-efficient). In this image preprocessing step the edge and contrast of the input image are going to be normalized by image enhancement by regionally. Detailed co-efficient is used to edge generation for the segmented regions and ARHE(Adaptive Region Histogram Equalization) is for contrast enhancement from the low level frequency for the segmented region. Finally IDWT(Inverse discrete wavelet transform) is used to reconstruct the enhanced image.

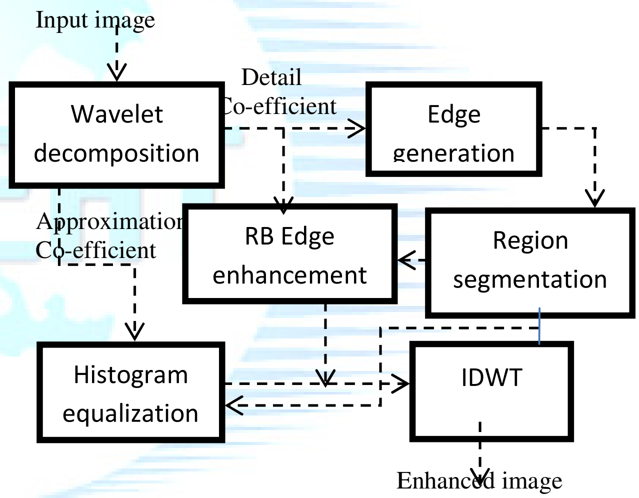

Fig. 1. Image preprocessing

1.1. Wavelet decomposition

Wavelet decomposition represents a signal as a set of basic function at different scales. 2-D decomposition is used in this work.

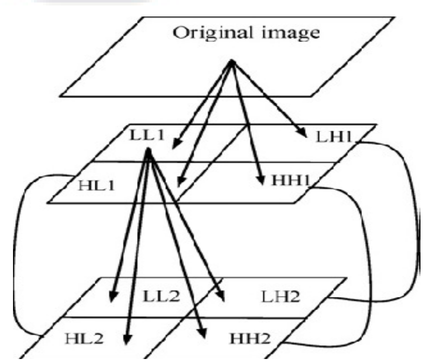

Fig.2. Wavelet decomposition

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In 2-D decomposition original image is divided into four sub-bands such as low-low(LL) is generated by approximation co-efficient, high-low(HL), low-high(LH), high-high(HH) are generated by detail co-efficient. In 1-D decomposition each sub-bands are in equal size such as original image size. But in 2-D decomposition the LL image is further divided into four sub-bands resultant image size is lesser than the original image hence padding is applied to the resulting image.

Edge Map Generation

The edges of the images are fully high-frequency information about the image that will scatter into several scales or resolution. In our work the product of detail co-efficient values from each decomposition level such as LH1 X LH2, HL1 X HL2, HH1 X HH2. Finally Edge map E is generated as follows,

E=sqrt((LH1 x LH2)+(HL1 x HL2)+(HH1 x HH2)).

Fig.3 Edge map image

1.2. Adaptive Region Based Segmentation

Algorithm:

1. Partition an edge map into blocks.
2. For each block, compute the average edge amplitude.
   a. If the edges in the block are weak(e.g less than a pre-defined threshold), merge it with adjacent weak blocks using the eight nearest neighbour methods and then mark it with 0;
   b. Otherwise, mark it with 1.
3. For a region marked with 0:
   a. If its grey-scale is similar to any of the regions marked with 1, then, mark them block to 1. This step removes the regions that have weak edges not due to light, but due to natural solid color, e.g., cheeks;
   b. Otherwise, this region is affected by illumination changes.
4. for the region marked with 1,
   Consider them as one whole region, the normal region.
5. End.

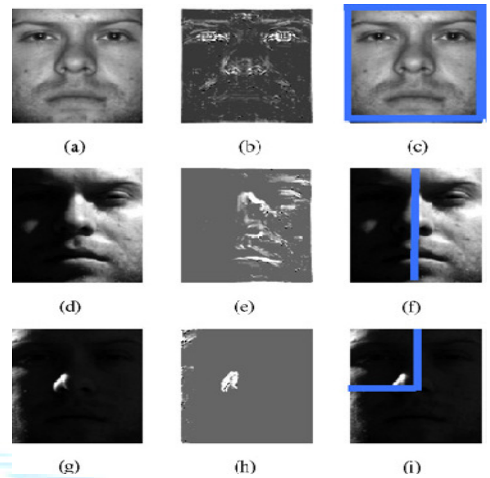

Fig.4. Segmented region for different illumination images.

3.System Architecture

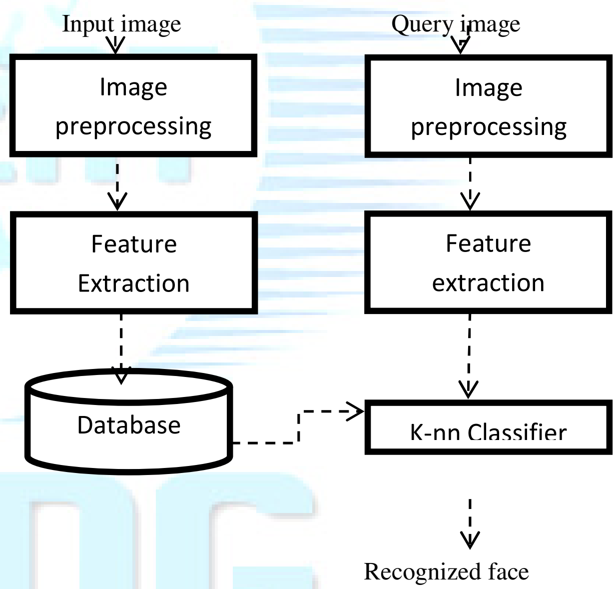

Fig 4. Block diagram of system architechture

4. Feature Extraction

4.1 Local Binary Patterns

The LBP operator takes a local neighborhood around each pixel, thresholds the pixels of the neighborhood at the value of the central pixel and uses the resulting binary-valued image patch as a local image descriptor. It was originally defined for 3x 3 neighborhoods, giving 8-bit integer LBP codes based on the eight pixels around the central one.

LBP is functioned as follows,

$$LBP(x,y)=\sum_{n=0-7} 2^n.s(i_n-i_c)$$

where in this case runs over the 8 neighbours of the central pixel, and are the gray-level values at end , and is 1 if and 0 otherwise.

42	33	40
78	56	55
96	121	65

→

0	0	0
1	56	0
1	1	1

→

$(11000011)_2$
LBP=195

Basic LBP operation

when histogramming LBPs the number of bins can be reduced significantly by assigning all nonuniform patterns to a single bin, typically without losing too much information.

4.2. Local ternary pattern

When using LTP for visual matching, we could use valued codes, but the uniform pattern argument also applies in the ternary case.

For simplicity, the experiments below use a coding scheme that splits each ternary pattern into its positive and negative halves, subsequently treating these as two separate channels of LBP descriptors for which separate histograms and similarity metrics are computed, combining the results only at the end of the computation. This is also used to extract texture feature. LBP is computationally faster than that of LPT.

5.Classification

K-nn(Nearest Neighbor) classifier is used to calculated the distance between the trained image and test image by minimum distance classification. Match between the trained and test image are classified by each 8 nearest neighbour values obtained from the extracted feature matrix. From the feature extracted by LBP technique, finally using nearest-neighbor classification in the histogram distance for recognition,

$$X^2(p,q)= (p-q)^2/(p+q)$$

Here p,q are image region descriptors (histogram vectors), respectively.

6.Experimental Result

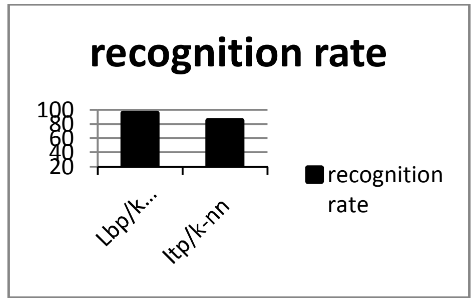

Fig-5.Recognition rate at different feature extraction.

Decomposition level and recognition rate:

Decomposition level	1	2	3	4
Recognition rate %	84.3	88.8	88.8	88.5

7.Future Work

The above work is done for the cropped images and back ground filled images. This may worked by back ground elimination technique images and also can include for occluded images such as beard and sunglass images.

Where it can difficult to identify partially occluded image such as 50% masked images, by using the technique such as image fusion, super imposition, ect.

8.Conclusion

Thus face is recognized under different illumination variation by image preprocessing and by enhancing local texture feature, Finally by k-nn classifier.

Reference

[1]. Xiaoyang Tan and Bill Triggs, “Enhanced Local Texture Feature Sets for Face Recognition Under Difficult Lighting Conditions” ,IEEE Transactions on Image Processing vol.19,No.6, pp 1635-1650, June 2010.

[2]. Shan Du, “Adaptive Region-Based Image Enhancement Method for Robust Face Recognition Under Variable Illumination Conditions” ieee Transactions on circuits and systems for video technology, vol. 20, pp.1165-1175, sept 2010.

[3] .SatyanadhGundimada and Vijayan K. Asari,“Facial Recognition Using Multisensor Images Based on Localized Kernel Eigen Spaces”, IEEE Transactions on Image Processing, vol. 18, pp. 1314-1325, june 2009.

[4]. Faisal R. Al-Osaimi, Mohammed Bennamoun, and AjmalMian, "Spatially Optimized Data Level Fusion of Texture and Shape for Face Recognition", IEEE Transactions On Image Processing, pp.1-24, August 2011.

[5].Athinodoros S. Georghiades, Student Member, IEEE, Peter N. Belhumeur, Member, IEEE, and David J. Kriegman, Senior Member, IEEE, "From Few to Many: Illumination Cone Models for Face Recognition under Variable Lighting and Pose", IEEE Transactions On Pattern Analysis And Machine Intelligence, Vol. 23, pp. 643-660, June 2001

[6].MinghuiDu,"Face Features Extraction Based on multi-scale LBP" International Conference on Signal Processing Systems, IEEE 2010.

[7] .RajkiranGottumukkal, "An improved face recognition technique basedon modular PCA approach" Elsevier, pp.429-436, Nov 2003.

[8]. Ngoc-Son Vu Alice Caplier, "Efficient Statistical Face Recognition across pose using Local Binary Patterns and Gabor wavelets", IEEE conference on Pattern Recognition 2009.

[9]. JeffreyHo, David Kriegman, Kuang-Chih Lee "Acquiring Linear Subspaces for Face Recognition under Variable Lighting" IEEE Transaction Pattern Anal. Match. Intell , Vol.27, No. 5, pp 684-698, May 2005.

[10]. Wenchao Zhang, Shiguang Shan, Xilin Chen, and Wen Gao, "Local Gabor Binary Patterns Based on Kullback–Leibler Divergence for Partially Occluded Face Recognition", IEEE signal processing letters, vol. 14, no. 11,PP. 875-880, NOV 2007.

[11] .S. Yan, D. Xu, B. Zhang, H. Zhang, Q. Yang, and S. Lin, "Graph embedding and extensions: A general framework for dimensionality reduction," IEEE Transaction Pattern Analysis Mach, Intell, vol. 29, no. 1, pp. 40–51, Jan. 2007.

[12]. Y.Adini**,** Y. Moses, and S. Ullman, 1997. Face recognition: The problem of compensating for changes in illumination direction. PAMI, 19(7), pp. 721–732. 51

[13]. W. Zhao, R. Chellappa, SFS based view synthesis for robust face recognition, Proceedings of the 4th Conference on Automatic Face and Gesture Recognition. 2000.

[14]. A. Shashua, R.R. Tammy, The quotient image: class-based rendering and recognition with varying illuminations, IEEE Trans. Pattern Anal. Mach. Intell. 23 (2), pp. 129–139, 2001.