An Evaluation of Gabor Orientation As a Feature for Face Recognition

Adams Kong
Forensics and Security Laboratory, School of Computer Engineering,
Nanyang Technological University, Singapore
adamskong@ieee.org

Abstract

Identifying a reliable feature is extremely important for all pattern recognition systems. The Gabor filter, which simultaneously captures spatial and frequency information, has been a vital component in numerous systems as a feature extractor. This filter produces three basic features — magnitude, phase, and orientation. Most face recognition methods based on Gabor filters use either the magnitude feature alone or a combination of the phase and magnitude features; very few are purely based on the phase feature, and the orientation feature is ignored. The aim of this paper is to evaluate these three basic features for face recognition using the FERET and AR face databases. The results show that the orientation feature is the most robust and distinctive feature, 20% and over 10% more accurate than the phase and magnitude features, respectively.

1. Introduction

The Gabor filter, which is derived from the uncertainty relation for information, can simultaneously capture spatial and frequency information to overcome the traditional signal representation in which a signal is represented either in the time domain or the frequency domain [1]. Originally, it was designed for one-dimensional signal decomposition. However, since the 1980s, it has been extensively used as a spatial and convolution filter motivated by research results in biological vision systems. Although the Gabor filter has been involved in a wide range of components for pattern recognition systems, its major application is feature extraction.

A Gabor filter is defined as

$$g_0(x,y)=\exp\{-\pi[x'^2 a^2+y'^2 b^2]\}\times\exp\{-2\pi i[u_0x'+v_0y']\} \quad (1)$$

where $x'=(x-x_0)\cos\alpha+(y-y_0)\sin\alpha$ and $y'=-(x-x_0)\sin\alpha+(y-y_0)\cos\alpha$ [2]. There are seven degrees of freedom in the two dimensional (2D) Gabor filter: (x_0, y_0) is the center of the filter in the spatial domain, $\omega_0=\sqrt{u_0^2+v_0^2}$ is the spatial frequency, $\tan^{-1}(v_0/u_0)$ is the relative orientation between the complex wave and the Gaussian function, a and b control the shape of the Gaussian function, and α is the orientation of the Gaussian function. Fig. 1 shows a Gabor filter. To eliminate brightness variations in images, the weight of the Gabor filter is modified to produce a zero direct current (DC) Gabor filter [3], which is defined as

$$g(x,y)=\exp\{-\pi[x^2a^2+y^2b^2]\}\times(\exp\{-2\pi i[u_0x+v_0y]\}-\exp(-\pi[u_o^2/a^2+v_0^2/b^2]) \quad (2)$$

It is worth emphasizing that the zero DC Gabor filter no longer reaches the infimum (greatest lower bound) of the uncertainty relation for information. In addition to DC components, researchers commonly normalize the power of the filter, i.e., $g_n=g/\|g\|$. Using this Gabor filter as a spatial filter for signal analysis, two basic Gabor features—phase and magnitude—can be defined as

$$P(I,g_n)=\tan^{-1}\frac{\int\int I(x,y)g_{ni}(x,y)dxdy}{\int\int I(x,y)g_{nr}(x,y)dxdy}, \quad (3)$$

$$M(I,g_n)=\sqrt{\left[\int\int I(x,y)g_{ni}(x,y)dxdy\right]^2+\left[\int\int I(x,y)g_{nr}(x,y)dxdy\right]^2}, \quad (4)$$

where I is an image and g_{nr} and g_{ni} represent the real and imaginary parts of a zero DC Gabor filter g_n. For convenience, g_n is used to denote $g_n(x, y)$. The same notation is employed for other symbols. If a bank of Gabor filters generally sharing the same parameters, except the parameter of orientation, α, is used, the orientation feature can be extracted. Mathematically, this feature extraction process can be represented as

$$\alpha_{\max}=\arg\max_{\alpha_i}(M(I,g_{n,\alpha_i})), \quad (5)$$

where g_{n,α_i} is a Gabor filter in the filter bank with parameter of orientation, α_i.

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In addition to these three basic features, the Gabor response, defined as $M(I, g_n)e^{P(I,g_n)}$, is used in many systems. It can be regarded as a combination of the phase and magnitude features. However, the focus of this paper is the three basic features, and therefore, the Gabor response is not evaluated.

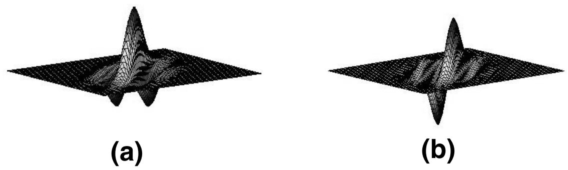

Fig. 1 (a) The real part and (b) the imaginary part of a Gabor filter

Among the basic features, the magnitude feature is the most popular for biometric technology. It has been applied to face, iris, and fingerprint systems. Compared with those of the magnitude feature, studies of the other two features — phase and orientation — are very limited. According to the best knowledge of the author, Daugman was the first who made use of the Gabor phase for personal identification. In 1993, he developed an iris recognition method, which is now referred to as IrisCode [4], based on coarsely quantized Gabor phases for iris representation. Recently, the relationship between IrisCode and clustering algorithms is discovered [5]. Because of Daugman's success, the author employed the Gabor phase for palmprint recognition in 2002 [6] and created a series of improved algorithms [7]. In 2007, Zhang et al. applied the phase feature to face recognition [10].

As compared with those of the phase feature, applications of the orientation feature are even more limited. The Competitive Code, developed in 2004, may be the only biometric algorithm purely based on the Gabor orientation [8]. However, an extensive study shows that the Gabor orientation is more effective than the Gabor phase for palmprint recognition [9]. Five studies [4-8] highlight the need for further investigation on the orientation feature for other biometrics.

The aim of this paper is to compare the orientation feature with the phase and magnitude features. Face recognition is selected for this evaluation because facial images possibly suffer from lighting variations and non-linear distortions (e.g., facial expression); therefore, the performance differences between the magnitude, phase, and orientation features under different image degradations can be analyzed. The unique contributions this paper makes include the following: 1) it is the first comparison of the Gabor phase, magnitude, and orientation features, and 2) it is the first attempt to use the orientation feature alone for face recognition [14]. The rest of this paper is organized as follows. Section 2 presents the details of this evaluation, including a face recognition algorithm and testing databases. Section 3 reports the experimental results, and section 4 provides concluding remarks.

2. Details of the evaluation

2.1. Databases

In this evaluation, two public face databases—FERET [11-12] and AR [13]—are employed. Two hundred subjects were randomly selected from the FERET database, and three images of each subject were chosen from sets fa, fb, and dup1. All the subjects in the AR database with eight images in sets 1 and 14-20 were selected. In total, 116 subjects were chosen from the AR database. The description of these data sets is provided in Table 1. More information about these data sets can be found in [11-13]. Images from set fa and set 1 are respectively considered as galleries for the FERET and AR databases, while the others are used as probes.

Table 1
Description of the testing data sets

Database	Data set	Facial expressions	Illumination conditions	Collection
FERET	fa	Neutral	Normal	First session
FERET	fb	Other expression	Normal	First session
FERET	dup1	Neutral and other expressions	Lighting variation	Different sessions
AR	1	Neutral	Normal	First session
AR	14	Neutral	Normal	Second session
AR	15	Smile	Normal	Second session
AR	16	Anger	Normal	Second session
AR	17	Scream	Normal	Second session
AR	18	Neutral	Left light on	Second session
AR	19	Neutral	Right light on	Second session
AR	20	Neutral	All sides' lights on	Second session

2.2 The algorithm for evaluation

Numerous face recognition methods based on the Gabor filter have been proposed. Some of them make use of complex preprocessing algorithms (e.g., three dimensional approaches) to eliminate lighting variations and distortions due to facial expressions, while others employ advanced classification techniques. To clearly observe the performance differences between these basic features under different image degradations, the author neither removes the lighting variations and distortions through preprocessing algorithms nor uses advanced classifiers.

The algorithm for this evaluation includes three components: preprocessing, feature extraction, and matching. The eye positions are manually located for alignment, and the aligned images are cropped and normalized to 128 x 128 preprocessed images. Figs. 2 and 3 show two sets of preprocessed images. Then, the preprocessed images are filtered by a bank of Gabor filters. Their parameters are $u_0 = 0$, b/a=2, $a = 1/6\sqrt{\pi}$, $\alpha_p \in \{0, \pi/6, \pi/3, \pi/2, 2\pi/3, 5\pi/6\}$, and $v_o = \frac{f_q\sqrt{2\pi}b}{6}$, where $f_q = \{0.5, 1.5, 2.5, 3.5, 4.5\}$. f_q is the number of cycles of the complex wave within 6 standard deviations in the y' direction. These parameters are partially based on physiological findings. Although the facial images are processed by a bank of Gabor filters, at each sample point, only the feature that is generated by the Gabor filter having maximum magnitude is used for matching. This feature selection scheme attempts to maximize the feature's stability. The number of Gabor filters can be reduced for real applications. However, the aim of this paper is to evaluate the features. Fig. 4 shows the extracted features.

For phase and orientation matching, a cosine measure defined as $\cos(\gamma_s(x,y) - \gamma_t(x,y))$, where $\gamma_s(x,y)$ and $\gamma_t(x,y)$ are either two phase or two orientation features from two different images at the same position (x, y), is used. If $\gamma_s(x,y)$ and $\gamma_t(x,y)$ are generated by two different Gabor filters, there is no reason to compare them. Therefore, the cosine measure for comparing two images is defined as $\sum_{(x,y)\in\Omega} \cos(\gamma_s(x,y), \gamma_t(x,y))/n$, where Ω is a set of points $\gamma_s(x,y)$ and $\gamma_t(x,y)$ from the same Gabor filter and n is the number of points in Ω. Similarly, a cosine measure defined as $\frac{\sum_{(x,y)\in\Omega} m_s(x,y) \times m_t(x,y)}{\sqrt{\sum_{(x,y)\in\Omega} m_s(x,y)^2}\sqrt{\sum_{(x,y)\in\Omega} m_t(x,y)^2}}$, where $m_s(x,y)$ and $m_t(x,y)$ are two magnitudes at position (x, y), is used to compare two image magnitudes. Although the eye positions are manually located, the alignment is still not perfect. One of the features is required to translate vertically and horizontally, and then, matching is performed again. Both the ranges of the vertical and the horizontal translation are –3 to 3. The maximum similarity obtained by translated matching is regarded as the final similarity measure. It should be emphasized that the feature vectors of magnitude, phase, and orientation have the same dimension; therefore, their performance differences are not due to the difference in dimensionality.

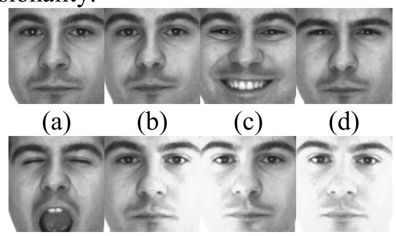

Fig. 2 Preprocessed images of the same subject from the AR database. (a)-(h) are respectively from sets 1 and 14-20.

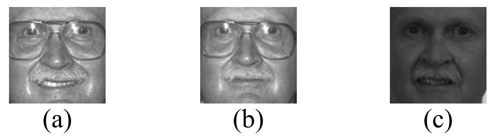

Fig. 3 Preprocessed images of the same subject from the FERET database. (a)-(c) are respectively from sets fa, fb, and dup1.

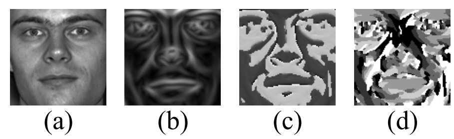

Fig. 4 An illustration of the extracted features: (a) original facial image, (b) magnitude feature, (c) phase feature, and (d) orientation feature.

3. Experimental results

Tables 2 and 3 list the recognition rates of the three features for the FERET and AR databases, respectively. The highest recognition rates in each row are highlighted. The last two columns in these two tables show the improvements of the orientation feature with respect to the magnitude and phase features. Table 4 summarizes their average performances. In addition to the tables, the cumulative match characteristic curves (CMC) for dup 1 of FERET are given in Fig. 5. Because of the page limit, other CMC curves cannot be included. These results clearly indicate that the orientation feature is the best for all the probe sets. The average improvements with respect to magnitude are 11% and 16% for the FERET and AR databases, respectively, and the average improvement with respect to phase is 20% for both databases. These results also show that the features react differently to distortions. The phase feature is very sensitive to facial expression, but robust to lighting variations, while the magnitude feature is sensitive to lighting variations, but robust to facial expression, and the orientation feature is robust to both.

Table 2 The recognition rates of the three features for the FERET database

Probe	Magnitude (M)	Phase (P)	Orientation (O)	Difference O-M	Difference O-P
fb	0.88	0.6950	0.9350	0.055	0.24
dup1	0.6150	0.6300	0.7800	0.165	0.15

Table 3 The recognition rates of the three features for the AR database

Probe	Magnitude (M)	Phase (P)	Orientation (O)	Difference O-M	Difference O-P
14	0.9310	0.9224	0.9828	0.0518	0.0604
15	0.5948	0.1293	0.6983	0.1035	0.569
16	0.8621	0.7155	0.9397	0.0776	0.2242
17	0.1983	0.1034	0.3362	0.1379	0.2328
18	0.8190	0.8362	0.9828	0.1638	0.1466
19	0.7155	0.8621	0.9655	0.25	0.1034
20	0.3534	0.6466	0.6983	0.3449	0.0517

Table 4 The average recognition rates of the three features in different data sets

Database	Magnitude (M)	Phase (P)	Orientation (O)	Difference O-M	Difference O-P
FERET	0.7475	0.6625	0.8575	0.11	0.195
AR	0.6392	0.6022	0.8005	0.1613	0.1983
Facial expression set (sets 15-17)	0.5517	0.3161	0.6581	0.1064	0.342
Lighting variation set (sets 18-20)	0.6293	0.7816	0.8822	0.2529	0.1006

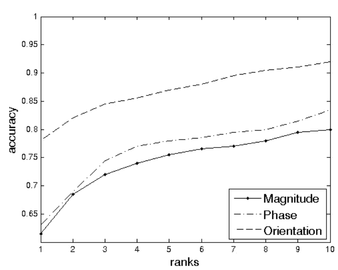

Fig. 5 Cumulative match characteristic curves for dup 1 of FERET

4. Conclusion

Using the Gabor filter as a feature extractor, three types of basic features — magnitude, phase, and orientation— can be obtained. Among these three features, the orientation feature draws the least attention. Because of the success of using the orientation feature for palmprint recognition [8-9], in this paper, it is evaluated for face recognition. Using the FERET and AR face databases as testing data, the experimental results clearly show that the orientation feature performs much better than both the magnitude and phase features. It provides 20% and over 11% improvements with respect to the phase and magnitude features, respectively. Although this paper and previous studies [8-9] have demonstrated the potential of the orientation feature, its recognition power is still far from being fully explored. However, other methods that can extract orientation fields of images may perform better than Gabor filters. Further investigation of orientation features is thus essential.

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