Robust Pose Invariant Face Recognition using DCP and LBP

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ABSTRACT

Face recognition plays vital role in biometric recognition systems, but the robustness of algorithm is still lacking in commercial applications. In this paper, pose invariant face recognition is proposed which focuses on the frontal as well as multi pose face recognition. For the face recognition local binary pattern and dual cross pattern texture features are used and for pose normalization roll, yaw and pitch of the face is used. For recognition of face support vector machine supervised algorithm is used. Experimental results on FERET dataset shows that proposed system is robust to pose variation and it witness significant increase in accuracy of face recognition.

Keywords : Dual Cross pattern (DCP), Face Recognition, Local Binary Pattern (LBP), Support vector machine (SVM).

I. INTRODUCTION

Real-world face recognition in unconstrained scenarios is still a major challenge for biometrics [4].Among enrolled face images are usually captured in controlled settings, using a predefined arrangement of subjects and capture devices, whereas the probes (test images) are captured in quite different settings [5], [6]. In automatic face recognition system, the main complicated task is that it involves detection of faces from a cluttered background, facial feature extraction, and face recognition[4],[5]. The problems or limitations for a automatic machine learning based face recognition system are facial expression change, illumination variation , ageing, pose change, scaling factor (i.e. size of the image), frontal vs. profile, presence and absence of spectacles, beard, mustache etc. and occlusion due to scarf, mask or obstacles in front. Face recognition has two types holistic face recognition and part based face recognition[6],[7]. Face recognition can be done for images and videos. In this paper, robust pose invariant face recognition system is proposed. For the feature extraction LBP and DCP features are considered along with roll, pitch and yaw of face for face normalization. For classification SVM algorithm is used and results are compared with KNN classifier.

This paper is organized as follows. Section II describes the review some related work on face recognition. In Section III gives details about dual cross pattern feature extraction. Section IV gives implementation details of dual cross pattern features. Section V elaborates local binary pattern feature extraction. Section VI presents pose normalization which consists of calculation of yaw, roll and pitch of facial points. Section VII presents the experimental results together with a comparison of different training strategies. Section VII concludes the paper with a brief discussion.

II. RELATED WORK

For the feature recognition normally two types of features are used, namely statistical and feature based methods. Statistical methods consists of PCA[8],[9], Eigenfaces[9], LDA[5],[7], ICA[11].Normally, statistical features such as PCA, LDA, ICA consider color information of face for the feature extraction. Statistical methods are simple, but lacks in representation of face and has lower accuracy. Feature based approaches consists of fourier transform[13], Gabor transform[22], Descrete Cosine Transform(DCT)[12],wavelet transform[10],[13],[14] etc. feature based method are performing good for face recognition but variant to face pose and illumination changes. Gabor is texture based algorithm and wavelet based approaches are shape based algorithms which are unreliable to pose variation during face recognition.

III. PROPOSED METHODOLOGY

The proposed methodology consists of three basic steps: preprocessing, Feature extraction andclassification as shown in Fig 1.

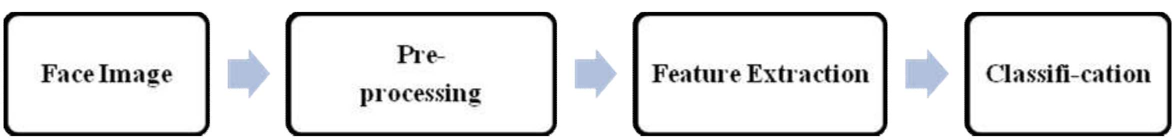


Figure 1. Generalized block diagram of face recognition

The preprocessing stage consists of color image to gray image conversion and Mean filtering of image Histogram equalization is used to reduce blur, shadow, unequal light distribution. For the feature extraction dual cross pattern (DCP) and local binary pattern (LBP) features are used. DCP and LBP are texture features extraction algorithms. For classification support vector machine and k nearest neighbor classifier is used. The detailed block diagram of proposed system is shown in fig. 2.

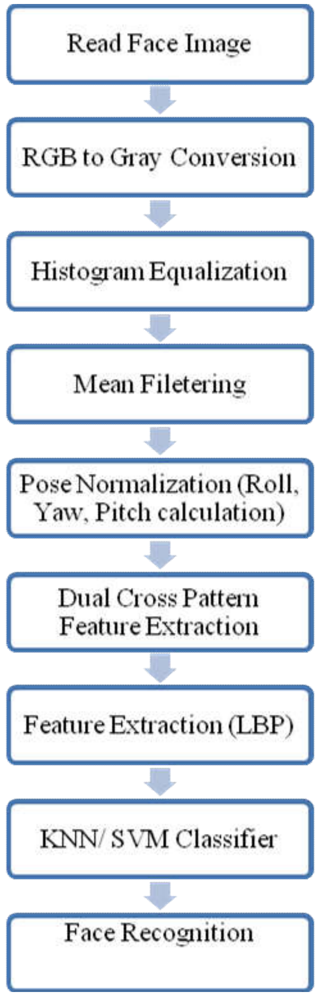


Figure2. Flow diagram of proposed methodology

IV. DUAL CROSS PATTERN FEATURES

The essence of DCP is to perform local sampling and pattern encoding in the most informative directions contained within face images. For face recognition, useful face image information consists of two parts: the configuration of facial components and the shape of each facial pose. Sixteen points are sampled around the central pixel O. The sampled points A0 to A7 are uniformly spaced on an inner circle of radius Rin, while B0 to B7 are evenly distributed on the exterior circle with radius Rex. component. The shape of facial components is, in fact, rather regular. After geometric normalization of the face image, the central parts of several facial components, i.e., the eyebrows, eyes, nose, and mouth, extend either horizontally or vertically, while their ends converge in approximately diagonal directions ($\pi/4$ and $3\pi/4$).

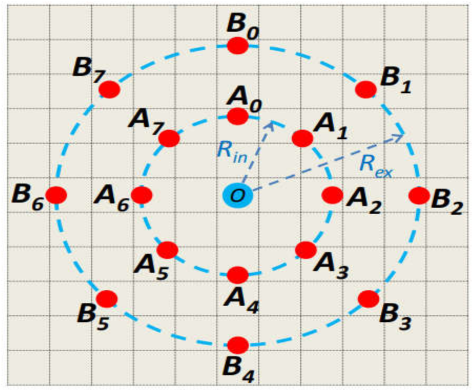


Figure. 3. Local sampling of Dual-Cross Patterns.

In addition, wrinkles in the forehead lie flat, while those in the cheeks are either raised or inclined. Encoding of the sampled points is realized in two steps. First, textural information in each of the eight directions is independently encoded. Second, patterns in all eight directions are combined to form the DCP codes. To quantize the textural information in each sampling direction, unique decimal number is assigned as given in (1).

$$DCP_i = S(I_A - I_0) * 2 + S(I_B - I_A), \quad 0 \leq i \leq 7 \tag{1}$$

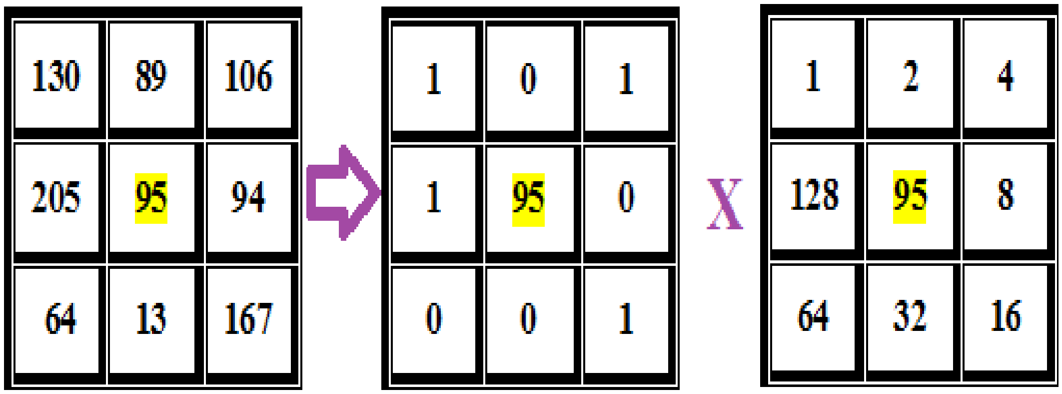
Where,

$$S(x) = \begin{cases} 1, & x \geq 0 \\ 0, & x < 0 \end{cases}$$

and Io, IAi , and IBi are the gray value of points O, Ai , and Bi , respectively. Therefore, four patterns are defined to encode the second-order statistics in each direction and each of the four patterns denotes one type of textural structures [1],[2].

V. LOCAL BINARY PATTERN

Local binary pattern extracts the texture features of images. LBP texture features are widely used because of its popular properties like, 1) Robustness against illumination changes in the images ; 2) they are very simple, fast and easy to compute; 3) No need of many predefined parameters to be set; 4) they are local features representing local texture variation ; 5) they are invariant to grayscale transformations and scaling; and 6) they have performed very well in many computer vision content based image retrieval applications [15],[16]. For the LBP feature extraction local 3×3 window is considered which slides over the all rows and columns of image. In the local 3×3 window all pixel values are compared with centered pixel intensity[17],[18]. If the value is greater than centered value then it is taken as 1 otherwise 0. Later decimal equivalent value is computed as shown in fig. 4.



LBP=1x1 + 0x2 + 1x4 + 0x8 + 1x16 + 0x32 + 0x64 + 1x128 = 145

Figure4. LBP operation example

For our implementation, we have selected radius(R) of 1,2,3 etc. The window size is calculated as W=2*R+1. Normally window size is selected as odd, because it is easy to find centered element in odd sized window rather than even sized window.

VI. POSE NORMALIZATION

Human face can adopt various poses, or pose may change due to facial expression, tiredness, makeup etc. While face recognition these changes may results in inaccurate face recognition as face recognition systems are normally trained for frontal and expressionless face poses. To tackle this problem, face roll, yaw and pitch is considered for face normalization[3].

Roll is measure of distortion in face and it is given by the angle θ between the line passing through the centers of the eyes and the x axis and it is given by (2):

$$roll = min\left(\left|\frac{2*\theta}{\pi}\right|, 1\right) \quad (2)$$

The higher value of roll results in worse distortion. For the yaw calculation left distance dl and right distance dr between the external corner of each eye and the nose tip is measured. Such distances tend to be equal in a frontal pose; otherwise, one of them increases at the expense of the other. The yaw component of the pose distortion is given by (3),

$$yaw = \frac{\max(dl,dr) - \min(dl,dr)}{\max(dl,dr)} \quad (3)$$

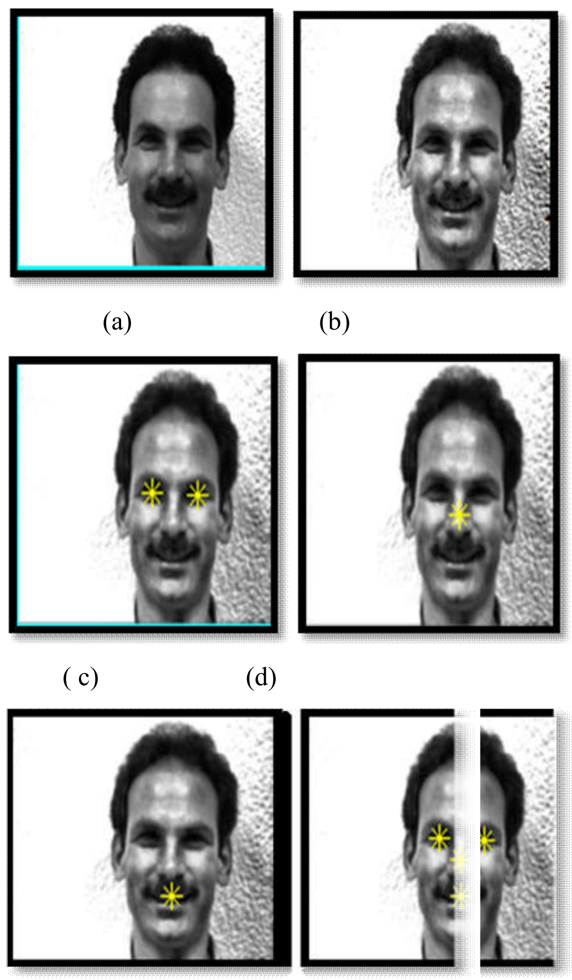
Similarly pitch of face is calculated. The distances of concern are eu and ed, which are, respectively, the distances to the root of the nose and of the chin from the nose tip. The pitch is given by (4),

$$pitch = \frac{\max(eu,ed) - \min(eu,ed)}{\max(eu,ed)} \quad (4)$$

All three factors range from 0 ie. almost no distortion to 1 ie. worst situation, corresponding to higher distortion.

VII. EXPERIMENTAL RESULTS

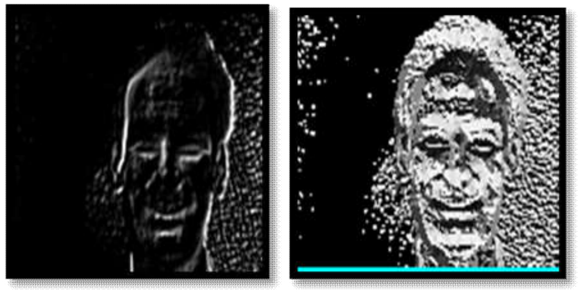
To demonstrate the effectiveness of the proposed algorithm in this paper, which has been implemented in MATLAB R2014a and Windows 7 Operating System, Intel(R) Core(TM) i3-2.64GHz Dual Core Processor CPU 4GB 3.10GHz RAM. Extensive experiments are performed on inhouse dataset and FERET dataset[21]. SVM is supervised learning discriminative classifier. Hyperplane separates the two classes with the help of kernel function. SVM is simple, memory efficient because it uses the support vectors as decision function, and effective in high dimentional feature space[19],[20]. The experimental results are shown in figure 5.



(a) (b)

(c) (d)

(e) (f)



(g) (h)

Figure 5. a) Original Face Image b) Preprocessed Image c) Eye Detection d) Nose detection e) Mouth detectionf) Eye, mouth, nose detection g) LBP features h) DCP features

The performance of DCP + LBP + SVM is measured on the basis of statistical measures such as percentage accuracy (5).

$$\% \text{ Accuracy} = \frac{\text{Correcly Classified Images}}{\text{Total Test Images}} X\ 100 \quad (5)$$

The performance results for combination of DCP and LBP is evaluated for different classifiers such as KNN and SVM are summarize in Table II.

TABLE II. Performance result of SVM and KNN

Algorithm	% Accuracy
DCP + LBP + SVM	97.50 %
DCP + LBP + KNN	93.00 %

VIII. CONCLUSION

In this paper, multi pose invariant face recognition is implemented using dual cross pattern feature along with local binary pattern feature. For the classification we have used SVM and KNN algorithm. The performance of SVM and KNN is compared , and it is found that DCP+LBP+SVM performs better than DCP+LBP+KNN.

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