Illumination invariance face recognition using complex wavelet packet transform

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***Abstract* - The illumination is one of the major problems in face recognition systems. The illumination effect is caused due to same face exposed under different lighting variations. In this paper, we propose a novel method for Illumination invariance face recognition called as complex wavelet packet transform. Wavelet is extracting very good features from the images, but it extracts features from the low frequency region only. But the features are also present in the high frequency region. To overcome this limitation going to the wavelet packet transform. In wavelet packet transform, extract features in both low and high frequency regions. In this paper, we concentrate only on high frequency regions, because the features are the strong points that mean high frequency components in the image and each decomposition level we combine all high frequency regions that means detailed coefficients. In wavelet packet based feature extraction not give the directional features for this limitation we use complex wavelet packet transform for getting the directional features. Correlation method is used to find the matching points in the two images. To overcome wrongly correlated point we use Homography estimation by using RANSAC. The experimental result shows that our method is simple comparing dual tree complex wavelet transforms based feature extraction.**

***Key words* - illumination variation, face recognition, complex wavelet packet transform.**

I. INTRODUCTION

Recognition of human face is the one of the important research areas in present days because identifying any person, face is the strong feature. There are so many applications in the face recognition like surveillance; security, and telecommunications, etc. face recognition can be performed by comparing selected facial features from the image and a facial database. In a face recognition system, so many problems are there first one is the detection of face in the image known as face detection. The second one is the extraction of invariant features from each image called feature extraction. The third one is match these features with another face image called matching.

Illumination variation is a serious problem in the performance of face recognition. The Illumination effect is due to the variation of same person face image under different lighting conditions [1]. Early research image gradient method is used to decrease the illumination variation. This method is simple but limited performance. In frequency domain use several algorithms such as wavelet transform [2], discrete cosine transform based method [3].

Figure 1: The same individual imaged with the same camera and seen with nearly the same facial expression and pose may appear dramatically different with changes in the lighting conditions.

A two-dimensional discrete wavelet transform (2D-DWT) is very simple method to extract the features in the image based on Multi-resolution Analysis (MRA), which decomposes an image into each frequency component using low-pass and high-pass filter, and then down sampling on each frequency component. Thus, MRA offers fast processing. The 2D-DWT is not giving the shift invariant features. This means the analysis using 2D-DWT is sensitive to changes in phase. A two-dimensional complex discrete wavelet transforms (2D-CDWT) [4] is used for calculating the directional components by using real and imaginary wavelet coefficients. By using Kingsbury's method, the 2D-CDWT can decompose the image into six directional components of the high-frequency components. The 2D-CDWT gives unclearness of the relation between frequency components and directional selection. As some improved methods of directional selection, the Curvelet Transform [5], Contourlet transform [6], and the 2D-wavelet directional filter [7] have recently attracted attention. The first two transforms can produce more directional components than the previous methods can. However, the directions and resolutions are also fixed in these methods. The last method has a flexible directional selection, but its computation speed is low. In this paper, we propose a new method for illumination invariant feature extraction called complex wavelet packet transform (CWPT)

II. COMPLEX WAVELET PACKET TRANSFORM

Complex wavelet packets transform having a real part $\psi^R(x)$ and an imaginary part $\psi^I(x)$. This wavelet will be called the complex mother wavelet. In addition, the complex mother wavelet is a Hilbert pair and orthogonal wavelet. Corresponding to the complex mother wavelet, there are the real part $\phi^R(x)$ and imaginary part $\phi^I(x)$ of the scaling function. An image f (x, y) can be represented in the expression (1). As an example, the separated parts RR(x, y) and RI (x, y) are shown in expressions (2) and (3). The separated parts IR(x, y) and II (x, y) are also represented by similar expressions:

$$f(x, y) = RR(x, y) + RI(x, y) + IR(x, y) + II(x, y), \qquad (1)$$

$$RR(x,y) = \sum_{k_x,k_y} C^{RR}_{0,k_x,k_y}\phi^R(x-k_x)\phi^R(y-k_y), \quad (2)$$

$$RI(x,y) = \sum_{k_x,k_y} C^{RI}_{0,k_x,k_y}\phi^R(x-k_x)\phi^I(y-k_y), \quad (3)$$

Where the scaling coefficients C^{RR}_{0,k_x,k_y} and C^{RI}_{0,k_x,k_y} are calculated from (4) and (5)

$$C^{RR}_{0,n_x,n_y} = \frac{1}{4}\sum_{k_x,k_y} f_{n_x-k_x,n_y-k_y}\overline{\phi^R(-k_x)\phi^R(-k_y)}, \quad (4)$$

$$C^{RI}_{0,n_x,n_y} = \frac{1}{4}\sum_{k_x,k_y} f_{n_x-k_x,n_y-k_y}\overline{\phi^R(-k_x)\phi^I(-k_y)}, \quad (5)$$

Where f_{n_x,n_y} is the discretized image of f(x, y) at (x, y) = (n_x, n_y). These scaling coefficients can be decomposed into wavelet coefficients by using the low-pass filters $\{a^R_k\}$, $\{a^I_k\}$ and the high pass filters $\{b^R_k\}$, $\{b^I_k\}$. In the 2D-CWPT, all the components of the LL, HL, LH and HH are filtered recursively. Additionally, the coefficients of each component are represented using an index (n, m) (where n, m are positive integers), where index **n** represents the number of frequency components about w_y and **m** represents the number of frequency components about w_x. Larger index values represent higher frequencies. For example, the scaling coefficients C^{RI}_{0,k_x,k_y} in equation (5) are represented as $d^{RI,(1,1)}_{0,k_n,k_y}$. Next, each wavelet coefficient $d^{RI,(1,1)}_{0,k_n,k_y}$ is decomposed to level −1 by using the low and high-pass filters and the calculation equations are shown in (6) –(9):

$$d^{RI,(2n-1,2m-1)}_{j,n_x,n_y} = \sum_{k_x,k_y} a^R_{2n_x-k_x} a^I_{2n_y-k_y} d^{RI,(n,m)}_{j+1,k_x,k_y}, \quad (6)$$

$$d^{RI,(2n,2m-1)}_{j,n_x,n_y} = \sum_{k_x,k_y} a^R_{2n_x-k_x} b^I_{2n_y-k_y} d^{RI,(n,m)}_{j+1,k_x,k_y}, \quad (7)$$

$$d^{RI,(2n-1,2m)}_{j,n_x,n_y} = \sum_{k_x,k_y} b^R_{2n_x-k_x} a^I_{2n_y-k_y} d^{RI,(n,m)}_{j+1,k_x,k_y}, \quad (8)$$

$$d^{RI,(2n,2m)}_{j,n_x,n_y} = \sum_{k_x,k_y} b^R_{2n_x-k_x} b^I_{2n_y-k_y} d^{RI,(n,m)}_{j+1,k_x,k_y}, \quad (9)$$

The scaling functions and complex wavelets used in the above equations are represented by expressions (10) – (13):

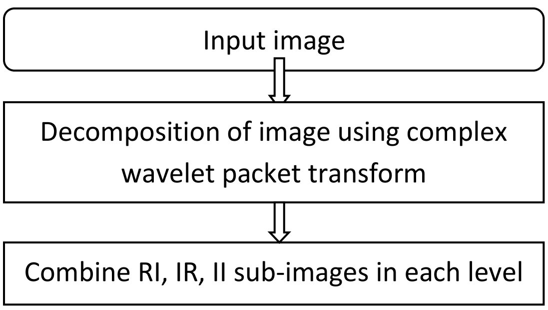
$$\phi^R_{j,k}(x) = \sqrt{2}^j \phi^R(2^j x - k), \quad (10)$$

$$\phi^I_{j,k}(x) = \sqrt{2}^j \phi^I(2^j x - k), \quad (11)$$

$$\psi^R_{j,k}(x) = \sqrt{2}^j \psi^R(2^j x - k), \quad (12)$$

$$\psi^I_{j,k}(x) = \sqrt{2}^j \psi^I(2^j x - k), \quad (13)$$

III. PROPOSED METHOD



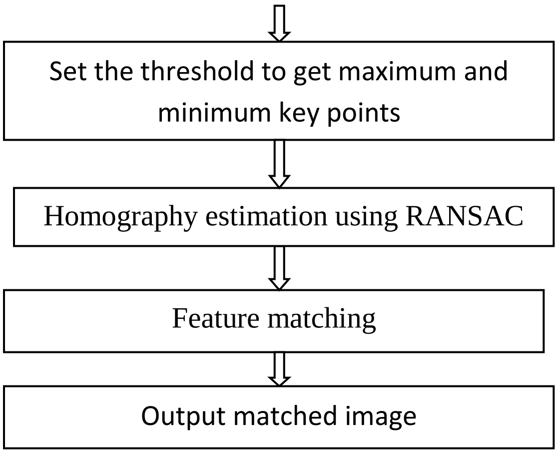


Fig2 Block diagram of the proposed method

3.1 Feature extraction using complex wavelet packet transform:

If an image is decomposed by the complex wavelet packet transform (CWPT) then four sub images can be obtained. One is real part of low-detailed sub-image can be obtained from the low frequency component RR (x, y). Second and third are the combination of real and imaginary part of detailed sub-images can be obtained from the high frequency components RI (x, y), & IR (x, y). Fourth one is the imaginary part of the detailed sub image can be obtained from high frequency component II (x, y) shown in equation (1). In the second level decomposition we decompose the high frequency components because a feature is a strong point in the image i.e. a high frequency component. In this paper, we decompose the image up to second level only and each level; we combine all high frequency components and leave the low frequency components in each level.

3.2 Feature matching:

Feature matching aims to detect the matched features from the boot images [8]. In this paper, we use correlation method to determine matched features between two images. In this method analyze pixels around each point in the first image and compares them with the pixels around every other point in a second image. The most common points are taken as matching pairs. It can be seen very well from the picture, however, that many points have been wrongly correlated. To overcome this drawback we use Homography Estimation. It can be used to project one of the two images on top of the other while matching the majority of the correlated feature points we require a Homography matrix, which has the opportunity to match the two images [9]. First identify the correct matched key points by using RANSAC. It is the algorithm to estimate the mathematical model of a set of observed data. Observed data contain both inliers and outliers. Where inliers correspond to a set of data that can be described by some set of parameters, whereas outlets cannot be described by a model. So, for an accurate model fitting, these outlets have to be eliminated.

3.3 Algorithm for proposed method:

Step1: take two input images of size 83X63

Fig3 input images of size 83X63

Step2: decompose the two input images using complex wavelet packet transform up to the second level

Step3: combine RI, IR, II sub-images in each level

Step4: set the threshold to get the maximum and minimum number of key points.

Step5: Project these points in an image by multiplying four times of each key point location because of the second level of complex wavelet packet decomposition the image can be analysis done on 1/4th part of the original image.

Step 6: Plot the maxima and minima key points which are obtained from the threshold. The red color circle indicates the maximum key point in the image and green color circle indicates the minimum key point in the image. Here total number of key points detected in both images is 439

Fig4 key point extraction

Step 7: After obtaining the key points in both the images the next step is identifying the matching points in both images.

Step 8: for identifying the correct matches we use RANSAC based homography estimation. Therefore the total matching key points obtained in both images is 33

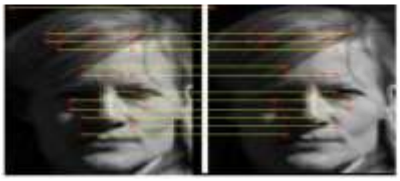


Fig5 key point matching

IV. RESULTS

Fig6 input images

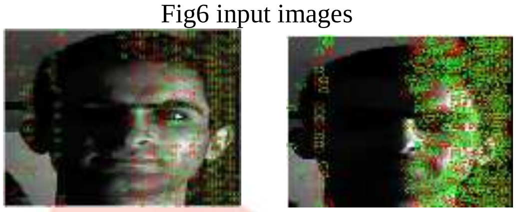


Fig7 key features in both images

Fig8 feature matching

CONCLUSION

In this paper a new method based on complex wavelet packet transform is developed to extract illumination invariant face recognition. The proposed method uses complex wavelet packet transform for the training images, and the testing images are reconstructed by combining the detailed coefficients in each decomposition level because the feature is a strong point it also presents in horizontal, vertical and diagonal regions. Compared with the other methods, the complex wavelet packet transform give a strong features with less number of coefficients. Therefore, in this method has better edge preserving ability in low frequency illumination fields and better useful information saving ability in high frequency fields. Experimental results on the Yale-B face database show that high recognition rates are achieved by the proposed method.

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