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Comparison of wavelet, Gabor and curvelet transform for face recognition

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There has been much research about using Gabor wavelet for face recognition. Other multiscale geometrical tools, such as curvelet and contourlet, have also been used for face recognition, thus it is interesting to know which method performs best, especially under illumination and expression changes. In this paper, we make a systematic comparison of wavelet, Gabor and curvelet for recognition, and find the best subband irrelevant to expression and illumination changes. We combine the multiscale analysis with subspace decomposition as our algorithm. Experiments show that for expression changes, the properties of the coarse layer of curvelet and wavelet are very good. Whilst for illumination changes, the low frequency parts of the two methods are similarly influenced, but the detail coefficients of curvelet and the high frequency of wavelet work fine with PCA, with the former outperforming the latter. When these two factors change simultaneously, the detail layer of curvelet is better relative to the others.

Keywords: wavelet transform, Gabor wavelet, curvelet transform, face recognition, multiscale analysis.

1. Introduction

Among the so many popular methods for face recognition, the wavelet transform is used [1] almost as widely as the subspace method. Its ability to capture localized time-frequency information of image motivates its use for feature extraction. The decomposition of the data into different frequency ranges allows us to systematically study the influence of intrinsic deformations due to expression or extrinsic factors (like illumination) on different subbands, and to pick out the best subbands irrelevant to these factors. Wavelet-based methods prune away these variable subbands, and focus on the subbands that contain the most relevant information so as to better represent the data. DAI DAO-QING and YAN HONG [2] gave a comprehensive review of the choice of wavelet subband and robust issue. KEMAL EKENEL and SANKUR [3] conducted experiments on the combinations of wavelet and subspace methods (PCA, LDA, ICA) and their performance. There are also many works in this aspect.

All these works are based on wavelet transform. Nevertheless, as we know, the wavelets used for image processing are the tensor product of 1D wavelet, thus they have only three directions, namely, horizontal, vertical and diagonal directions. Wavelets are optimal when capturing point singularities, and they can reveal the image features across edges, but not the features along edges. As for high dimensional signals like images, there exist higher order singularities, and wavelets do not have advantages in this regard.

The curvelet transform has been proposed [4–6] as a multiscale geometric analysis tool, which can show the image features both at each scale and different directions. It takes no time to realize the features of the face images include curves, which form the curved singularities of the face images. Hence the use of curvelet transform for facial feature extraction is reasonable. We [7, 8] and authors of [9] proposed to use curvelet for face recognition simultaneously, and in this work we study the performance of curvelet transform combined with subspace method, under the above mentioned variations. In [3], KEMAL EKENEL and SANKUR study how to choose best wavelet subbands regarding the illumination and expression changes. In this paper we do a parallel work in curvelet domain, and make a comparison between the two schemes. To be more specific, curvelet transform results in four scales, each of which is used as features. Together with the best wavelet subband suggested in [3] used as features, we choose the best one in the presence of illumination and expression changes.

With regard to orientation selectivity, Gabor wavelet [10] also has different directions and scales. Hence it is favorable to draw Gabor wavelet in this comparison. It has been proved that the kernels of Gabor wavelets are similar to the 2D receptive field profiles of the mammalian cortical simple cells, also, the Gabor wavelets are optimal for measuring local spatial frequencies [11]. Gabor wavelet used as feature extraction for face recognition has also been studied extensively by researchers [12–16]; and in this study we make a comparison of the two methods regarding expression and illumination changes.

The paper is organized as follows. Section 2 reviews the wavelet method for face recognition. Section 3 reviews Gabor wavelets. Section 4 introduces the curvelet transform and its usage in face recognition. Section 5 presents the experiments and analysis. Finally there is a conclusion in Section 6.

2. Wavelet method for face recognition

Wavelet has been employed for face recognition for a long time, and a thorough study of the method has been performed. Here we give a brief account of the methodology

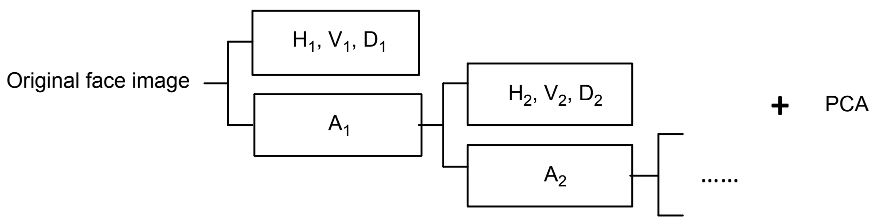

Fig. 1. Diagram of wavelet and subspace method for face recognition.

and the results. The diagram of the method is shown in Fig. 1. The original face image is decomposed into approximate, horizontal, vertical, and diagonal coefficients, *i.e.*, A_1, H_1, V_1 and D_1, and then A_1 is repeatedly decomposed into A_2, H_2, V_2 and D_2, and the process goes on until three to five levels of decomposition are done. Hence we get coefficients at different levels and directions, which will then be processed by PCA/LDA because of their high dimensionalities. The core issue in this process is the choice of wavelet basis and wavelet subband under the presence of expression, pose, and illumination changes.

Researches have been conducted in this concern and from the above work we know the following facts: 1) Facial expressions and small occlusions affect the intensity manifold locally, so under frequency-based representation, only high-frequency spectrum is affected; 2) Changes in pose or scale of a face and most illumination variations affect the intensity manifold globally, in which only their low-frequency spectrum is affected; 3) Only a change in face will affect all frequency components. So there are no special subbands whose all coordinates are not sensitive to these variations. Kemal Ekenel and Sankur [3] conducted comprehensive experiments and found that the horizontal components obtained at level one or two result in the highest recognition rates under illumination changes. The reason is that the horizontal components remove any horizontal illumination pattern, *e.g.*, one cheek darker, the other lighter. In all, the proper wavelet subband should be specified under different factors.

Now we give a brief analysis of the wavelet method. The wavelet transform can be interpreted as a multiscale differentiator or edge detector that represents the singularity of an image at multiple scales and three different orientations – horizontal, vertical, and diagonal. Each image singularity is represented by a cascade of large wavelet coefficients across scale. In essence, wavelets are good at catching zero-order singularities, or namely, point singularities. However, two-dimensional piecewise smooth signals like images also possess 1D singularities, *i.e.*, singularities along curves. And it is obvious that the features of face images are multidirectional, and we need to consider features of different orientation. So we need such transform that can yield both scale and orientation information of images.

3. Gabor wavelet for feature extraction

The Gabor wavelet consists of a group of Gabor filters at different frequencies and directions. A Gabor filter is a Gaussian function modulated by a complex sinusoid. The Gabor kernel is defined as:

$$\psi_{u,v}(\mathbf{z}) = \frac{||\mathbf{k}_{\mathbf{u},\mathbf{v}}||}{\sigma^2} \exp\left(-\frac{||\mathbf{k}_{\mathbf{u},\mathbf{v}}||^2 ||\mathbf{z}||^2}{2\sigma^2}\right)\left[\exp(i\,\mathbf{k}_{\mathbf{u},\mathbf{v}}\mathbf{z}) - \exp\left(-\frac{\sigma^2}{2}\right)\right] \tag{1}$$

where u, v are the direction and scale of Gabor kernel, respectively; $\mathbf{z}$ is the coordinate of a pixel in facial image, denoted by $\mathbf{z} = (x, y)$; $||...||$ stands for norm operation;

σ controls the width of the Gaussian envelope; $\mathbf{k}_{\mathbf{u},\mathbf{v}} = k_v \exp(i\phi_u)$ describes responses of the filter on different directions and scales, $k_v = k_{\max}/f^v$, $\phi_u = \pi u/8$, where $k_{\max}$ is the maximum frequency, and f is the spacing factor between kernels in the frequency domain [8].

The set of Gabor kernels in Eq. (1) are all self-similar since they can be generated from the mother wavelet, by scaling and rotation via the wave vector $\mathbf{k}_{\mathbf{u},\mathbf{v}}$. Each kernel is a product of a Gaussian envelope and a complex plane wave, while the first term in the square brackets in Eq. (1) determines the oscillatory part of the kernel and the second term compensates for the DC value. Gabor wavelet has good characteristics in space frequency, space position and direction selectivity.

4. Curvelet method for face recognition

To overcome the weakness of wavelets in higher dimensions, and to better capture the curve singularities and hyperplane singularities of high dimensional signals, CANDES and DONOHO [4–6] proposed curvelet transform. Curvelet transform directly takes edges as the basic representation elements and is strongly anisotropic. It is optimal in representing curved singularities in images or higher dimensional signals. The detail and fine coefficients of curvelet are strongly orientation-sensitive, which is a useful property for detecting curves in images. Curved singularities can be well approximated with very few coefficients and in a non-adaptive manner. This is why they are referred to as "curvelets". They are very useful in representing the edges of images and this is the multiresolution, band pass, and directional function analysis method, which possesses the three characteristics of best image representation, as proposed by the physiology graduate school. The scheme of curvelet for face recognition is shown in Fig. 2.

5. Experiments and analysis

5.1. Database

We use three databases in our experiment, namely the Yale, ORL and CAS-PEAL [17] database. The first two are widely known, so we only introduce the last one. The CAS-PEAL face database contains 99 594 images of 1040 individuals (595 males and 445 females) with varying pose, expression, accessory, and lighting (PEAL), as

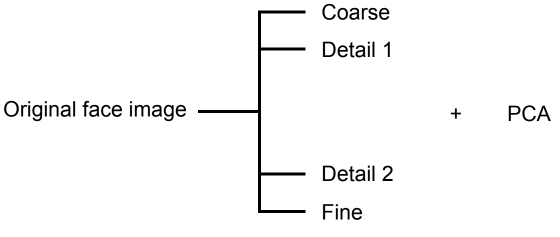

Fig. 2. Diagram of curvelet method for face recognition.

well as three other variations of background, distance and aging. Each image size is 360×480 pixel. For each subject, 9 cameras spaced equally in a horizontal semicircular shelf are setup to simultaneously capture images across different poses in one shot. Each subject is also asked to look up and down to capture 18 images in another two shots. It also considered 5 kinds of expressions, 6 kinds of accessories (3 glasses, and 3 caps), and 9 lighting directions.

In this work, we choose two libraries of CAS-PEAL database. One is the Expression library. Under environmental light mode, the volunteers were asked to show expressions of laugh, frowning, surprise, closing eyes and mouth *etc*., which cause great changes of facial Expression. The other one is the Lighting library. In the acquisition of illumination image library, nine cameras are working at the same time, resulting in 9 different facial images for each person.

5.2. Training set and test set configuration

We have a training set, test set and an outer test set which consist of faces from other database used to test false acceptance rate (FAR) and false rejection rate (FRR). For each database, we conduct several groups of tests with different training set, test set and outer test set selected. Take the Yale database as example, we choose 6 and 5 images for training and test set, respectively, with an order cycle from the 11 images per person. For the outer test set, we choose one image for each of 5 people in ORL database.

In Yale B library, we select 10 images for each of 38 persons, with 5 images per person for training and test set. In CAS Expression library, we choose 50 persons, each having 5 images, 3 in training set and 2 in test set. In Lighting library, we choose 50 persons, 9 images for each person, 5 for training and 4 for test set.

5.3. Parameter setting

Wavelet face recognition. In this part, we directly use the conclusion from multiresolution face recognition [3], *i.e*., db4 is chosen as the wavelet basis. For illumination database, the second level horizontal coefficients are chosen; and for expression changes, the third level approximation coefficients are chosen.

Gabor wavelet face recognition. We select the most widely used parameters and use the whole coefficients, *i.e*., $\sigma = 2\pi$, $k_{\max} = \pi/2$, $f = \sqrt{2}$ and $v \in \{0, 1, 2, 3, 4\}$, $u \in \{0, \ldots, 7\}$, where the selected values of v and u represent five scales and eight directions, respectively.

Curvelet face recognition. In our experiments, firstly the curvelet transform is performed for each face image, then the coarse, detail and fine coefficients are obtained. Then we use PCA on each layer, and record the recognition rates. The reconstructed images with each layer are shown in Fig. 3.

To see the coefficients at different directions, we arrange the coefficients of the second detail level into 8 groups; and by remaining one group and discarding other coefficients and then performing an inverse transform, we get the image at each direction relating to each group. Altogether we get 8 images at corresponding directions, as shown in Fig. 4. We can see that the images show the orientation selectivity of curvelet transform. To be more specific, the facial organs can be seen in the second and third images, while the outline can be seen in the sixth and seventh images.

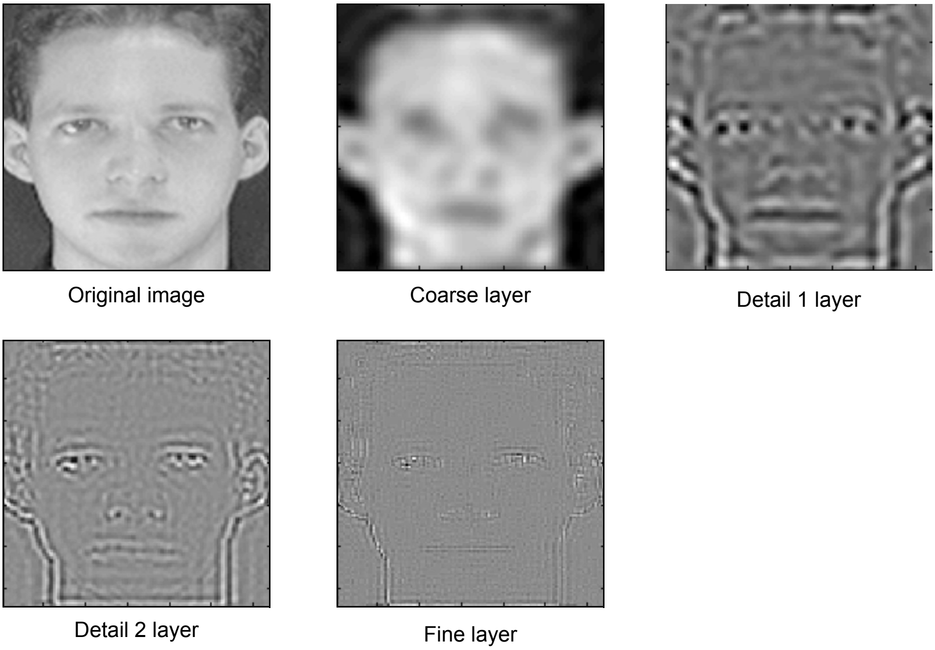

Fig. 3. Reconstructed image using different layers of curvelet coefficients.

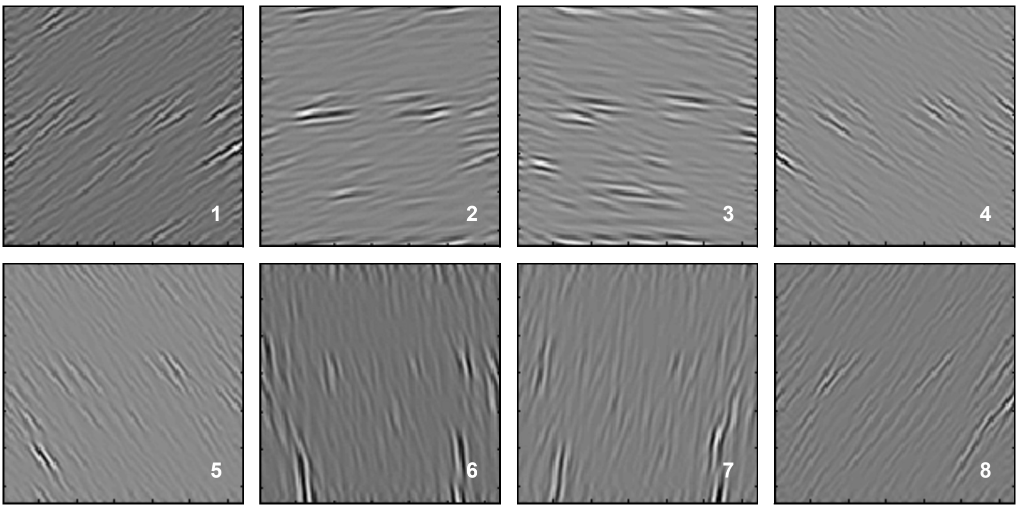

Fig. 4. Reconstructed images using 8 directions of detail 2.

5.4. Details of drawing ROC (receiver operating curve)

The ROC works with false acceptance rate (FAR) and false rejection rate (FRR). In order to get these values, we use a secondary database as outer database from which the faces other than the normal faces are drawn. For test on ORL database, we choose 10 persons each having 3 images from Yale database as outer dataset. For Yale database, we choose 5 persons each having 3 images from ORL database as outer dataset. In CAS Lighting and Expression database, we also choose another 10 different persons each having 3 images from the same database as outer dataset.

Since we use nearest neighbor classifier, the minimum distance between a test image, coming from either normal faces or alien faces, and all the training images are found; then we use a threshold distance to determine whether the test image is accepted or rejected. The threshold distance is determined by the following procedure: we first find the distances for all test images in normal faces to the training images, called inner distances; and then we find the distances for all test images in outer database to training images, called outer distances. In practical case, the maximum inner distance would be greater than the minimum outer distances, with exceptions when the features are best separated for inner database and outer database. Then we set the range of threshold distance to be the minimum outer distance to maximum inner distance. Figure 5 is one group of inner distances and outer distances for two algorithms.

5.5. Experiments on Expression database

In this part, we test the performance of the wavelet, Gabor and curvelet transform combined with PCA on ORL and CAS Expression databases under expression changes. For a group of tests, the results are similar and typical ROC curves of the experiment results are shown in Figs. 6 and 7. We can see that the properties of the coarse coefficients of curvelet and wavelet are very good, and they obtain high recognition rates. This means that the coarse layer of wavelet and curvelet both work fine under

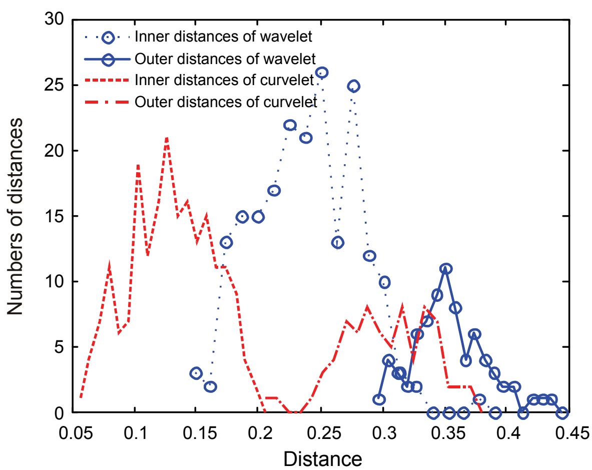

Fig. 5. One group of results of inner distances and outer distances for two algorithms.

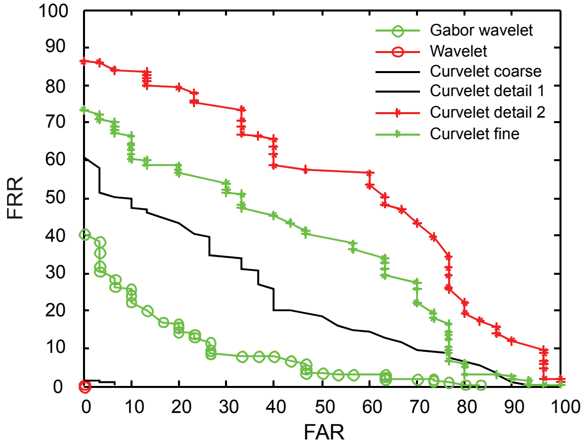

Fig. 6. The ROC curves of three algorithms under ORL database.

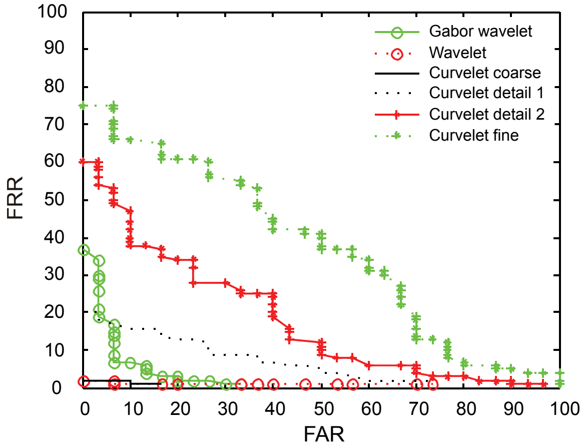

Fig. 7. The ROC curves of three algorithms under CAS Expression database.

expression changes. In fact, the coarse layer of curvelet is just Meyer wavelet, so the results are reasonable. The Gabor coefficients, and also details and fine layer of curvelet are not so good, which shows that the orientation selection is not suitable in this case.

5.6. Experiments on Lighting library

In this experiment, we perform the same procedures on CAS Lighting database under illumination changes. The ROC curves are shown in Fig. 8. It can be seen that the coarse coefficients of curvelet work badly, but the detail coefficients of curvelet and the high frequency of wavelet work fine with PCA, which verifies that illumination change mainly affects the low frequency subband of curvelet. The detail coefficients are robust against facial illumination change. At the same time, we also find that

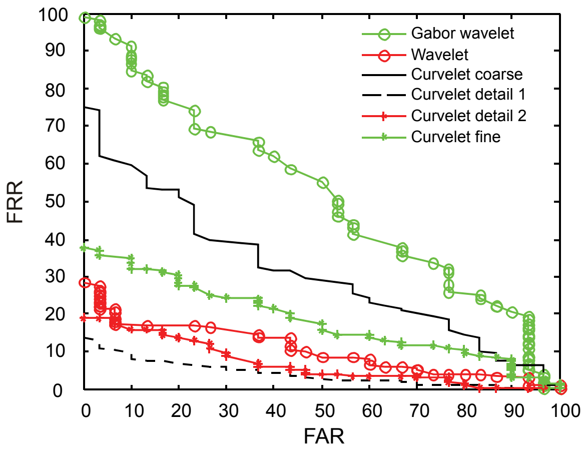

Fig. 8. The ROC curves of three algorithms under CAS Lighting database.

the performance of Gabor wavelet is poor, which shows the serious influence to Gabor wavelet by lighting changes.

5.7. Experiments on Expression and Lighting library

The Yale face database includes both lighting and expression changes, on which the ROC curves of the three methods are shown in Fig. 9. In this experiment, we choose the second level horizontal high frequency coefficients of wavelet.

We find that Gabor wavelet still keeps the worst, and intermediate and high frequency coefficients of curvelet are better relative to the other methods. The recognition rates by details and fine coefficients of curvelet are higher than that by the high frequency coefficients of wavelet. So when lighting and expression change simultaneously, we should select the detail 1 layer of curvelet.

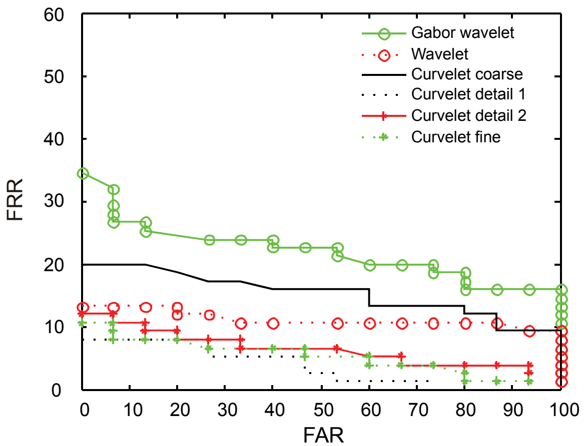

Fig. 9. The ROC curves of three algorithms under Yale database.

6. Conclusions

In this paper, we did a comparison of wavelet, Gabor wavelet and curvelet transform for face recognition under illumination and expression changes, and searched for the best subband irrelevant to these changes. We can conclude that for expression changes, the properties of the coarse coefficients of curvelet and wavelet are very good, because the expression change mainly affects detail coefficients. Also, the low frequency parts of the two methods are similarly influenced in presence of illumination changes, but the detail coefficients of curvelet and the high frequency of wavelet work fine with PCA. Meanwhile, we find that the detail layer of curvelet works better than the best wavelet subband. The Gabor wavelet is by no means the best method in our comparison. For both expression and illumination changes, the detail layer of curvelet is better relative to the other methods. Therefore, in practical application, curvelet is a better choice compared with wavelet and Gabor wavelet.

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