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Robust Facial Feature Localization using Improved Active Shape Model and Gabor Filter

Hui-Yu Huang
Engineering, National Formosa University, Taiwan
E-mail: hyhuang@nfu.edu.tw

Shih-Hang Hsu
National Formosa University, Taiwan
19866191@gm.nfu.edu.tw

Abstract

Face location under the environment of illumination chagne is a serious problem, in order to reduce illumination effect, in this paper, we propose a facial feature location method based on improved active shape model (IASM) and Gabor filter to reduce the intensity contrast and to enhance edge information. First, face images are preprocessed by the proposed illumination normalization method using Gabor wavelets. Then, reducing Gabor kernels based on the similarity of Gabor feature vector, the location of facial features can fit more efficient and fast by the proposed feature-based weighted warping. Through our proposed method, it not only obtains the better face alignment, but also overcomes the active shape model (ASM) method which caused the failure for aligned target. Experimental results demonstrate that the proposed system is superior to active shape model (ASM) method for Yale database with varied illumination database (Yale database) or JAFFE database with seven type facial expressions.

1. Introduction

In face recognition, illumination variation is not easy work. It is well known that the variations of illumination may change face appearance dramatically so that the variations between the images of the same face. Hence, there are many studies have been worked this effect on face recognition recently [1,2,3]. If these effects are considered, the face recognition rate can be improved and be more robust.

Generally, pattern recognition problem relies upon the inherent features within the pattern. In order to copy with the effects of illumination variations on facial localization to recognize, Zhang and Gao [1] proposed a practical face recognition system which includes various poses and expressions with varying illuminations. For facial feature extraction, many techniques, such as Fourier transformation, wavelet transformation, and Gabor filtering, are usually adopted to extract the efficient facial features. The Gabor filters have been used in many applications, such as computer vision, image processing, etc. It is well known that the Gabor filters are robust against the local distortions, preventing the control points from sticking into local minimum during optimization.

For face image, its data format usually represents as high-dimensional format to retain rich information; however, thus these will become very hard to analyze those of attributes. Due to this factor, efficient reducing the dimension for face image is necessary and thus can obtain fast and good recognition result. In order to reduce the dimension and improve the computational complexity, in this paper, an efficient representation method which is insensitive the varying illumination is proposed for facial feature localization.

The rest of the paper is organized as follows. Section 2 describes our proposed method. The experimental results are presented in Section 3. Finally, we discuss the conclusions.

2. Proposed Method

In our proposed method, the mainly procedures include the extraction of Gabor features, reducing of Gabor kernels, local feature-based weighted warping, dimension reduction in IASM and 2D profile extension. Details of procedures are presented in the following subsections.

2.1 Gabor filters and feature extraction

Gabor filters, which are generated form a wavelet expansion of the Gabor kernels [4], exhibit desirable attributes of spatial locality and frequency domains optimally. Hence, in our approach, we use the 2D Gabor filter to modulate the orientations and frequencies for facial feature extraction. The 2D Gabor filter is expressed as

$$\varphi_{\mu,\upsilon}(z) = \frac{\| k_{\mu,\nu} \|^2}{\sigma^2} e^{\left(-\frac{\|k_{\mu,\nu}\|^2\|z\|^2}{2\sigma^2}\right)} \left(e^{\left(ik_{\mu,\nu} z\right)} - e^{\left(-\frac{\sigma^2}{2}\right)} \right), \quad (1)$$

where μ and υ denote the orientation and scale of the Gabor kernels, $z = (x, y)$, including φ (frequency) and σ

(bandwidth) parameters [4, 5]. The wave vector $k_{\mu,\upsilon}$ is defined as

$$k_{\mu,\nu} = k_\nu \cdot e^{i\phi_\mu} \tag{2}$$

where $k_\nu = \dfrac{k_{\max}}{f^\nu}$ and $\phi_\mu = \dfrac{\pi\mu}{8}$. $k_{\max}$ is the maximum frequency, and f is the spacing factor between kernels in frequency domain.

The term $k = 2^{-\frac{s}{2}}(2^{-\pi})$ is represented each scale value is Gabor wavelet transform. The term $-e^{\left(-\frac{\sigma^2}{2}\right)}$ is represented the deduction illumination noise [3].

Generally, Gabor filter is used to eight orientations, $\mu \in \{0,1,\cdots,7\}$ and five different scales, $\upsilon \in \{0,1,\cdots,4\}$ [5] as the transform parameters. Thus, it needs 5×8 filters to extract Gabor features.

2.2 Reduction of Gabor kernels

Because evaluating all 5x8 filters to convolve the facial image is quite time consuming. Hence, in order to reduce the computational complexity and improve the performance, we use Phase-Sensitive Similarity Function [6, 7] to match kernels [8] and choose high frequency components to represent feature diversity in the database.

Owing to 2D Gabor filter has the characteristic of angle symmetry, here, we chose the orientation in the range [90, 180] and three smaller scales to cover more high frequency signal. Based on this viewpoint, for the parameters in Gabor filter, the last four orientations μ =(4,5,6,7) and the first three scales ν =(0,1,2) are selected to use in our experiments.

2.3 Local feature-based weighted warping (LFWW)

According to Beier-Neely algorithm [9] shown in Fig.1, variables u means fraction region, and v is interval length . The corresponding formulas are briefly as follows. The line segment $\overline{PQ}$ will be mapping the line segment $\overline{P'Q'}$ given feature point X, The mapping position X' in the destination image from X is determined by the following formulas

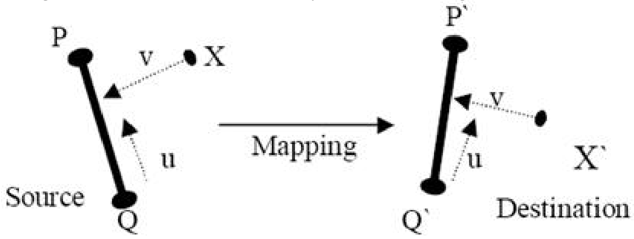

Figure 1. Single line pair.

$$u = \frac{\overrightarrow{(XP)} \times \overrightarrow{(QP)}}{\| \overrightarrow{QP} \|^2}, v = \frac{\overrightarrow{(XP)} \times \overrightarrow{(QP)}^{\perp}}{\| \overrightarrow{QP} \|^2} \tag{3}$$

$$X' = P' + u(\overrightarrow{Q'P'}) + v(\overrightarrow{Q'P'})^{\perp}, \tag{4}$$

where $(\overline{Q'P'})^{\perp}$ is a vector with the same length and perpendicular to $\overline{PQ}$.

A weighting of the coordinate transformation for each line segment is presented in order to more than one pair of line segments. The weight for the line i and line length is expressed as

$$\omega_i = \left[\frac{length^p}{(a + dist)} \right]^b, \tag{5}$$

where a, p, and b are the constants to control the warp that adjusts the smoothness of warping, falloff of strength with distance and rewarding longer line respectively [10]. The final mapping position of X is computed by

$$X' = \frac{\sum \omega_i X'_i}{\sum \omega_i}. \tag{6}$$

We use the Beier-Neely algorithm to decide and detect the local feature-based weighted warping (LFWW) for face images. Based on the above calculation, we can obtain good warping information because warping integrating ability is more powerful than affine transformation. Hence, active integrating reliable features can verify and simultaneously save time-consuming computation by means of this LFWW to map X in the destination.

2.4 Dimension reduction in IASM algorithm

Based on invariant feature and template matching characteristics, ASM [11] used the principal component analysis (PCA) to process the high-dimensional data. Then the fast iterative computation can be completed which obtained the convergence by using manual landmark points. Based on the above, we also adopt this viewpoint to apply to our proposed IASM to reduce the dimension and computational time. For s as shape vector matrix, each s corresponds to the eigenvalue (λ_s).

$$\left(\sum_{i=1}^{t} \lambda_i \Big/ \sum_{i=1}^{s} \lambda_i \right) \geq \alpha. \tag{7}$$

According to [12], the α in Eq. (7) is as a dimension reduction adjustment factor which mainly can effectively reduce the dimension. Hence, for sorted eigenvalues, the first t eigenvectors satisfying the Eq. (7) are selected. Here, we set α=0.95.

2.5 IASM 2D-profile extension

For feature points location based on ASM of profile matching is more influential and sensitive. In order to solve the given profile line on the strongest edge which will cause the matching error, such as shown in Fig. 2(a), it shows the mapping error in 1D profile searching. Hence, we extend it from 1D to 2D shown in Fig. 2(b) to decrease the location error. Fig. 2(b) shows the center of the rectangle positioned in the current feature point. For each point, a rectangle with side length of m is chosen so that the error of location can be decreased.

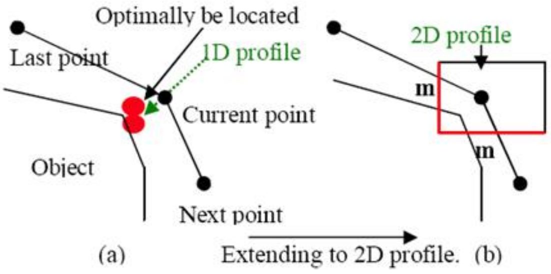

Figure 2. (a) Profile search 1D, (b) extending to 2D for (a).

3. Experimental Results and Discussion

In our experiments, we use two database JAFFE face database [13] and Yale face database-B [14]. The former database contains 213 images of 7 facial expressions (6 basic facial expressions + 1 neutral) posed by 10 Japanese female models, the latter database contains 5760 single light source images of 10 subjects, each seen under 576 viewing conditions (9 poses × 64 illumination conditions).

For evaluating the system performance, we adopt the average localization error (E) to measure, and it is expressed as [7, 12]

$$E = \frac{1}{n \times m} \sum_{i=1}^{n} \sum_{j=1}^{m} \left| p(i,j) - p'(i,j) \right|, \tag{8}$$

where n is the number of the test images, m is the number of the landmark in each image, and $P(i,j)$ is the manually-labeled position of the jth feature point on the ith image, $P'(i,j)$ is the position localized by the ASM algorithm. In addition, based on Eq. (8), the average localization error by the proposed IASM algorithm is compared with that of ASM method. The improved ratio (I) to measure the improvement percentage of the proposed IASM method is defined as Eq. (9). When I is positive, the proposed IASM method is superior to ASM.

$$I = \frac{E_{\text{ASM}} - E_{\text{proposed-IASM}}}{E_{\text{ASM}}} \times 100\%. \tag{9}$$

In order to evaluate the localization for our proposed IASM method, we perform the comparative experiments twice, with using manually labeled two eyes and Viola–Jones face detector [7, 15], respectively. Tables 1 and 2 show the experimental results for JAFFE and YALE_B databases, respectively. From Tables 1 and 2, it is clear that our proposed IASM method can obtain the lower location error and good improvement performance than the ASM method. Figure 3 shows the results corresponding to the different face expressions under against illumination. Figure 4 shows the comparison results with the ASM method and our proposed IASM method. For Fig. 3, we can obtain a good facial location under the different expression variations using the special mesh defined by us.

For Fig. 4, it is obvious that the result using our proposed IASM method can represent a good fitting than the ASM method. For more exaggerated expressions such as laughter or surprise, it still exists the problem of local minimum.

In addition, under the insufficient illumination shown in Fig. 5(b), we can also obtain a better facial location. In other words, it can be demonstrated that this approach is robust to the effect of illumination variation in facial location, such as shown in Fig. 5(d). That is, the ASM method is not appropriate as preprocessing step in the facial feature extraction. In our experiments, it may have about 37.5% facial information to be lost in the detection process using the ASM method.

4. Conclusions

In this paper, we have presented an efficient facial localization using IASM method and Gabor filter to locate facial features as well as identify the individual in an image. This method can efficiently deal with the problem of illumination variation in face recognition. Compared with the ASM algorithm and our IASM method, the improved ratio can achieve 54.14% in JAFFE database and YALE_B database is 63.92%. Consequently, the results show that our approach can be robust to illumination variation.

Table 1. Performance with JAFFE database.

Evaluation method	ASM	Proposed IASM	Improved ratio
Manually labeled	3.72	2.13	42.74%
Viola–Jones face detector	11.63	5.33	54.14%

Table 2. Performance with YALE_B database.

Evaluation method	ASM	Proposed IASM	Improved ratio
Manually labeled	5.56	4.07	26.79%
Viola–Jones face detector	30.44	10.98	63.92%

5. Acknowledgments.

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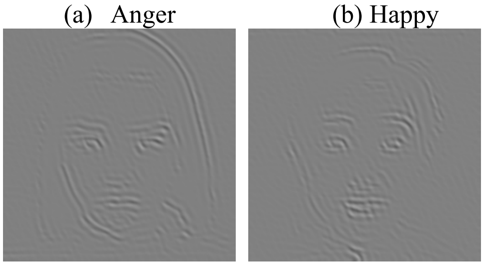
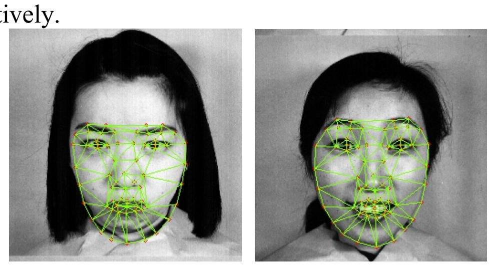
(a) Anger (b) Happy

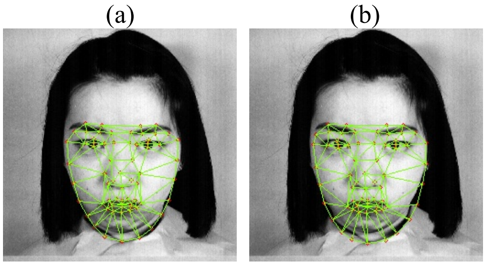


(c) (d)

Figure 3. (a) and (b) face images in JAFFE database. (c) and (d) Real part of Gabor filter corresponding to (a) and (b), respectively.

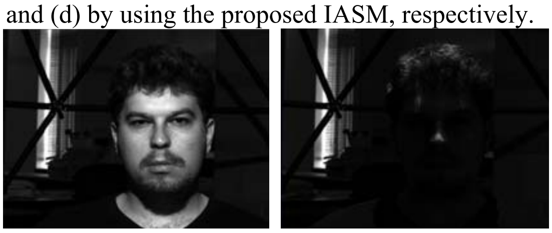


(a) (b)

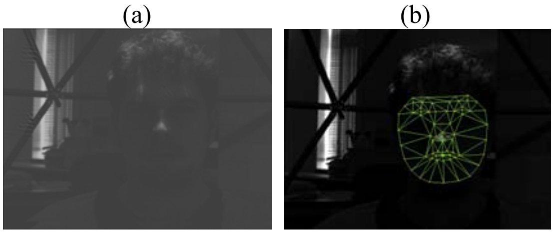


(c) (d)

Figure 4. Comparison results with the ASM and our proposed IASM method. (a) and (b) Results of using the ASM. (c) and (d) Results of merged Fig.3 (a) and (c), Fig. 3(b) and (d) by using the proposed IASM, respectively.



(a) (b)



(c) (d)

Figure 5. (a) Face image in YALE_B database. (b) Low illumination for (a). (c) Result of the proposed method for (b). (d) Face fitted robustly.

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