Multiband and Spectral Eigenfaces for Face Recognition in Hyperspectral Images

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ABSTRACT

Spectral reflectance properties of local facial regions have been shown to be useful discriminants for face recognition. To evaluate the performance of spectral signature methods versus purely spatial methods, face recognition tests are conducted using the eigenface method for single-band images extracted from the hyperspectral images. This is the first such comparison based on the same dataset. Selected sets of bands as well as PCA transformed bands are also used for face recognition evaluation with individual band processed separately. A new spectral eigenface method which preserves both spatial and spectral features is proposed. All algorithms based on spectral and/or spatial features are evaluated under the same framework and are compared in terms of accuracy and computational efficiency.

Keywords: face recognition, hyperspectral image, spectral eigenface

1. INTRODUCTION

Most current face recognition systems discriminate human faces using distinctive geometric facial features of each human being.[1–3] Many of them have performed well on large databases acquired using controlled indoor settings.[4] However, these systems tend to perform poorly where there are face orientation changes. One study,[5] for example, showed that there is significant degradation in recognition rate for images of faces that are rotated more than 32° from the frontal image that is used to train the system. Many researchers have proposed methods for accurate face recognition which is more robust to face orientation.[6–8] Most recently, a 3D morphable face model has been used for face identification across different poses.[9] This approach has provided promising performance on a 68 subject dataset. However, this system is currently computationally intensive and requires considerable manual intervention. Unknown illumination has also been an important factor for performance degradation. Systems based on spatial discriminants have been surprisingly successful for face recognition under different indoor illumination conditions.[10] However, the verification rate of the best recogntion systems can drop as much as 40% under unknown outdoor illumination.[10] Algorithms based on spatial features may also have subpar performances when there is patial face occlusion or imaging time delay between the taget image and the test image to be identified.

Some of the above limitations, like pose and illumination variation, can be overcome by spectral information based methods. Spectroscopy has been a valuable tool for a large number of applications. In remote sensing, researchers have used hyperspectral data for effective material identification in scenes where other sensing modalities are ineffective.[11] As hyperspectral imaging systems have become economically available, computational methods developed initially for remote sensing problems have been transferred to other areas like biomedical applications[12] and food industry.[13] Spectral properties of human face have also emerged as useful information for accurate face recognition. Based on a dataset of 200 human subjects, the spectral face recognition method,[14] which only utilizes a few local reflectance spectra for discrimination, performs surprisingly well for front-view face images of variant facial expressions. Unlike the geometric feature based methods, the reflective spectral property of human tissues is largely invariant to face orientation. It was shown that good recognition rate is

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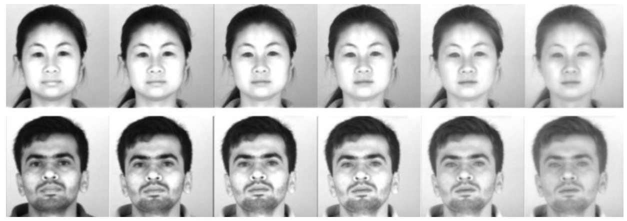

Figure 1. Selected single-band images of two subjects

achieved for faces rotated up to 90°. This pose invariance performance is superior compared to other methods which are not based on 3D models.

Evaluation of different face recognition algorithms using a common dataset has been of general interests. It provides a solid statistical basis to draw reasonable conclusion on different methods which were developed with datasets that varies in database size, image resolution and ethnic composition. The Face Recognition Technology (FERET) program[4] and the Face Recognition Vendor Test (FRVT)[10] are two largest evaluation programs which provide independent government evaluations for various face recognitions algorithms and commercially available facial recognition systems. As hyperspectral imaging is a completely different from the normal digital imaging in visible spectral range, it is unlikely to evaluate the performance of spectral signature methods using existing normal digital image datasets like in FERET and FRVT.

The CSU Face Identification Evaluation System[15] provides a standard set of well known algorithms and established experimental protocols which can be applied to various datasets. It supplies a solid platform for the evaluation of face recognition methods in hyperspectral images. In this work, single-band images are extracted from hyperspectral images with multiple bands. Evaluation process based on eigenfaces[16] is performed for each individual band, as well as selected multiple bands without inter-band constraints. A new multiband algorithm based on spectral eigenfaces is also proposed to improve face recognition performance in hyperspectral images. The new algorithm adds inter-band constraints to existing spatial features. The spectral eigen face method is compared with single- and multiple-band algorithms in accuracy and computational complexity.

2. FACE RECOGNITION IN SINGLE-BAND IMAGES

Hyperspectral imaging provides full spectral information, normally in radiance or reflectance, for each pixel in the image. That is, in the spectral domain, there are a series of values for each pixel corresponding to different wavelength within certain spectral range. The reflectance spectra of one material remain rather constantly in different images while different materials exhibit distinctive reflective properties due to different absorbing and scattering characteristics for lights at certain wavelength. The reflectance spectrum is also called the hyperspectral signature as it is a unique feature for each material. In the spatial domain, there is one gray scale image, a band, which represents the hyperspectral imager responses of all pixels around certain central wavelength with a narrow spectral response function. In previous study,[14] seven hyperspectral face images were collected for each of the 200 human subjects. These images have a spatial resolution of 468×494 and 31 bands for each 0.01μm over the near-infrared (0.7μm-1.0μm). Figure 1 shows calibrated hyperspectral face images of two subjects at seven selected bands which are sampled at each 0.06μm over 0.7μm-1.0μm. We can see that the ratio of pixel values on skin or hair between different bands are dissimilar for the two subjects. That is, they have unique hyperspectral signatures for each tissue type. Based on these spectral signatures, a Mahalanobis distance based method was applied for face recognition tests and excellent face recognition rates were achieved, especially for front-view faces. However, the performance evaluation is yet to be explored by comparing it with classic face recognition methods based on the same dataset.

To implement the performance evaluation of face recognition based on spectral signatures, the CSU Face Identification Evaluation System[15] is selected for the user friendly interface for data transformation. It provides a standard set of well known algorithms and established experimental protocols, along with support of various platforms. We selected the Principle Components Analysis (PCA), a.k.a Eigenfaces,[16] algorithm and used

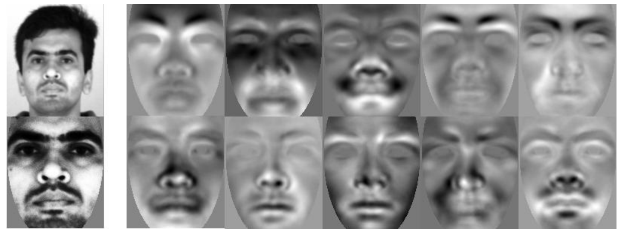

Figure 2. Example of eigenfaces in one single-band

cumulative match scores in FERET study[4] for the performance comparison. To prepare for the face recognition tests, a gray scale image was extracted for each of the 31 bands from a hyperspectral image. The gray scale images were resampled to 234×247 to suppress photon noises of the camera. The coordinates of both eyes were manually positioned before processed by CSU evaluation programs. In the CSU evaluation system all images were transformed and normalized so that they have fixed spatial resolution at 130×150 and the eye coordinates are the same. The images were also applied with an ellipse mask to void non-facial features. Histogram equalization was also completed for all images before face recognition tests in the evaluation system. For each of the 200 human subjects tested, there are three front-view images with the first two (fg and fa) in neutral expression and another (fb) in happiness. All 600 images were used to generate the eigenfaces. Figure 2 shows one sample single-band image before and after the normalization, and the first 10 eigenfaces of the dataset. The number of eigenfaces used for face recognition was determined by selecting the significant eigenfaces which accounts for 90% of total energy.

For the w^{th} band image of of hyperspectral images $\mathbf{u}$ and $\mathbf{v}$, the Mahalanobis Cosine distance[17] is used to match two images. Assume $u_{w,i}$ is the projection of the w^{th} band of $\mathbf{u}$ onto the i^{th} eigenface, and $\sigma_{w,i}$ is the standard variation of projections from all w^{th} band images onto the i^{th} eigenface. Denote $\mathbf{u}_w = (u_{w,1}, u_{w,2}, \cdots, u_{w,I})$, we have the Mahalanobis projection of $\mathbf{u}_w$ as $\mathbf{m}_w = (m_{w,1}, m_{w,2}, \cdots, m_{w,I})$ where $m_{w,i} = u_{w,i}/\sigma_{w,i}$. Similarly, $\mathbf{n}_w$ is the Mahalanobis projection of $\mathbf{v}_w$. Consequently, the Mahalanobis Cosine distance between $\mathbf{u}$ and $\mathbf{v}$ at the w^{th} band is defined as

$$D_{\mathbf{u},\mathbf{v}}(w) = -\frac{\mathbf{m}_w \cdot \mathbf{n}_w}{|\mathbf{m}_w||\mathbf{n}_w|} \tag{1}$$

which is essentially the negative of cosine function between two vectors. Obviously the distance increases from -1 for identical match to 1 for opposite match. For all 200 subjects, the fg images were grouped in the *gallery* set and the fa and fb images were used as *probes.*[4] Note the experiments follow the *closed universe* model where the subject in every image in the probe set is included in the gallery. For each probe image, the Mahalanobis Cosine distances between it and all gallery images were calculated and sorted. If the subject intended to identify is included in the group of gallery images with the N shortest distances, we call the probe is correctly matched in top N. In ideal situation where N equals one, the probe is perfectly recognized. The cumulative match score is defined as the percentage of correct matches from all probes. Specifically, the cumulative match score in top 1 is noted as the recognition rate in this work. Figure 3 shows the cumulative match scores of all 31 bands in top 1, top 5 and top 10 matches respectively. Here band 1 stands for the image sampled at 700 nm and band 31 stands for 1000 nm. It is shown that all bands have constantly high recognition rates, with more than 96% of the probes correctly identified as top 1 and over 99% in top 10. It is also observed that there are slight degradation at top 1 matches for bands approaching 700 nm or 1000 nm. This is mainly caused by lower SNR and defocus of the camera within those spectral ranges. Figure 4 compares the cumulative match scores of the spectral signature method and the best of single-band eigenface method. We can see that the spectral signature method performs very well but somewhat worse than the best of single-band method for matches within top 8. The advantage of spectral methods in pose invariant recognition was discussed in previous work but not the main interest of this paper.

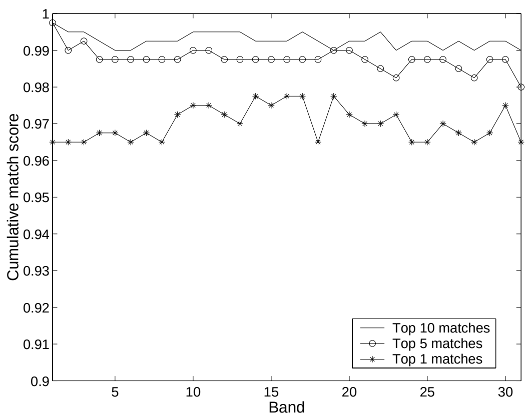

Figure 3. Cumulative match scores of single-band images at different wavelengths

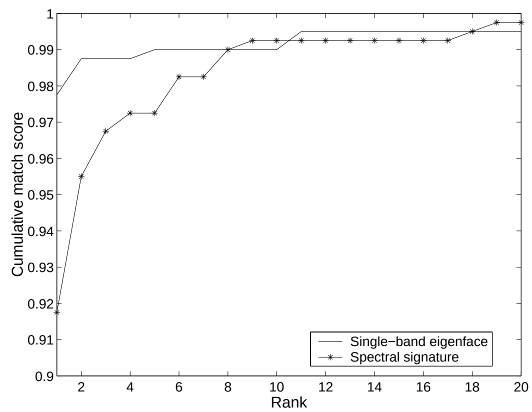

Figure 4. Cumulative match scores of spectral signature method and the best of single-band eigenface method

3. FACE RECOGNITION IN MULTIBAND IMAGES

It has been shown that both spatial and spectral features in hyperspectral face images are good discriminants for accurate recognition. It is an immediate interest to see the extent of performance improvements when both features are utilized. An intuitive solution to combine both features would be defining distance between images $\mathbf{u}$ and $\mathbf{v}$ based on multiple bands. We now define the new distance as

$$\mathbf{D}_{\mathbf{u},\mathbf{v}} = \sqrt{\sum_{w=1}^{W} (1 + D_{\mathbf{u},\mathbf{v}}(w))^2} \tag{2}$$

where w takes values from a group of W selected bands. Note the additive of 1 is to ensure a positive sum before the square.

From figure 1 we can see that the spatial features from different bands are normally correlated. The spectral redundancy can be removed by Principle Component Transformation (PCT).[18] For hyperspectral image $\mathbf{u} = (\mathbf{u}_1, \mathbf{u}_2, \cdots, \mathbf{u}_W)$, it is linearly transformed as $\mathbf{u}' = (\mathbf{u}'_1, \mathbf{u}'_2, \cdots, \mathbf{u}'_W)$, where $\mathbf{u}'_i = \sum_j \epsilon_{ij} \mathbf{u}_j$. The principle components $\mathbf{u}'_1, \mathbf{u}'_2, \cdots, \mathbf{u}'_W$ are orthogonal to each other and the total image variances are optimally redistributed among the components. The principle components are ordered descendingly for the amount of variances they accounts for. Figure 5 shows a sample single-band image at 700 nm and the first five principle components, which are all extracted or transformed from the same hyperspectral image. We can see that the first principle image resembles the single-band image most while the second and third highlight features of lips and eyes. It is also shown that, comparing with the original single-band image, there are few visible features left in the fourth and fifth principle components.

Figure 6 shows the recognition rates of different multiband eigenface methods. First we selected the bands in original ascending spectral order and completed eigenface recognition tests for the first one band, two bands and up to 31 bands respectively. We also sorted all 31 bands in descending order of recognition rate and finished

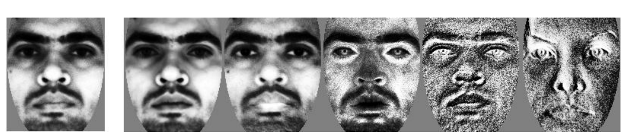

Figure 5. Five principle band images of one subject after PCT

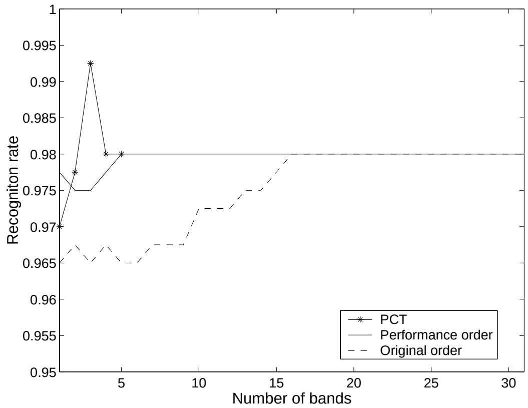

Figure 6. Recognition rate of multiband eigenface methods

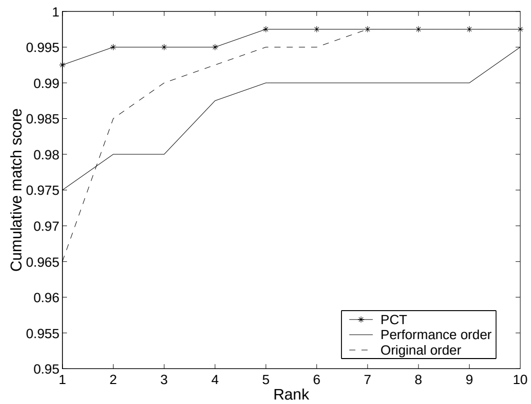

Figure 7. Cumulative match scores of multiband eigenface methods

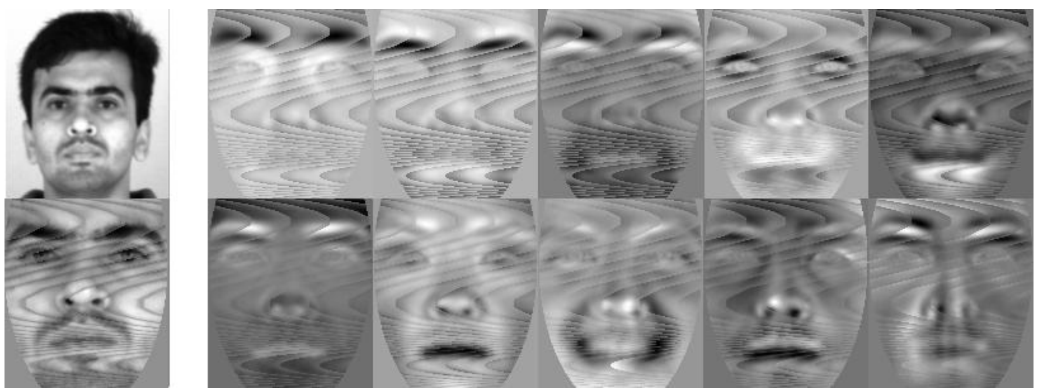

Figure 8. One sample spectral-face and the first 10 spectral eigenfaces

the same procedure for the face recognition tests. From figure 6 we can see that both methods reach highest recognition rate at 98% when more bands were used. However, when the number of bands is less than 16, the multiband method performs better if the bands were sorted in advance from the highest recognition rate to the lowest. We also used the first 5 principle components for multiband recognition. It is shown in figure 6 that over 99% of the probes were correctly recognized when using the first three principle bands together. Increasing number of principle bands after 3 causes performance degradation. Note that the PCT was performed on each hyperspectral image individually with different sets of ϵ_{ij}. It is possible to implement PCT using the same coefficients for faster computation but it is not covered in this paper.

Figure 7 also compares the recognition performance of three multiband methods dicussed in last paragraph. To maintain the same computation complexity for fair comparison, all three algorithms used the first three bands only. It is interesting to see that, comparing to original spectral order, sorting bands by performance in advance has better recognition rate at top 1 but somewhat performs worse when more matched candidates are considered. In either case, the multiband method based on PCT is the best. From the experiments we can see that multiband eigenface methods produce better recognition rates but there are substantially more computations required. The PCT based multiband method has the best performance with highest computation expense.

4. FACE RECOGNITION USING SPECTRAL EIGENFACES

It is shown in section 3 that multiband eigenface methods can significantly improve the front-view face recognition rates. In these algorithms, the multiple bands are processed independently without any constraint in the spectral

Figure 9. A sample image composed from 31 bands with low spatial resolution

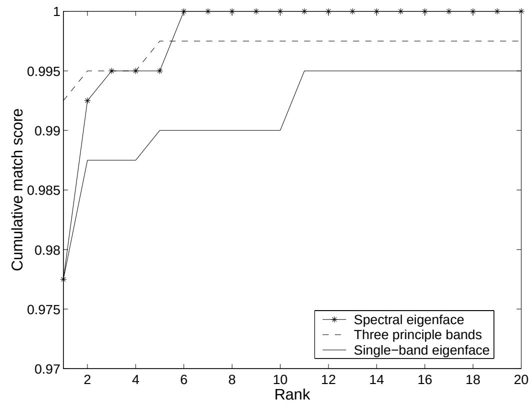

Figure 10. Comparison of spectral eigenface method with single-band and multiband methods

domain. A previous study[14] has shown that the spectral properties of different tissue types on the face are all useful discriminants. For multiband methods, the spectral ratio between different bands could provide additional discriminants between human faces. Composing a large image by laying 31 single-band images one by one is a simple solution to preserve spectral features. Note the composition needs to be done before quantization in single-band images to avoid removing spectral constraints. Using this method, the computation complexity of eigenvalue computation will be a concern since the spatial resolution is much higher. Resampling the single-band image to lower resolutions is one possible way to decrease computational expense. However some useful spatial features are also lost in the resampling process. Figure 9 shows an image containing 31 bands after resampling to approximately equal amount of pixels as a 130×150 single-band image. It is clear that a lot of detail spatial features missed after resampling.

A new multiband image, called spectral-face, is proposed to preserve both spectral and spatial properties. The spectral-face has the same spatial resolution as a single-band image so the spatial features are largely preserved. In spectral domain, the pixel values in the spectral-face are extracted sequentially from band 1 to band 31 then from band 1 again. For example, the value of pixel i in spectral-face equals to the value of pixel i in band w where w is the remainder of i divided by 31. Figure 8 shows an original single-band image together with the normalized spectral-face image in the left column. Note that for the normalization of spectra-face images there is no histogram equalization to prevent lose of spectral properties. It is clearly seen that the face has more spatial features in detail comparing with those in figure 9. And the recursive patterns on the face demonstrates the variation in spectral domain. With the normalized spectral-face images, the same eigenface technique is applied for face recognition. The first 10 spectral eigenfaces are shown in the right side of figure 8. It is interesting to observe that the eighth spectral eigenface highlights the teeth feature in smiling faces.

The spectral eigenface method was applied to the same dataset as previous single-band and multiband methods. The cumulative match scores of matches from top 1 to top 20 are shown in figure 10. The best of single-band methods, which is band 19 at 880 nm, is included for performance comparison with spectral eigenface method. It is shown that the spectral eigenface method has better performance for all matches from top 1 to top 20. The best of multiband methods, which combines the first three principle bands, is also compared. It has the highest recognition rates for the best two matches. However it has a miss beyond top 20 while the spectral eigenface method recognizes all probes within top 6. Also note that the multiple principle band method requires more computation tasks.

5. CONCLUSION

Previous work[14] has shown that spectral signatures are powerful discriminants for face recognition in hyperspectral images. Various methods utilizing spectral and/or spatial features were evaluated using one hyperspectral face image dataset. Previous method using local spectral properties has shown excellent results with least computation. The single-band eigenface method used spatial features exclusively and performed noticeably better than pure spectral method. However the computation task increases significantly for eigenfaces generation and projection. The recognition rate was further improved in multiband methods which demand more computation power. The best performance was achieved with the highest computation complexity when the first three principle bands were used together. To do this a hyperspectral image with 31 bands needs to be reduced to three principle bands using principle component transformation. The spectral eigenface method is proposed to solve the conflict between performance and speed. Before processing, it transforms a multiband hyperspectral image to a spectral-face image which samples from all bands recursively while preserves the spatial resolution. It was shown that it performs as well as PCT-based multiband method with much less computation complexity similar to single-band eigenface method.

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