模式识别研究进展

——2007年全国模式识别学术会议论文集

■模式识别国家重点实验室 编

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2007 年全国模式识别学术会议

Chinese Conference on Pattern Recognition (CCPR2007)

2007 年 12 月 11 日~12 日　北京

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前 言

模式识别(Pattern Recognition)是对感知信号(图像、视频、声音等)进行分析，对其中的物体对象或行为进行判别和解释的过程。模式识别能力普遍存在于人和动物的认知系统，是人和动物获取外部环境知识并与环境进行交互的重要基础。研究模式识别的理论和方法，使计算机实现人的视觉、听觉信息处理等模式识别能力，对智能机器的研制、智能人机交互、信息有效利用、人类健康和社会安全等具有重要的意义。

20 世纪 60 年代以来，模式识别研究和应用取得了巨大的进展。1966 年，IBM 和 IEEE 组织召开了第一个以“模式识别”为题的学术会议；1972 年，第一次国际模式识别大会召开；1974 年，国际模式识别协会(IAPR)开始筹建并于 1978 年正式成立。这些活动极大地推动了模式识别领域的发展。我国学者从 20 世纪 70 年代初开始模式识别研究。1981 年，中国自动化学会成立模式识别与机器智能(PRMI)专业委员会。作为 IAPR 的成员组织，PRMI 委员会自成立以来陆续主办了全国性模式识别学术会议十多次，并与其他学会协办全国及国际性含模式识别内容的各类会议三十余次和模式识别类的全国竞赛两次，有力地推动了国内模式识别学科的发展和与国际学术界的交流。近年来，模式识别的很多技术在国民经济、国家安全和社会生活中得到了成功的应用和推广，一些新的理论和方法在学术界受到了广泛的关注。同时，应用需求不断地提出新的技术问题，从而推动模式识别理论与方法的进一步发展。

为了进一步促进模式识别研究的快速发展，加强国内外同行间的学术交流与合作，由中国自动化学会和中国科学院自动化研究所主办、中国自动化学会模式识别与机器智能专业委员会和模式识别国家重点实验室共同承办，在北京召开 2007 年全国模式识别学术会议(Chinese Conference on Pattern Recognition, CCPR2007)。会议向国内外同行征集有关模式识别理论方法研究和应用技术开发的学术论文，并邀请国内外知名专家做特邀报告。本次会议自 2007 年 8 月发布征文通知到 9 月 23 日截稿，在较短的征文时间里共收到 117 篇投稿。会议程序委员会委员和部分其他专家应邀对论文进行评审，每篇论文指定 3 名评审专家。在综合专家评审意见的基础上，有 57 篇论文被接收到本次会议上发表。这 57 篇论文的方向分布如下：模式识别基础(分类与学习)10 篇，计算机视觉与图像分析 15 篇，生物特征与生物信号处理 11 篇，文字识别 7 篇，语音和语言处理 5 篇，模式识别和视觉应用 9 篇。

我们热忱欢迎参加本次会议的各地专家和代表，并预祝会议取得圆满成功。

2007 年全国模式识别学术会议
名誉主席：戴汝为
大会主席：马颂德，T.S. Huang
程序委员会主席：张钹，谭铁牛

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第一部分

模式分类与机器学习

A Feature Extraction Method Based on Phase Information for Face Recognition

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Abstract: *The illumination changes are one of the main limitations on the applications of facial recognition techniques because the performance can be severely degraded by the illumination interference due to the self shadowing and specular reflections. In this paper, a new illumination invariant face recognition method is proposed to cope with the challenge of illumination variations based on phase information. It is developed on a recent method called phase congruency, which can extract the illumination free features regardless of its image intensity and contrast. Experiments using CMU-PIE face database with small training samples have shown that the proposed method outperforms the tradition PCA and Eigenphase method.*

Keywords: *Face recognition, feature extraction, phase congruency, PCA, Eigenphase*

一种基于相位信息的人脸特征提取

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摘 要： 光照问题会显著地降低人脸识别效果，是人脸识别系统应用应当解决的一个技术难题。在本文中，我们提出了一种基于相位信息的人脸特征提取算法，该算法具有对光照变化的鲁棒性。主要是采用最近一种新的相位一致性方法，该方法具有提取光照不变的特性，而不考虑图象的灰度大小和差别。在 CMU-PIE 数据库中采用小样本进行的实验表明，该提取方法传统的 PCA，Eigenphase 等方法要好。

关键词： 人脸识别，特征提取，相位一致性，主成分分析

1 Introduction

Face recognition has been an active research area in the past two decades, arising from the demand of surveillance, access control, and so on. As far, face recognition performs well under controlled environment, in other words, that target is presented with frontal view, normal illumination, and slight pose change. Under such conditions, the recognition performance can achieve as high as 99%. However when it is exposed to complex scenario with respect to illumination, expression, and pose variation, the recognition accuracy can decrease sharply [12]. In an attempt to eliminate the impact of illumination changes, Fisherface[13] and 3D linear subspace[14] are proposed which are proved to be effective. However, the limitation is that those algorithms often require more training images to eliminate the variation of faces caused by the illumination changes. Besides, the 3D algorithm is a little complex to implement. Those algorithms are generally operate in the space domain.

Recently, many attentions have been paid to the frequency domain where a face image can be represented either as magnitude or phase spectrum. It is proved that phase spectrum can not only enhance the performance of speech recognition [4, 5], but also improve the recognition accuracy of faces under various illumination changes [6]. However, PCA performed in the whole frequency domain gains no advantage over PCA in the spatial domain in terms of the relationship between the eigenvectors in frequency domain and spatial domain [6]. It is reasonable to build model of phase spectrum by reconstructing the phase information. As a consequence, such kind of structural model likely yields an effective method which can eliminate the impact brought by illumination. However, partial information will be lost in the reconstruction of phase image. We proceed to the adoption of algorithm which can capture the phase image without reconstruction process.

Phase congruency [1, 7] is a dimensionless quantity that is invariant with respect to image intensity change and contrast. As a substitute of gradient-based feature detector, such characteristic could be applied to any image to preserve the feature points regardless of its magnification and illumination. Compared with edge-map based face recognition methods, such as Eigenedge or Eigenhill [8] that need to set a predefined threshold, the extraction of edges and corners using phase congruency without threshold is a promising favorable choice. Previous work on iris recognition [9, 10] has already demonstrated the effectiveness of the phase congruency in segmentation and feature extraction. In [15, 16], phase congruency is combined with gabor wavelets to detect the salient local features in face recognition to reduce the high dimensions. We argue that the extraction of illumination free features by phase congruency is much better than the Eigenphase, as the proposed algorithm contains more information which can facilitate the recognition process without reconstruction. First, the image is computed by phase congruency based on log gabor filters to extract the illumination robust features. Then, the PCA is adopted to reduce the feature dimensions before being forwarded to a classifier using Euclidean distance. Our focus lies in the application of phase congruency in the extraction of illumination invariant features for face recognition.

The remainder of our paper is arranged as follows, section 2 describes the related work. The proposed new algorithm is detail illustrated in section 3. Following experiment is shown in section 4. Finally, conclusion together with future investigation is drawn in section 5.

2 Related Works

2.1 The Phase-only Reconstruction

Given a face image and its Fourier representation,

$$A(x) = |A(x)| \exp(i * \phi(x)) \tag{1}$$

where $A(x)$ is the magnitude spectrum, and $\phi(x)$ is the phase spectrum. By setting $|A(x)|$ to unit 1, $A(x)$ is represented as phase only,

$$A(x) = \exp(i * \phi(x)) \tag{2}$$

Then by inverse Fourier transform of A(x),

$$A_{IFFT}(x) = IFFT(A(x)) \tag{3}$$

Thus we get the reconstruction result exclusively obtained from the phase spectrum. As we stated before, the phase information contains more features which could be utilized to model the feature representation. To demonstrate the effectiveness of phase information, we reconstruct the image by using magnitude and phase information, respectively. This can be evidenced in the [Fig. 1]. The

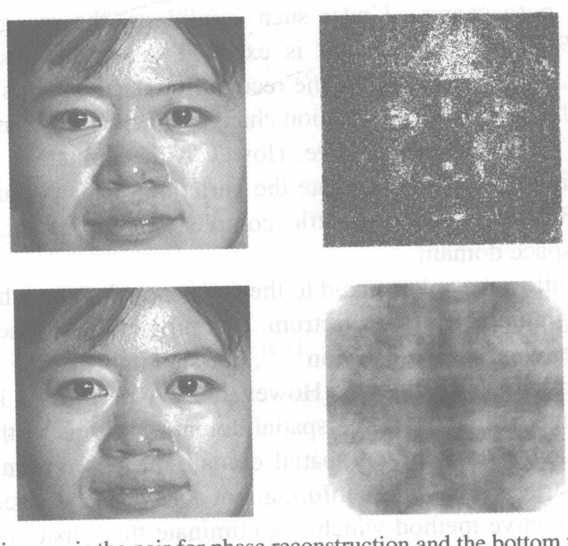

Figure 1 The top two images is the pair for phase reconstruction and the bottom two images is the pair for magnitude reconstruction

reconstructed image using phase contains origin structure. In contrast, the image which is reconstructed by magnitude loses the big picture. Moreover, the phase information is also a good candidate for the illumination robust feature extraction. We will present the ideas in the later experiment analysis.

2.2 Eigenphase

M. Savvieds et.al.[6] propose a new algorithm called eigenphase utilizing the phase spectrum with the aim of extracting illumination free features. First they constructed the phase-only representation image using the equation (1) and (2). And after the extraction of the desired features, tradition PCA technology is applied on the reconstructed image. The main different between the Eigenphase and Eigenface is the obtaining of covariance matrix.

$$COV_s = \sum_{i=1}^{N} \{(x-m)\}\{(x-m)\}' \tag{4}$$

$$COV_f = \sum_{i=1}^{N} \{F_{DFT}(x-m)\}\{F_{DFT}(x-m)\}' \tag{5}$$

Where COV_s and COV_f represent the covariance matrix in the space and frequency domain respectively. The F_{DFT} is the Fourier basic vectors used to transform the x. And the relationship between the eigenvector in space and frequency domain is as follows,

$$v_s = F_{DFT}^{-1} v_f \tag{6}$$

Where v_s refers to the eigenvector in the space domain and v_f in the frequency domain.

3 Proposed Algorithm

3.1 Phase Congruency and Local Energy Model

Morrone et al [1] first define the phase congruency function in terms of Fourier series expansion at location x.

$$PC(x) = \max_{\bar{\phi}(x)\in[0,2\pi]} \frac{\sum_n A_n \cos(\phi_n(x) - \bar{\phi}(x))}{\sum_n A_n} \tag{7}$$

Where A_n represents the nth amplitude of Fourier component, $\phi_n(x)$ is the corresponding local phase at x, and $\bar{\phi}(x)$ is the amplitude weighted mean local phase angle of the whole flourier terms at the corresponding location. $PC(x)$ aims to find a $\phi(x)$ which can maximize itself.

As it denotes, $PC(x)$ is really an awkward quantity to calculate. Alternatively, Venkatesh and Owens [2] shows that phase congruency can be found through the searching of the local energy peak.

$$E(x) = \sqrt{H(x)^2 + I(x)^2} \tag{8}$$

Where $H(x)$ is the Hilbert transform of $I(x)$, i.e. $H(x)$ is the 90° phase shift of $I(x)$. As it can be deferred from the figure, $E(x)$ equals to the $PC(x)$ scaled by the sum of whole frequent components.

$$E(x) = \sum A_n(x) PC(x) \tag{9}$$

$E(x)$ can be calculated by convolving with even and odd filters.

3.2 The New measure of Phase Congruency

In this section, we will use the 2D log-gabor filter to compute the phase congruency. Logarithm gabor function, suggested by Field [3], it comprises two components, namely the radial filter component and angular filter component.

The radial filter:

$$S(\omega)=\exp\left(\frac{-(\lg(\omega/\omega_o))^2}{2(\lg(k/\omega_o))^2}\right) \quad (10)$$

where ω_o is the filter's center frequency. To obtain the constant-shape ratio filters the term k/ω_o must also held to be constant for varying ω_o.

The angular filter:

$$S(\theta)=\exp\left(\frac{-(\theta-\theta_0)^2}{2T(\Delta\theta)^2}\right) \quad (11)$$

Where θ_0 denotes the orientation, $\Delta\theta$ is the orientation spacing between filters, and T is the scaling factor.

Similarly, let I denote the image signal, M_{so}^e and M_{so}^o denote the even-symmetric (cosine) and old-symmetric (sine) at scale S and orientation O respectively.

$$e_{so}(x)=I(x)*M_{so}^e \quad (12)$$

$$o_{so}(x)=I(x)*M_{so}^o \quad (13)$$

$$A_{so}(x)=\sqrt{e_{so}(x)^2+o_{so}(x)^2} \quad (14)$$

And its phase is calculated by

$$\phi_{so}(x)=a\tan 2(e_{so}(x),o_{so}(x)). \quad (15)$$

The sum of all frequency amplitude is got by

$$\sum_o\sum_s A_{so}(x)=\sum_n\sqrt{e_n(x)^2+e_o(x)^2} \quad (16)$$

Due to the insensitivity measuring of the phase congruency using the cosine of phase deviation, P.Kovesi[7] develop a more sensitive measure making use of the sine of the phase deviation according to the fact that the cosine of the phase deviation should be large and the sine phase deviation should be small. Therefore, the new calculation of phase congruency based on a more sensitive deviation function is as follow,

$$\Delta\phi_{so}(x)=\cos(\phi_{so}(x)-\overline{\phi}_o(x))-|\sin(\phi_{so}(x)-\overline{\phi}_o(x))| \quad (17)$$

With the help of the new deviation function, the new phase congruency can be defined as,

$$PC_2(x)=\frac{\sum_o\sum_s W_o(x)\lfloor A_{so}(x)\Delta\phi_{so}(x)-T_o\rfloor}{\sum_o\sum_s A_{so}(x)+\varepsilon} \quad (18)$$

where ε has the same function as before, $W_o(x)$ is the weighting factor. T is the estimated noise influence threshold when necessary.

Now the mean phase angle at direction O can be estimated by a unit vector,

$$\left\langle\overline{\phi}_e(x),\overline{\phi}_o(x)\right\rangle=\frac{1}{\sqrt{(F(x)^2+H(x)^2)}}(F(x),H(x)) \quad (19)$$

Using the dot and cross products, one can form the equation as follows,

$$\begin{aligned}&A_n(x)(\cos(\phi_n(x)-\overline{\phi}(x))-|\sin(\phi_n(x)-\overline{\phi}(x))|)=\\&(e_n(x).\overline{\phi}_e(x)+o_n(x).\overline{\phi}_o(x))-|e_n(x).\overline{\phi}_o(x)-o_n(x).\overline{\phi}_e(x)|\end{aligned} \quad (20)$$

Viewing from the Figure 2, it is supposed that the phase congruency preserves more information by directly applying on the original image instead of the operation on the reconstructed image. Evidently, the latter operation result seems to be blurred. Later we will give the experiment result to support our finding.

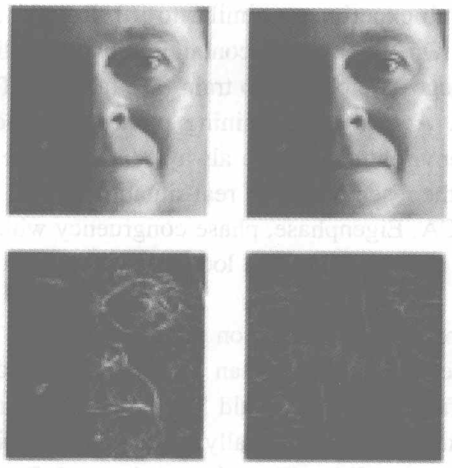

Figure 2 Lleft column phase congruency on original image. Right column phase congruency effect on reconstructed image

3.3 Log-Gabor Based Matching

We select 4 scales and 6 orientations of log-Gabor filters for the magnitude component representation. Each scale and orientation characterizes different features of origin image in the spatial domain.

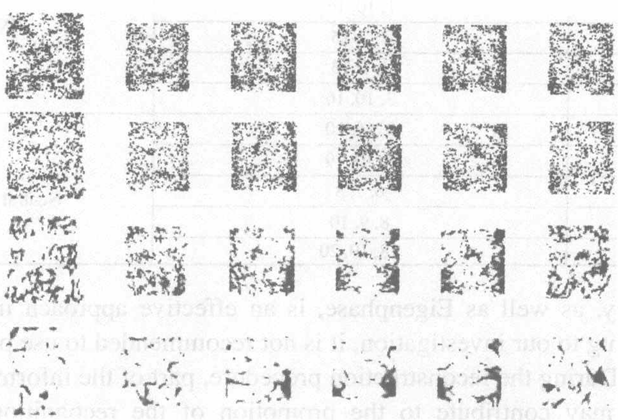

Figure 3 Magnitude representation of log gabor transformed images

4 Experiments

In order to evaluate which algorithm is much more robust under extreme lighting conditions, CMU-PIE face database is a preferable choice [11] which has different lighting conditions. In our approach, we select 30 persons. Each person is comprised of 21 training images captured by 21 different lighting sources with background light off.

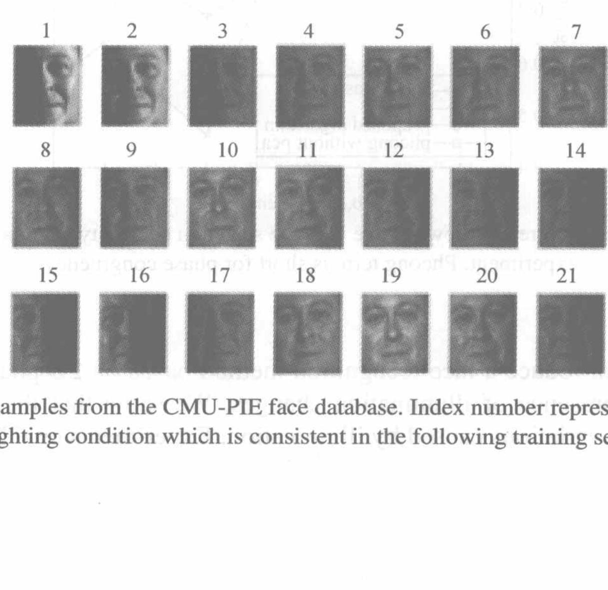

Figure 4 21 samples from the CMU-PIE face database. Index number representing different lighting condition which is consistent in the following training sets

We plan to conduct 10 sub experiments similar to [6]. Roughly, the sub experiments can be categorized into two types. One is images containing extreme light and another is images containing neutral light. 3 images are chosen to train (see table 1). Test images are selected from index 1, with incremental 3. Actually, the training procedure generally carries out on neutral lighting and test in the real environment which always exposes to extreme lighting, so the latter category is more likely to be the resemblance of real situation.

We compare tradition PCA, Eigenphase, phase congruency with and without the adoption of phase reconstruction, aiming to provide a detail look at which is much superior in the presence of illumination conditions.

Through our investigation, applying PCA on phase congruency after the extraction of phase information may not provide better results than the former. In addition, we also provide the evidence that taking the fusion image could produce better results than without fusion pre-processed. In real- time situation, test generally carried out in various lighting conditions while training is on room environment condition like sub experiment 6, 7, 8, 9, 10. Even though, the new proposed algorithm still achieves more than 90% except the experiment 7.

Table 1 Categorization of two training datasets: one is under extreme condition, another is neutral one

Sub experiment	Index number (total 21 images)	
1	3, 7, 16	Extreme lighting conditions
2	1, 10, 16	
3	2, 7, 16	
4	4, 7, 13	
5	3, 10, 16	
6	3, 16, 20	Neutral lighting conditions
7	7, 10, 19	
8	6, 7, 8	
9	8, 9, 10	
10	18, 19, 20	

Phase congruency, as well as Eigenphase, is an effective approach in eliminating lighting condition. But according to our investigation, it is not recommended to use phase congruency after phase reconstruction. During the reconstruction procedure, part of the information is lost, although the lost information may contribute to the promotion of the recognition rate in Eigenphase approach. It is not the same case as in phase congruency which operates on the whole image. So it is better to directly apply the phase congruency.

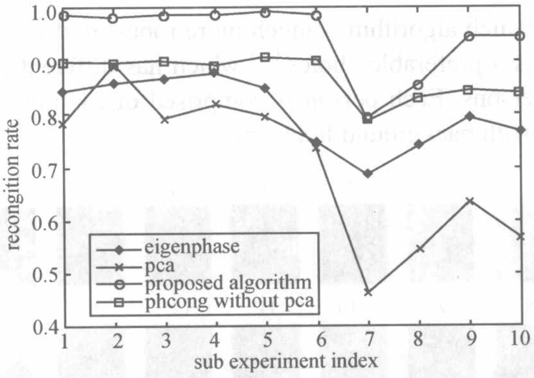

Figure 5 Comparison result shows above with the selection of twenty eigenfaces in each sub experiment. Phcong term is short for phase congruency

5 Conclusions

In this paper, we introduce a face recognition method based on 2D phase congruency, which is robust against the presence of illumination changes. We show that the phase information is useful to cope with the variations caused by illumination. Experiments on CMU-PIE face database demonstrate our assumptions. Future work will be extended to tackle pose variation and expression changes. It is also noticed that the suitable preprocessing step might contribute the final performance.

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