Near Infrared Face Recognition Using Orientation-based Face Patterns

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Abstract: An orientation-based face recognition method is proposed and applied to near infrared images in this paper. Two algorithms, FPW (face pattern word) and FPB (face pattern byte), are derived from the orientation-based method. The FPW (or FPB) algorithm actually extracts the orientational information using a set of Gabor wavelet transforms, and uses Hamming distance (HD) for face identification. The bit code of orientations are optimized with respect to HD and put into a 32-bit word (FPW) or 8-bit byte (FPB). The performance is evaluated by face recognition rate and compared with three classical algorithms, PCA, LDA and EBGM (elastic bunch graph matching). Our experiments are conducted with a ASUNIR face database that currently consists of near infrared (NIR) images from 79 subjects. The experimental results show that the FPW algorithm achieves 98.43% of recognition rate; while the results of PCA, LDA and EBGM are 74.68%, 94.94% and 96.20%, respectively.

1 Introduction

Face recognition is a suitable technique for human identification and security applications especially at highly-populated sites (e.g., airports, borders). Face images can be acquired at a distance with less subject collaboration. On the other hand, fingerprint recognition and iris recognition requires closely contact to the imaging devices and much more collaborations from subjects. In the past two decades, visible face recognition has been sufficiently investigated. Some well known face recognition methods are Principal Component Analysis (PCA) [MP01], Linear Discriminant Analysis (LDA) [LPV03], Elastic Bunch Graph Matching (EBGM) [Wi97], and Local Binary Pattern (LBP) [BA10], [Xi10]. However, the performance of visible face recognition dramatically reduces down with poor illumination [SS02], [Be06]. The poor performance caused by illumination can be improved by using infrared or multispectral face images [GBM10].

The face recognition approaches using thermal (long wave infrared, LWIR) images or the fusion of thermal and visible images can improve the recognition performance. There is no illumination (lighting) requirement in thermal face imaging. Buddharaju *et al.*

[Bu07] proposed to localize the superficial vessel network using thermal images, and then to extract the branching points (referred to as thermal minutia points) from the vascular network as features for face recognition. Similar work was reported by Akhloufi and Bendada [Ak08], where the blood vessels were used as a thermal faceprint. Bebis *et al.* [Be06] suggested two fusion schemes for eigenface recognition, i.e., pixel-based and feature-based fusion of visible and thermal imagery. Arandjelovic *et al.* [AHC06] proposed a decision level fusion of visual and thermal images. Both experimental results [Be06], [AHC06] showed the improvement of using fusion, and meanwhile revealed a performance decrease when eyeglasses were present. Kong *et al.* [Ko05] concluded that thermal face recognition is especially useful for identifying faces under uncontrolled illumination conditions or for detecting disguises. Selinger *et al.* [SS01] claimed that thermal face imagery is superior to comparable visible imagery.

Near-infrared face recognition is another solution to improve the recognition performance although it requires proper illumination (lighting) condition. Zhao and Grigat [ZG05] proposed an automatic near infrared face recognition system with 12 IR-LEDs for illumination. The eyes were detected and then used for face detection. The DCT (discrete Cosine transform) and SVM (support vector machine) were employed for facial feature extraction and classification, respectively. The system performance depended on the accuracy of eyes detection, and a high recognition rate (96.15%) was achieved with manual eye localization. Li *et al.* [Li07] proposed an near infrared face recognition system equipped with 18 NIR LEDs and claimed their recognition process was illumination invariant. LBP features were extracted from NIR images, and LDA and AdaBoost were used as classifiers, respectively. They also proposed a solution for face and eye detection that could deal with the variations of illumination conditions and the eyeglasses conditions. Their methods were compared with other literature methods such as PCA and LDA. They found that LBP features plus AdaBoost classifier gave the highest verification rate (91.8%).

Multispectral face recognition or score fusion can further increase the system performance. Chang *et al.* [Ch08] demonstrated the image quality enhancement of fusing multispectral face images (e.g., visible and thermal) but did not report any recognition performance. Bendada *et al.* [BA10] compared several face recognition algorithms (PCA, LDA, etc.) by extracting the local binary pattern (LBP) and the local ternary pattern (LTP) from four-band face images (i.e., Visible, SWIR, MWIR, LWIR), and found that LDA algorithm performed the best on the Visible dataset (92%). No fusion results were presented in their work. In addition, the score-level fusion of multispectral face scores is an efficient approach due to the process of low dimensional data. A few of work were reported in score-level fusion for face recognition [Na08], [Zh11]. It is lack of comprehensive study and comparison in the area of multispectral face recognition. A part of the reason may be lack of publically available multispectral face database. We will discuss the multispectral face recognition in a separate paper in the near future.

In this paper, a set of orientation-based face patterns are formed by Gabor wavelet transforms and the orientation bit code optimized by Hamming distance, which are termed as face pattern word (FPW) and face pattern byte (FPB). The proposed methods are tested with an ASUNIR face database and compared with three classical methods including PCA, LDA, EBGM. This research work will be integrated into the framework of multispectral face recognition and score level fusion [Zh11] in the future. The rest of paper is organized as follows. The orientation-based face recognition algorithms (FPW, FPB) are described in Section 2. The experiments are conducted on a ASUNIR face database, and the results and discussions are presented in Section 3. Finally, the summary and conclusions are given in Section 4.

2 Orientation-based face recognition

A given face image is first preprocessed such as normalization, face detection and alignment [Zh10]. Gabor wavelet transform (GWT) is then performed to extract facial features from a face image, which are the binary bit code of maximal orientational responses. Multiple-band orientational codes are then put into a face pattern word (FPW) or a fce pattern byte (FPB) pixel-by-pixel. Next, Hamming distance (HD) [HBF09] is calculated with the extracted face patterns (FPW or FPB) to measure the similarities among faces, and identification is made with the shortest HD. For algorithm evaluation and comparison, the verification rate is computed after running a number of tests on a closed-set. A higher verification rate means a better recognition algorithm.

2.1 Face pattern word

A set of GWTs can be simply parameterized with M bands (frequencies or scales) by N orientations. For instance, 8×16 GWT means a set of GWTs at 8 bands (M=8) by 16 orientations (N=16). The 8×16 GWT produces 256 coefficients (128 magnitudes plus 128 phases) per pixel. We use the magnitudes of GWT coefficients to create our face patterns. A *face pattern word* (FPW) is formed pixel by pixel for each face. At each pixel, a 32-bit FPW is encoded according to the orientational magnitude strength at each frequency band. An example of FPW creation with 8×16 GWT is given as follows. At each frequency band (from 1 to 8), the index (0-15) of *maximal* magnitude among 16 orientations (0.00°, 11.25°, 22.50°, ..., 157.50°, 168.75) is encoded with 4 bits. The 4-bit orientational code is put into the FPW by the frequency order, i.e., the lowest (highest) frequency corresponds to the lowest (highest) 4 bits in the 32-bit FPW. Eventually, the FPWs come up with the same dimensions of the face image but with the depth of 32 bits. The FPWs are stored as feature vectors in the database, which will be compared with that of the probe face during the identification process. A FPW can be stored in a 32-bit double word as normally mentioned as 32-bit FPW (per pixel) in the context, but its valid dimension could be of 24 bits per pixel (for 8×8 GWT).

2.2 Face pattern byte

An 8-bit *face pattern bye* (FPB) is created for each pixel on a face image. First, at each pixel, an M-dimension vector, $\mathbf{V}_m$, is created to store the orientation code representing the orientational magnitude strength (O_{mn}) at each frequency (refer to Eq. (1a)). At each frequency band (from 1 to 8), the index (0-15) of *maximal* magnitude among 16 orientations is coded with 4 bits in order to maximize the orientation difference (among subjects in database). The 4-bit orientational code is first put into an 8-dimension vector ($\mathbf{V}_m$) by the frequency order, i.e., the lowest (highest) frequency corresponds to the lowest (highest) index of $\mathbf{V}_m$. A FPB is then formed with the most frequent orientations (called *mode*) among some bands (refer to Eqs. (1b-c)). Specifically, the high half-byte (the most significant 4 bits) in a FPB, FPB_{HHB}, is the mode of high 4 bands (m = 5~8); whereas FPB_{LHB} is the mode of low 4 bands (m = 1~4). $B_{\mathrm{FM}} = 1$ only when the frequency of mode, f_{M}, is greater than or equal to 2, otherwise $B_{\mathrm{FM}} = 0$ (see Eq. (1d)). The factor of B_{FM} will avoid choosing any orientation mode of as a pattern in FPB if its frequency is only 1. This could make FPB immunized from noise. It is clear that a FPB can code up to 16 orientations ($N \leq 16$) but there is no limit to bands (M). Typically 8 or 16 orientations are good for most applications.

$$\mathbf{V}_m = O^{\mathrm{BC}}[Index(Max(O_{mn}))], \tag{1a}$$

$$FPB_{\mathrm{LHB}} = Mode(\mathbf{V}_m|_{m=1\sim M/2}) \cdot B_{\mathrm{FM}}, \tag{1b}$$

$$FPB_{\mathrm{HHB}} = Mode(\mathbf{V}_m|_{m=M/2+1\sim M}) \cdot B_{\mathrm{FM}}, \tag{1c}$$

$$B_{\mathrm{FM}} = \begin{cases} 1, \text{if } f_{\mathrm{M}} \geq 2 \\ 0, \text{otherwise} \end{cases} \tag{1d}$$

where O_{mn} is the GWT magnitude at Frequency m and Orientation n; $m = 1\sim M$ and $n = 1\sim N$. The FPBs are stored as the feature vectors of the gallery faces in database, which will be compared with that of the probe face during the identification process. A FPB is usually stored in an 8-bit byte, but its valid dimension could be of either 8 bits per pixel (for 8×16 GWT) or 6 bits per pixel (for 8×8 GWT).

2.3 Variations of face patterns

Similar to FPB, a set of variant face patterns can be derived from FPW. For example, using the mode of 8-band FPW (the most common orientation among 8 frequency bands) can form a 4-bit face pattern nibble (FPN) [Zh11]. We will examine the performance of using the lower four-band FPW, or using the lower half byte (low frequencies) of FPB, or using the higher half byte (high frequencies) of FPB.

2.4 Orientation bit code

Because Hamming distance (HD) is computed by checking the bitwise difference between two face patterns (e.g., FPW), the orientational bit code should favor the HD calculation. The FPW is designed to reflect the orientational significance (or strength) along with frequency scales (locations). Therefore, the closer (neighboring) orientations should have less bitwise difference, whereas the further (orthogonal) orientations should have more bitwise difference. Notice the nature of that 180°-apart orientations (such as 0° and 180°, 45° and 225°) are actually same (i.e., circularly neighboring). Clearly, the "natural coding" does not favor the HD calculation because the bit-code difference (HD) between two neighboring orientations, 0 (“0000B”, in binary format) and 15 (“1111B”), is 4.

Two cost functions are defined in the following equations. A set of optimal bit code should minimize the HD of neighboring orientations (d_{nbr}^{BC}), meanwhile maximize the HD of orthogonal orientations (d_{oth}^{BC}).

$$d_{nbr}^{\mathrm{BC}} = \sum_{n=0}^{N-1}\left[d_{\mathrm{HD}}(O_n^{\mathrm{BC}}, O_{n-1}^{\mathrm{BC}}) + d_{\mathrm{HD}}(O_n^{\mathrm{BC}}, O_{n+1}^{\mathrm{BC}})\right], \tag{2a}$$

$$d_{oth}^{\mathrm{BC}} = \sum_{n=0}^{N-1}\left[d_{\mathrm{HD}}(O_n^{\mathrm{BC}}, O_{n+N/2}^{\mathrm{BC}})\right], \tag{2b}$$

where O_n^{BC} is the *bit code* (BC) at Orientation n, N is the total number of orientations. Keep in mind of the fact of circular neighboring. Thus, set $n = N$-1 when $n < 0$, and let $n = 0$ when $n > N$-1.

A set of optimal bit code should minimize the HD of neighboring orientations, meanwhile maximize the HD of orthogonal orientations. According to Eqs. (2), the solutions for $N = 8$ (d_{nbr}^{BC}=16 and d_{oth}^{BC}=16) and $N = 16$ (d_{nbr}^{BC}=32, d_{oth}^{BC}=64) are found as follows.

$$O_n^{\mathrm{BC}}|_{N=8}=\{110, 100, 000, 010, 011, 001, 101, 111\} \tag{3a}$$

$$O_n^{\mathrm{BC}}|_{N=16}=\{1110, 1010, 1000, 1100, 0100, 0110, 0010, 0000, 0001, 0101, 0111, 0011, 1011, 1001, 1101, 1111\} \tag{3b}$$

Examining Eq. (3b), any two neighboring bit code (including left and right neighbors; using the circular neighbors at two boundaries) has only one bit difference; while any two orthogonal bit code (e.g., 1st vs. 9th) has four bit difference.

(a) (b) (c)

Figure 1: Visualization of FPB (8×16): (a): One NIR face from ASUNIR database (320×320); (b) low half-byte of FPB features (low-frequency); and (c) high half-byte of FPB features (high-frequency).

We use the order statistics to create face patterns from GWT magnitudes, which can eliminate insignificant information (by considering the float-point numbers of GWT coefficients) but remain sufficient disparity for face identification. One sample face from the ASUNIR database is presented in Fig. 1a, and the extracted FPB features ($M = 8$, $N = 16$) are visualized as two images in Fig. 1b & c, where the colors correspond to 16 different orientations. The FPW features are not presented in this paper.

3 Experimental results and discussions

The experiments of NIR face recognition were conducted on an ASUNIR face database and evaluated by reporting verification rates. The "ASUNIR face database" currently consists of the NIR face images from 79 subjects (refer to Fig. 1a). The NIR images were captured indoors under proper illumination by a FLIR SC6000 near infrared camera (640×512 pixel original resolution; spectral range: 0.9~1.7µm). Three images per subject were randomly selected, one of which was used as a probe image (or the test image), two of which were used as the gallery images (or the training images). All face recognition algorithms (FPW, FPB, PCA, LDA, EBGM) were implemented and tested on the same database. Keep in mind that PCA and LDA require a training process, while EBGM, FPW, and FPB do not need any training.

All images were normalized, and the face portion was then detected and extracted. Notice that the size of an extracted face is usually smaller than the resolution of original image in database (refer to Fig. 1a). Next, all faces are automatically lined up. The general preparation processes (including normalization, face detection and alignment) can be found somewhere else [Zh11], [Zh10]. For each image, the face patterns (FPW, FPB) are created by GWT (8×8 or 8×16). The bit code given in Eq. (3a) and Eq. (3b) were used in the current experiments. All face patterns are then ANDed with the face mask (not presented in this paper but can be found in Reference [Zh10]). In other words, the facial features outside the face area are excluded during face matching. The HDs are finally computed and compared between the *probe* image and all *gallery* images in database. The *face verification rate* is the percentage of correctly identified images (or subjects) against the total number of images (subjects) in entire database.

To have fair comparisons, the three classical algorithms (PCA, LDA, and EBGM) were tested with the same ASUNIR database. Taking one image from each subject forms a test subset; and the rest two images form a train subset. PCA and LDA utilize Euclidean distance for face matching, while EBGM uses a similarity metric [Wi97] for face matching. The experimental results are presented in Table 1, where only the top-1 match (the shortest distance or the highest similarity) results were reported.

TABLE 1: The verification rates (%) of five face recognition algorithms tested on three databases (# subjects). FPW & FPB were formed with 8×16 GWT.

Database\Method	**FPW**	**FPB**	**PCA**	**LDA**	**EBGM**
ASUNIR (79)	*98.43*	97.25	74.68	94.94	96.20
ASUDC (96)	97.28	*97.92*	77.08	90.63	93.75
ASUIR (96)	93.06	*96.88*	67.61	91.67	93.75

From the results shown in Table 1, the FPW is the best recognition algorithm (98.43%), while The FPB is the second best (97.25%). The EBGM is the best one (96.20%) among three classical algorithms listed in Table 1. The LDA performs very well (94.94%) since two sample faces per subject are available in the training subset. The performance of PCA is the worst (74.68%).

In Table 1, the performance of five algorithms tested on other two databases are also listed (notice that FPW(8×16) using the "bit code" defined in Eq. (3b)). The ASUDC and ASUIR databases include 288 visible images and 288 thermal images from the same 96 subjects (3 images per subject), respectively (the details are given somewhere else [Zh11]). The 79 subjects in ASUNIR are the portion of 96 subjects in ASUDC and ASUIR. The FPB algorithm performed the best on these two databases. Over the three difference databases, the FPB algorithm has close performance, which demonstrates its reliability. Let us compare the performance of different databases. Overall, the NIR database results the best performance against the other two. Meanwhile notice the illumination requirement for NIR imaging.

The variations of FPW and FPB algorithms were tested on the same ASUNIR database and their results are shown in Table 2. The performance of FPW(8×16) is slightly better than that of FPW(8×8), while the FPB algorithm has the same performance under two parameters (i.e., reliable). FPW(subband_1) actually used the orientation features from Band 1 through Band 3, while FPW(subband_2) used the orientation features from Band 1 through Band 4. Surprisingly, FPW(subband_1) resulted a slightly higher recognition rate (98.82%) in comparison with FPW(8×16). FPB(subband_1) used the orientation features of the lower half byte (low frequencies), while FPB(subband_2) used the orientation features of the higher half byte (high frequencies). The performance of both FPB variations dropped down, and the FPB(subband_2) had a bigger decrease.

TABLE 2: The verification rates (%) of the variations of FPW & FPB algorithms tested on the ASUNIR database

Algor.\Param.	**8×16**	**8×8**	**Subband_1**	**Subband_2**
FPW	98.43	98.04	98.82	97.25
FPB	97.25	97.25	96.47	94.12

The FPB algorithm has a stable performance over different databases because it uses the most common orientation features (mode), which makes it less sensitive to noise. For the similar reason, using low-frequency features ("Subband_1" in Table 2) in FPW or FPB shows better performance since the high-frequency features are tend to be interfered by noise.

In the future we will test the proposed algorithms on a large database, and integrate the NIR face recognition into the framework of multispectral face recognition and score level fusion [Zh11]. Imagine a human identification system equipped with multispectral imaging devices (e.g., visible, NIR, LWIR) that works ideally under normal illumination condition at daytime (via 3-score fusion), and still functions properly at nighttime (with the inputs of a thermal imaging camera).

4 Conclusions

Two orientation-based face recognition algorithms are proposed and tested on a near infrared (NIR) face database, and their performance are compared with three classical algorithms, PCA, LDA, EGBM. Experimental results show that the FPW algorithm performs the best (98.43%) with the ASUNIR database. When comparing the recognition performance across three different databases, the ASUNIR database gives the best result, furthermore the FPB algorithm is relatively reliable. The most common orientations are used as FPB features, which makes the FPB algorithm immunized from noise interferences. The variations of the FPW and FPB algorithms are also explored. It must be realized that NIR imaging requires a certain level of illumination. Integrating the NIR face recognition into a framework of multispectral face recognition will have the potential to develop a robust human identification system. This will be part of our future research efforts.

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