QUATERNION CORRELATION FILTERS FOR FACE RECOGNITION IN WAVELET DOMAIN

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ABSTRACT

In this paper, a new frequency domain face recognition method using wavelet decomposition and quaternion correlation filters is proposed. The wavelet decomposition of the face image leads to a wavelet subband representation, which contains four subband images corresponding to four orthogonal channels. These four subbands can be encoded into a 2-D quaternion number array. The quaternion correlation filter method is developed for performing pattern recognition on multi-channel 2-D signal jointly. The proposed method has been shown to achieve significant improvement in face recognition results compared to traditional advanced correlation filter method for handling illumination variations of face images. We experimented with the CMU PIE database consisting of 65 people with 21 illumination variations per person, showing that our method can achieve close to 100% recognition accuracy using just a *single* training image of a person under neutral frontal lighting and testing on all other un-seen harsh illuminations.

1. INTROCUTION

Human face recognition is currently a very active research area with focus on ways to perform robust biometric identification. However, face recognition is a challenging task because of the variability of the appearance face images even for the same subject as it changes due to expression, occlusion, illumination, pose, aging etc. Many algorithms have been developed to focus on the varying illumination as it is one of the most difficult problems. Among the different approaches, frequency domain methods [1] have been shown to exhibit better tolerance to illumination variations than traditional methods. In [2] the "CoreFace" method has been shown to outperform PCA, LDA and 3D-linear subspace methods [2]. The Eigenphase [3] method further investigates that phase information in the frequency domain is more illumination tolerant representation than original Eigenfaces and other standard methods. In this paper, we propose a new frequency domain face recognition method that transforms the original image to wavelet domain and utilize quaternion correlation filters for multi-band signal processing. We show that we are able to obtain robust illumination-tolerant face recognition when we only use a single face image for training. (Many of the discussed methods can not be applied when given only a single training image).

Our proposed method includes two stages, wavelet decomposition and quaternion correlation. The wavelet decomposition provides a multi-resolution analysis of the image, so as to offer additional features that are jointly localized in frequency and space and has had some success in face recognition applications [4]. In our proposed method, we apply discrete wavelet decomposition (DWT) to transform the face image into a multi-band representation, and we apply quaternion correlation filters [5] to perform multi-band processing *jointly*.

Quaternion correlation filter is naturally designed for 2-D multi-channel recognition. These quaternion correlation filters are based on quaternion algebra, originally introduced by Hamilton in 1843 [6]. A quaternion number is a generalization of the complex number and can be considered as a number with a real part and a [7] imaginary part consisting of three orthogonal components as follows.

$$q = a + b\mathbf{i} + c\mathbf{j} + d\mathbf{k}\,, \tag{1}$$

where a, b, c, d are real and $\mathbf{i}, \mathbf{j}, \mathbf{k}$ are imaginary operators. Therefore a 2D quaternion array can carry four channels, one for each subband. The quaternion correlation filter not only models the intra-channel structure characteristics as the traditional correlation filter does, but it also models the inter-channel structure characteristics since it jointly processes the multiple channels, and thus provides a natural way to combine the correlation outputs from the 4 channels.

In this paper we show that the proposed face recognition method effectively exploring the multi-resolution characteristics of the face image by combining the wavelet decomposition and the quaternion correlation. We show the proposed method outperforms the traditional advanced correlation filter method and also the traditional advanced correlation filters trained independently on each wavelet subband. The paper is organized as follows. In Section 2, wavelet decomposition is reviewed and in section 3, the quaternion correlation filter method is presented; the numerical experimental results are shown in Section 4 and we conclude the paper in Section 5.

2. WAVELET DECOMPOSITION

The wavelet transform decomposes the original signal into different scales and resolutions, providing more insight of the joint space-frequency characteristics of the original signal. The discrete wavelet decomposition (DWT) can be viewed in a tree structure, where the original signal is passed through a low pass filter and a high pass filter, and then downsampled by 2 to get the low frequency and high frequency components of the original signal respectively (shown in Fig. 1). The decomposition can be iteratively applied to the low frequency band and the high frequency band as well to generate a wavelet decomposition tree.

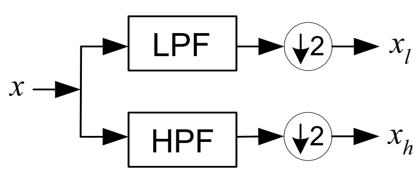

Fig. 1 The wavelet decomposition tree

This process is implemented by projecting the original signal to the wavelet basis functions to obtain wavelet coefficients. The 2-D wavelets are the Cartesian product of the 1D wavelet, so a 2-D image will be decomposed into 4 parts corresponding to LL, HL, LH and HH frequency bands respectively. An example of 1-level Haar wavelet decomposition of a face image is shown in Fig. 1, where the LL band represent the approximation of the original image and the HL, LH and HH bands represent the details of the original image.

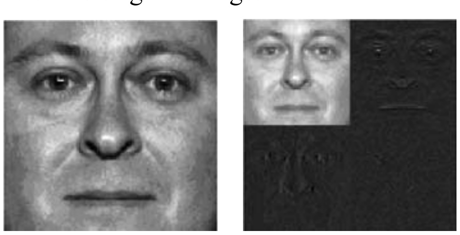

Fig. 2: Left: original image; Right: the 1-level wavelet decomposition.

The Daubechies (db) family of wavelets is one of a number of wavelet families and it provides orthogonal decomposition basis. In our method we show good results with Daubechies (db) family of wavelets.

3. QUATERNION CORRELATION FILTER

We introduce the method of combining wavelet decomposition and quaternion correlation filters (which we will refer as 'Wavelet + quaternion filter') for face recognition below. The concept of how this method is used includes both the enrollment stage and the recognition stage. During the enrollment stage, one or multiple images of each individual subject's face images are acquired. The 2-D DWT of these training images are performed to decompose the original images into four subbands. These subbands images are then encoded into a 2-D quaternion array as follows:

$$f(\mathbf{x}) = f_{LL}(\mathbf{x}) + f_{LH}(\mathbf{x})\mathbf{i} + f_{HL}(\mathbf{x})\mathbf{j} + f_{HH}(\mathbf{x})\mathbf{k} \qquad (2)$$

where $\mathbf{x}$ represents the image coordinates, and $f_{LL}(\mathbf{x})$, $f_{LH}(\mathbf{x})$, $f_{HL}(\mathbf{x})$ and $f_{HH}(\mathbf{x})$ represent the four wavelet sub-band images. The Quaternion Fourier transform (QFT) [7] is performed to transform the quaternion image to the quaternion frequency domain. The quaternion correlation filter is designed based on the QFT of the training images and stored for each subject, as shown in Fig. 3.

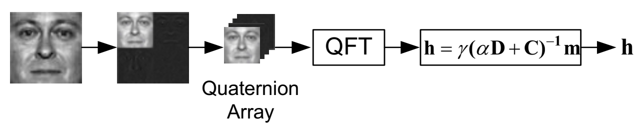

Fig. 3 The enrollment stage of the wavelet+quaternion filter method.

In the recognition stage, the testing image is transformed into quaternion frequency domain just as was performed during training. Then the resulting quaternion frequency domain representation is cross-correlated with every quaternion correlation filter (QCF) in the database using the specialized 2-D quaternion correlation (QC) [7]. From the magnitude value of each quaternion correlation output, a similarity score is computed. The testing image will be labeled into as the same class as the filter that generates the largest similarity score. The recognition process is illustrated in Fig. 4.

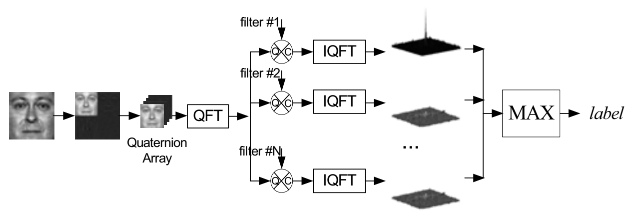

Fig. 4 The recognition stage of the wavelet+quaternion filter method.

3.1. Quaternion Correlation Filters

A well-designed correlation filter should yield large peak values in correlation output plane from the true identity and no discernible peaks for other people. To make the correlation peak sharp, the correlation filter should be designed to suppress the neighboring peak values (i.e. correlation values around the peak). At the same time, the output noise variance of the correlation output noise should be minimized to suppress the effect of input noise. These two optimization criteria are conflicting as filters that emphasize higher spatial frequencies typically produce sharper peaks; however emphasizing higher spatial frequencies also emphasizes the effect of input noise. Thus we import a methodology to optimal tradeoff between these two criteria, which leads to the unconstrained optimal tradeoff quaternion filter (UOTQF), which has the closed form solution shown in Eq.(3). The derivation of this filter can be found in [6], and is in the same form of the traditional unconstrained optimal tradeoff filter (UOTF) [1]

$$\mathbf{h} = \gamma(\alpha\mathbf{D} + \mathbf{C})^{-1}\mathbf{m} \tag{3}$$

where $\mathbf{h}$ is the designed frequency domain filter represented in the vector form. $\mathbf{m}$ represents the mean of the frequency domain training images in the vector form. $\mathbf{D}$ is a diagonal matrix, where the main diagonal is the average power spectrum of the training images. $\mathbf{C}$ is also a diagonal matrix, representing the noise power spectral density (psd). Typically we assume a white noise model, thus $\mathbf{C}$ takes the form of an identity matrix. Finally α and γ are tradeoff parameters, which can be tuned to obtain the optimal tradeoff between the maximizing the discrimination ability and minimizing the output noise variance of the filter $\mathbf{h}$. In this formulation of the UOTQF filter, all vector and matrix terms are quaternion number arrays, while for the UOTF filters they are all complex number arrays.

One fitness measure of the peak sharpness is the peak-to-sidelobe-ratio (PSR) [1] defined as follows

$$PSR = \frac{Peak - mean(sidelobe)}{std(sidelobe)} = \frac{p - m}{\sigma} \tag{4}$$

where peak refers to the value of the peak on the correlation output plane and sidelobe refers a fix-sized surrounding area off the peak. Large PSR values indicate the better match of the test image and the filter.

4. NUMERICAL EXPERIMENTS

Our experimental results are shown using the illumination subset of the CMU-PIE database [8], which contains 65 subjects, each with 21 different illuminations. The normalized and cropped face images for one subject are shown in Fig. 3. The Daubechies (DB) family is used for the wavelet decomposition. First we experimentally select the best basis function from the DB family for wavelets. We take image #7, which is under the neutral frontal illumination, as the training image, train a QCF and test with other harsh unseen 20 illumination variations for each person. We repeat this for other correlation filter approaches to see the performance comparison of our proposed approach.

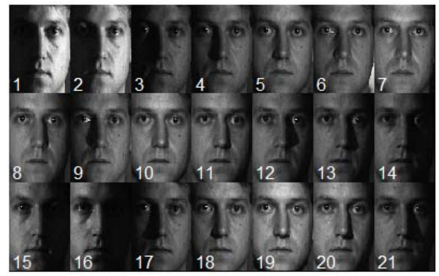

Fig. 5. Sample images of CMU-PIE database

We have shown the results for three experiments: Wavelet+UOTQF (our proposed approach), Wavelet+UOTF and UOTF which are the other advanced correlation filters that have had success. The procedure of experiment-I has been illustrated in Fig. 3 and Fig. 4. For experiment-II, after wavelet decomposition, in training stage we design four UOTF filters, one for each wavelet decomposition subband. In the testing stage, we get four PSR values from four correlation output planes for each subband, and sum them up to get a single similarity score, which is used for making a recognition decision. In experiment-III, the traditional advanced UOTF filter method is applied on the original image, and the result is used as the baseline for comparison. The designed filters are tested on all images under different illuminations.

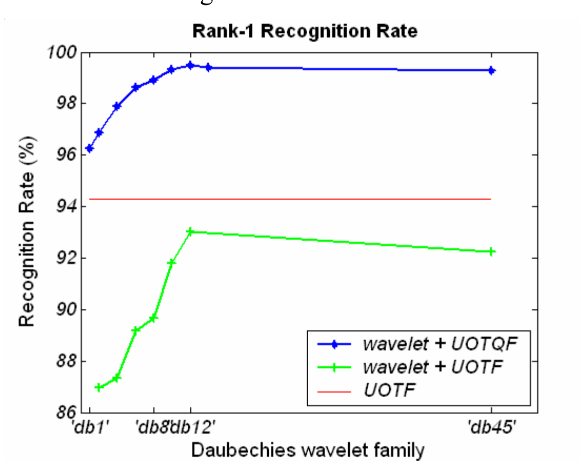

Fig. 6. The rank-1 recognition rate for different wavelet decomposition basis.

From the Fig 6 we can see that the recognition performance varies as we use the different wavelet bases. Empirically we found that the recognition rate increases as the length of the wavelet basis increases, and reaches the maximum when using the Daubechies-12 and gradually decreases after that. Therefore for the rest experiments in this paper, we only show results when the db12 analysis filter is used for wavelet decomposition.

The other interesting fact we can see from Fig. 6 is that simply combining wavelet decomposition and traditional advanced correlation filters does not increase the face recognition rate, but actually decreases it. However, combining the wavelet decomposition with the quaternion correlation filter *consistently* improve the recognition performance because of the ability of the quaternion filter to model the inter-subband structure as well as the intra-subband structure characteristics. These consistent results are also shown in the following experiments shown below where we investigate the performance of the proposed method when we use training images with different illumination conditions. Again we use only one image for training the correlation filters, and we show four experiment results of using different training image. For instances, images #7 and #19 are neutral frontal illumination, images #5 and #11 are under moderate left or right illumination, The designed filters are tested on all other unseen harsh illuminations. The Matched Filter (MF) (i.e. normalized correlation) method is tested for comparison. The recognition performance of three methods: Wavelet+UOTQF, Wavelet+UOTF and UOTF are shown in Table. 1.

Table 1. The rank-1 recognition rate (**%**) of CMU PIE illumination subset when the ***single*** **training image** is under near frontal illumination.

Training image	#5	#7	#11	#19
Wavelet UOTQF	95.9	99.5	95.0	99.5
Wavelet UOTF	89.2	94.3	85.8	94.3
UOTF	86.7	96.8	86.7	93.8
Matched Filter (normalized correlation)	45.2	44.5	50.5	48.3

From table 1 we can see that the proposed wavelet UOTQF method consistently outperforms the wavelet UOTF method and the OTF method when we use different (single) training image under different lighting condition and the advanced correlation filters performs much better than the Matched filter (i.e. the normalized correlation). By using the wavelet UOTQF method, we achieve ~10% improvement for near frontal lighting and get ~100% recognition rate for neutral frontal illumination. These results also show that simply combining the wavelet decomposition with the traditional advanced correlation filter does not provide benefit of multiresolution analysis(MRA). However, with our proposed approach, multi-resolution wavelet analysis greatly enhances recognition performance using just a single training image.

5. CONCLUSIONS

In this paper we introduced a new frequency domain method for performing illumination tolerant face recognition by combining the wavelet decomposition and the quaternion correlation filter techniques. The wavelet analysis decomposes the original image into four subbands and provides space-frequency analysis insight of the original image. By using the quaternion correlation filter we are able to model the inter-subband characteristics as well as the intra-subband characteristics of the decomposed representation, so that we are able to jointly process four subband channels simultaneously. The numerical experiments on CMU PIE data set shows that the proposed method achieve most improvement when trained using only a *single* near frontal lighting mug-shot training image and test on unknown, variable lighting face images. Our results outperform other comparable advanced correlation filter algorithms. In the future, we will evaluate pose tolerance of these filters.

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6. REFERENCES

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