Improved Gabor Wavelet Transform Feature Extraction Algorithm Postprint

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Abstract

To address the problem of high feature vector dimensionality resulting from feature concatenation in Gabor wavelet magnitude- and phase-based face feature extraction methods, an improved Gabor wavelet transform feature extraction algorithm is proposed. The algorithm computes local magnitude features and local phase features, thereby enhancing the local correlation of each pixel; subsequently, weighting coefficients are determined experimentally to perform weighted fusion of the magnitude and phase features. Experimental results demonstrate that, compared with the original algorithm, the proposed approach reduces feature vector dimensionality while improving the final face recognition rate.

Full Text

Preamble

Feature Extraction Algorithm Based on Improved Gabor Wavelet Transform

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Abstract: Aiming at the problem that the feature cascading method for face feature extraction based on Gabor wavelet amplitude and phase results in high-dimensional feature vectors, this paper proposes an improved Gabor wavelet transform feature extraction algorithm. The algorithm calculates local amplitude features and local phase features, enhancing the local correlation of each pixel. It then selects weighting coefficients through experiments to fuse amplitude and phase features via weighted combination. Experimental results demonstrate that compared with the pre-improved algorithm, the proposed algorithm reduces the dimensionality of the feature vector while improving the final face recognition rate.

Key words: Gabor wavelet; feature extraction; local amplitude feature; local phase feature; weighted fusion

0 Introduction

Feature extraction is one of the most critical technologies in face recognition systems, referring to the process of obtaining distinctive data through computational analysis of face images to describe facial characteristics. However, existing face feature extraction methods exhibit low robustness against external interference factors such as illumination and pose, making them unsuitable for general applications. Therefore, the problem this paper addresses is finding a robust face description feature for complex environments [1].

With the continuous development of image acquisition technology, an increasing number of images are captured under complex conditions, affected by external factors including illumination, pose, and occlusion. For instance, when illumination changes significantly, face images of the same person may exhibit greater variation than those of different individuals under the same illumination conditions, because changes in lighting obscure the texture information of faces in darker areas, causing substantial differences in facial features for the same person. When face pose changes excessively or partial face information is occluded, key facial features may be missing, preventing complete feature extraction. Consequently, traditional feature extraction algorithms perform inadequately on such images. Research has shown that Gabor wavelets resemble visual neurons in mammalian visual systems and demonstrate excellent information extraction performance in local spatial regions. Due to their favorable directional selectivity, multi-scale properties, and insensitivity to illumination and pose variations, Gabor wavelets have been widely applied in image processing and pattern recognition [2–4].

Therefore, to further enhance the representational capability of features extracted by Gabor wavelet transform-based algorithms and reduce feature dimensionality, this paper proposes an improved Gabor wavelet transform feature extraction algorithm. The algorithm computes local amplitude and phase features for each pixel to replace the original amplitude and phase features, strengthening local correlations. It employs weighted fusion of amplitude and phase features to reduce face feature vector dimensionality while improving representational capacity.

1 Related Work

Current face feature extraction algorithms based on Gabor wavelet transform can be categorized into analytical methods and holistic methods according to the size of the image transformation region [5].

Analytical methods compute Gabor wavelet features for each specifically marked region, requiring the selection of feature domains or points (such as eyes, nose, mouth, etc.), then obtaining Gabor features from these marked regions and combining them into a "Gabor jet." Lades et al. [6] first proposed the Gabor wavelet dynamic link architecture for face recognition, representing faces as lattice-like sparse graphs where nodes were marked with Gabor wavelet transform feature vectors from image positions and edges with distance vectors connecting nodes, performing recognition based on similarity between nodes and connections. However, searching for feature points in images involves substantial computation. To address this issue, Wiskott et al. [7] used elastic graph matching to label key facial parts, performed Gabor wavelet transformation on these key areas, and finally cascaded Gabor wavelet features from multiple key parts. The elastic graph matching process remained time-consuming. To avoid elastic graph construction, Kalocsai et al. [8] directly performed Gabor wavelet transform on key facial feature points and cascaded these features. However, analytical methods require manual labeling of key facial feature points, making the process cumbersome.

Holistic methods apply Gabor wavelet transform to the entire image without requiring manual marking of feature points. Liu et al. [9] used multi-scale and multi-directional Gabor kernel functions to convolve complete face images, using extracted Gabor amplitude features as face feature vectors. Shan et al. [10] combined Gabor amplitude features with Boosting strategies to reduce feature dimensionality, obtaining AdaGabor features for face recognition. Previous methods extracted only Gabor amplitude features, ignoring Gabor phase features. In fact, Gabor phase features contain rich information for classification and recognition, and research has demonstrated that Gabor phase features exhibit high robustness to external factors such as illumination variation [11]. Zhang et al. [11] proposed a histogram model based on Gabor wavelet phase information, employing Gabor wavelet transform and spatial region histograms to achieve good robustness against external variations. To further enhance robustness of Gabor wavelet transform-based feature extraction algorithms, reference [12] extracted both Gabor amplitude and phase features from faces and cascaded them to obtain final face feature vectors. However, current Gabor wavelet amplitude and phase-based feature extraction methods rarely consider relationships within the local neighborhood of amplitude features, resulting in weak local correlation of amplitude features. Moreover, the combination of amplitude and phase features primarily uses concatenation, leading to high-dimensional final face feature vectors with suboptimal representational capability.

In summary, analytical methods involve cumbersome manual feature labeling processes. Holistic methods based on Gabor wavelet amplitude information perform well for face feature extraction under constrained conditions because filtered amplitude information effectively reflects facial texture features. However, under complex conditions, local facial texture features may change, reducing the representational capability of features extracted by Gabor wavelet amplitude-based methods for faces affected by environmental interference. Methods based on Gabor wavelet amplitude and phase information incorporate phase information that is robust to illumination and other external factors, enhancing feature representational capability, but the concatenation approach results in high feature dimensionality.

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2 2D Gabor Wavelet Transform

Gabor wavelets constitute a family of complex functions generated through scaling and rotation of the Gabor function, possessing excellent video localization characteristics and multi-resolution performance capable of extracting subtle local variations in images. For image filtering, 2D Gabor wavelet transform is employed. The definition of the 2D Gabor wavelet kernel function is given by Equation (1) [14]:

$$k_{u,v} = k_v e^{i\phi_u}, \quad k_v = \frac{k_{\max}}{f^v}, \quad \phi_u = \frac{u\pi}{8}$$

where z represents the coordinate value of a pixel in the image, denoted as $z = (x, y)$; $k_{u,v}$ represents the center frequency of the filter, $k_{u,v} = (k_v \cos\phi_u, k_v \sin\phi_u)^T$, where $u(u = 0, 1, 2, \dots, 7)$ indicates the orientation of the Gabor filter, $v(v = 0, 1, 2, 3, 4)$ indicates the scale, and K represents the total number of orientations. i is the complex operator, $\| \cdot \|$ denotes the Euclidean norm, σ determines the ratio of Gaussian window width to wavelength, and typically $\sigma = 2\pi$ yields optimal experimental results.

Generally, Gabor feature maps can be obtained through convolution operations between the image and Gabor wavelet kernel functions. As shown in [Figure 1: see original paper], A can be regarded as the image to be processed, and B as the Gabor wavelet kernel function. The convolution operation is represented as:

$$C_{i,j} = \sum_x \sum_y A(i - x, j - y) \cdot B(x, y)$$

where $F_{u,v}(z)$ represents the feature image obtained from Gabor wavelet convolution, $I(z)$ represents the original image, and $*$ denotes the convolution operation.

3.1 Gabor Local Amplitude Feature

Feature extraction algorithms based on Gabor amplitude statistical characteristics extract amplitude feature information that is less susceptible to external interference compared to global image features. Since 2D Gabor wavelets are complex-valued, their real and imaginary parts can be expressed as:

$$G_{u,v}^{\mathrm{Re}}(z) = \frac{k_{u,v}^2}{\sigma^2} \exp\left(-\frac{k_{u,v}^2\|z\|^2}{2\sigma^2}\right)\left[\cos(k_{u,v}\cdot z) - \exp\left(-\frac{\sigma^2}{2}\right)\right]$$

$$G_{u,v}^{\mathrm{Im}}(z) = \frac{k_{u,v}^2}{\sigma^2} \exp\left(-\frac{k_{u,v}^2\|z\|^2}{2\sigma^2}\right)\sin(k_{u,v}\cdot z)$$

According to Equation (3) in Chapter 2, the obtained Gabor features are also complex-valued, with real part $\mathrm{Re}(F_{u,v}(z))$ and imaginary part $\mathrm{Im}(F_{u,v}(z))$. The amplitude feature is given by Equation (6):

$$M_{u,v}(z) = \sqrt{\mathrm{Re}(F_{u,v}(z))^2 + \mathrm{Im}(F_{u,v}(z))^2}$$

After obtaining the Gabor amplitude features through convolution, to enhance local correlation of amplitude features, we compute local amplitude features for each pixel to replace the original amplitude features. This paper selects a 3×3 window as a pixel' s neighborhood, calculating the average amplitude of the surrounding eight pixels to replace the amplitude of the central pixel. When a pixel is located at the boundary of the amplitude feature map, amplitudes outside the map are padded with zeros. Assuming pixel z_0 with neighborhood pixels $z_i (i = 1, 2, \dots, 8)$ distributed as shown in [Figure 2: see original paper], its amplitude $M'_{u,v}(z_0)$ is calculated by Equation (7):

$$M'_{u,v}(z_0) = \frac{1}{8}\sum_{i=1}^{8} M_{u,v}(z_i)$$

This yields the local amplitude feature map $M'_{u,v}(z)$. To effectively represent global image features and reduce dimensionality, the local amplitude feature map is further divided into several rectangular, non-overlapping sub-blocks of equal size. The number of sub-blocks is denoted as K. The mean $\mu_{u,v,k}^M$ and standard deviation $\sigma_{u,v,k}^M$ of each sub-block $I_k (k = 0, 1, \dots, K-1)$ are calculated using:

$$\mu_{u,v,k}^M = \frac{1}{mn/K}\sum_{z\in I_k} M'_{u,v}(z)$$

$$\sigma_{u,v,k}^{M} = \sqrt{\frac{1}{mn/K} \sum_{z \in I_k} (M'_{u,v}(z) - \mu_{u,v,k}^{M})^2}$$

The amplitude features of image I can then be represented as:

$$\{M_{u,v,k}^{\mu}, M_{u,v,k}^{\sigma} \mid u = 0, 1, \dots, U, v = 0, 1, \dots, V, k = 0, 1, \dots, K-1\}$$

where U and V represent the number of orientations and scales of the Gabor wavelet kernel functions, respectively.

3.2 Gabor Local Phase Feature

Since Gabor wavelet phase features exhibit strong discriminability against illumination variation, this section extracts local phase features from Gabor wavelet transformed images using Daugman' s method [15] and fuses them with local amplitude features to obtain features more robust to illumination.

Daugman' s method performs binary conversion on each pixel' s information in the 2D Gabor wavelet transformed image, determining binary values based on the sign of real and imaginary components. The conversion rules are given by Equations (11) and (12) [15]:

$$P_{\mathrm{Re}}^{u,v}(z) = \begin{cases} 0, & \mathrm{Re}(F_{u,v}(z)) > 0 \\ 1, & \mathrm{Re}(F_{u,v}(z)) \leq 0 \end{cases}$$

$$P_{\mathrm{Im}}^{u,v}(z) = \begin{cases} 0, & \mathrm{Im}(F_{u,v}(z)) > 0 \\ 1, & \mathrm{Im}(F_{u,v}(z)) \leq 0 \end{cases}$$

where z represents a pixel coordinate, $\mathrm{Re}(F_{u,v}(z))$ and $\mathrm{Im}(F_{u,v}(z))$ denote the real and imaginary information, and $P_{\mathrm{Re}}^{u,v}(z)$ and $P_{\mathrm{Im}}^{u,v}(z)$ represent the binary conversion values. The coordinate formed by each pixel' s real and imaginary information corresponds to a point in the complex coordinate system, as shown in [Figure 3: see original paper].

Let $\theta_{u,v}(z)$ denote the phase angle of coordinate z. When $\mathrm{Re}(F_{u,v}(z)) > 0$, $\theta_{u,v}(z)$ lies in Quadrant I or IV; when $\mathrm{Re}(F_{u,v}(z)) \leq 0$, $\theta_{u,v}(z)$ lies in Quadrant II or III. Similarly, relationships for $\mathrm{Im}(F_{u,v}(z))$ can be derived. Therefore, Equations (11) and (12) can be transformed into Equations (13) and (14):

$$P_{\mathrm{Re}}^{u,v}(z) = \begin{cases} 0, & \theta_{u,v}(z) \in \text{Quadrant I or IV} \\ 1, & \theta_{u,v}(z) \in \text{Quadrant II or III} \end{cases}$$

$$P_{\mathrm{Im}}^{u,v}(z) = \begin{cases} 0, & \theta_{u,v}(z) \in \text{Quadrant I or II} \\ 1, & \theta_{u,v}(z) \in \text{Quadrant III or IV} \end{cases}$$

Equations (13) and (14) only perform binary conversion on real and imaginary information separately without encoding their relationship. In the complex plane, the phase angle $\theta_{u,v}(z)$ satisfies the relationship described by Equation (15):

$$\theta_{u,v}(z) = \tan^{-1}\left(\frac{\mathrm{Im}(F_{u,v}(z))}{\mathrm{Re}(F_{u,v}(z))}\right)$$

The binary encoding rule for $\tan(\theta_{u,v}(z))$ follows Equation (16):

$$P_{\tan}^{u,v}(z) = \begin{cases} 0, & \theta_{u,v}(z) \in \text{Quadrant I or III} \\ 1, & \theta_{u,v}(z) \in \text{Quadrant II or IV} \end{cases}$$

To enhance correlation between each pixel' s phase feature and its local neighborhood, a 3×3 window is again selected as a pixel' s neighborhood. The binary codes of the eight surrounding positions are XORed with the central pixel' s code to generate eight new binary codes, which are then arranged in order to form an 8-bit binary number and converted to a decimal value representing the central pixel' s phase feature. When a pixel is located at the boundary of the phase feature map, phase feature codes outside the map are padded with zeros. The specific operation process is illustrated in [Figure 4: see original paper].

Assuming image I has size $m \times n$, the local phase feature map is divided into K rectangular, non-overlapping sub-blocks of equal size. Each sub-block image is $I_k (k = 0, 1, \dots, K-1)$. The mean $\mu_{u,v,k}^P$ and standard deviation $\sigma_{u,v,k}^P$ of each sub-block are calculated using:

$$\mu_{u,v,k}^P = \frac{1}{mn/K} \sum_{z \in I_k} P_{u,v}(z)$$

$$\sigma_{u,v,k}^P = \sqrt{\frac{1}{mn/K} \sum_{z \in I_k} (P_{u,v}(z) - \mu_{u,v,k}^P)^2}$$

The phase features of image I can be represented as:

$$\{P_{u,v,k}^{\mu}, P_{u,v,k}^{\sigma} \mid u = 0, 1, \dots, U, v = 0, 1, \dots, V, k = 0, 1, \dots, K-1\}$$

where U and V represent the number of orientations and scales of the Gabor wavelet kernel functions, respectively.

3.3 Feature Fusion

Feature fusion involves comprehensive analysis, evaluation, and decision-making of multiple features to obtain an integrated feature that maximizes each feature' s contribution to the result. Current Gabor wavelet transform amplitude and phase feature fusion most commonly employs concatenation, which treats each feature as equally important and assumes equal influence on the final recognition result. This approach cannot maximize each feature' s contribution to correct recognition. Weighted feature fusion assigns weights to each feature, determining their contributions through experiments. Let W_M denote the amplitude feature weight and W_P denote the phase feature weight, with each weight ranging from 0.1 to 0.9 and satisfying $W_M + W_P = 1$. The final fused feature is calculated by Equation (21):

$$\mathrm{MIX}_{u,v,k} = W_M \cdot M^{\mu}_{u,v,k}\sigma + W_P \cdot P^{\mu}_{u,v,k}\sigma$$

where u, v, and k represent the orientation number, scale number of Gabor wavelet kernel functions, and feature map block number, respectively.

3.4 Algorithm Description

The improved Gabor wavelet transform feature extraction algorithm consists of four main components: (1) performing 2D Gabor wavelet transform on face images, (2) extracting amplitude features and computing local amplitude features for each pixel, (3) extracting phase features and computing local phase features for each pixel, and (4) performing weighted fusion of local amplitude and phase features.

The pseudocode for the improved Gabor wavelet transform feature extraction algorithm is presented as Algorithm 1.

Algorithm 1: Improved Gabor Wavelet Transform Feature Extraction Algorithm

Input: A face image of size $m \times n$
Output: Feature vector of the face image

1. Initialize z_0 as the coordinates of the first pixel
2. For $i = 1$ to U: 3. For $j = 1$ to V: 4. Compute $F_{u,v}(z) = I(z) * G_{u,v}(z)$ // 2D Gabor wavelet transform 5. Compute $\mathrm{Re}(F_{u,v}(z)) = I(z) * \mathrm{Re}(G_{u,v}(z))$ 6. Compute $\mathrm{Im}(F_{u,v}(z)) = I(z) * \mathrm{Im}(G_{u,v}(z))$ 7. End for
3. End for
4. For each pixel z in $m \times n$: 10. Compute $M_{u,v}(z) = \sqrt{\mathrm{Re}(F_{u,v}(z))^2 + \mathrm{Im}(F_{u,v}(z))^2}$
   11. Compute $M'_{u,v}(z) = \frac{1}{8}\sum_{j=1}^{8} M_{u,v}(z_j)$ // Local amplitude feature
5. End for

6. For $k = 1$ to K: 14. Compute $\mu^M_{u,v,k}$ and $\sigma^M_{u,v,k}$ // Mean and std of amplitude features per block
7. End for
8. For each pixel z in $m \times n$: 17. Compute $\theta_{u,v}(z) = \tan^{-1}\left(\frac{\mathrm{Im}(F_{u,v}(z))}{\mathrm{Re}(F_{u,v}(z))}\right)$ 18. If $0 < \theta_{u,v}(z) < 90$ or $180 < \theta_{u,v}(z) < 270$: $P^{u,v}_{\tan}(z) = 0$ 19. If $90 < \theta_{u,v}(z) < 180$ or $270 < \theta_{u,v}(z) < 360$: $P^{u,v}_{\tan}(z) = 1$ 20. Compute $P_{u,v}(z_0) = \sum_{j=1}^{8} P^{u,v}_{\tan}(z_j) \oplus P^{u,v}_{\tan}(z_0)$ // Local phase feature
9. End for
10. For $k = 1$ to K: 23. Compute $\mu^P_{u,v,k}$ and $\sigma^P_{u,v,k}$ // Mean and std of phase features per block
11. End for
12. For $k = 1$ to K: 26. Compute $\mathrm{MIX}_{u,v,k} = W_M \cdot M^{\mu}_{u,v,k}\sigma + W_P \cdot P^{\mu}_{u,v,k}\sigma$ // Weighted fusion
13. End for

4.2 Selection of Block Size

For Gabor wavelet transform-based feature extraction algorithms, appropriate block size significantly impacts the representational capability of extracted features. When block size is small, sub-block images are large, resulting in insufficient feature richness. Conversely, when block size is large, sub-images are small, leading to high feature dimensionality and susceptibility to noise. Therefore, for three different face datasets, features are extracted using the proposed algorithm, Gabor amplitude+phase feature extraction algorithm, and Gabor amplitude feature extraction algorithm. Principal Component Analysis (PCA) is applied for dimensionality reduction, and a Support Vector Machine (SVM) is used for classification. Face recognition rates are calculated under different block sizes. Using leave-one-out cross-validation, 20 tests are conducted for each block size, and average recognition rates are computed. [Figure 6: see original paper] compares face recognition rates under different block sizes.

The results show that beyond certain block numbers, the proposed algorithm and Gabor amplitude+phase algorithm maintain consistently high recognition rates without decline, while Gabor amplitude algorithm exhibits significant fluctuations. This occurs because for poorly illuminated face images, facial features like eyes, nose, and mouth are less distinct. Although large block numbers somewhat compromise continuity, Gabor phase information provides strong compensation for illumination variations, preventing recognition rate degradation. The proposed algorithm achieves maximum recognition rates with smaller block numbers compared to the Gabor amplitude+phase algorithm, primarily due to its consideration of local correlation in amplitude features.

From Figure 6: see original paper, the optimal block numbers are 36 for Gabor amplitude, 32–128 for Gabor amplitude+phase, and 16–128 for the proposed algorithm on the Yale dataset. Since larger block numbers incur greater time costs, the minimum optimal values are selected: 36, 32, and 16 blocks respectively. Similarly, Figure 6: see original paper shows optimal block numbers of 64, 49, and 32, while Figure 6: see original paper shows 64, 49, and 25 for the three algorithms on Yale B and CMU-PIE datasets respectively.

4.3 Selection of Feature Fusion Weight Parameters

Since the proposed algorithm fuses Gabor amplitude and phase features, experiments test different feature weights to determine optimal parameters. As described in Section 3.3, amplitude feature weight is W_M and phase feature weight is W_P, with $W_M + W_P = 1$ and weight range $0.1 \sim 0.9$. Three face datasets are processed using the proposed algorithm with different weight parameters. PCA is applied for dimensionality reduction and SVM for classification. Face recognition rates are computed. Using leave-one-out cross-validation, 20 tests are performed for each weight setting, and average recognition rates are calculated. compares face recognition rates under different feature weight parameters.

The results indicate that when amplitude weight W_M is large and phase weight W_P is small, recognition rates for all three datasets are relatively low. This occurs because all datasets contain illumination variations, and phase features exhibit good robustness to such changes, requiring larger W_P. The proposed algorithm achieves maximum recognition rates on Yale dataset when $W_M = 0.3, W_P = 0.7$, on Yale B dataset when $W_M = 0.4, W_P = 0.6$, and on CMU-PIE dataset when $W_M = 0.4, W_P = 0.6$. For consistency, amplitude weight $W_M = 0.3$ and phase weight $W_P = 0.7$ are selected.

Table 1: Comparison of Face Recognition Rate Under Different Feature Weight Parameters

Weight Parameters	Yale Dataset	Yale B Dataset	CMU-PIE Dataset
$W_M = 0.1, W_P = 0.9$	94.2%	96.8%	95.4%
$W_M = 0.2, W_P = 0.8$	95.1%	97.5%	96.2%
$W_M = 0.3, W_P = 0.7$	**96.3%**	**98.1%**	**97.8%**
$W_M = 0.4, W_P = 0.6$	95.8%	98.1%	97.8%
$W_M = 0.5, W_P = 0.5$	94.7%	97.2%	96.9%

4.5 Comparison of Feature Extraction Average Time

This experiment compares the average feature extraction time of the proposed algorithm, Gabor amplitude+phase algorithm, and Gabor amplitude algorithm across three datasets. The average extraction time for each algorithm on each dataset is computed. Results are shown in .

The proposed algorithm' s average feature extraction time is slightly higher than the Gabor amplitude+phase algorithm due to additional computations for local amplitude features and weighted fusion. The Gabor amplitude+phase algorithm' s time is higher than the Gabor amplitude algorithm because of added phase feature extraction. Despite increased time, the proposed algorithm achieves higher recognition rates. It enhances feature representational capability and reduces feature vector dimensionality while accepting a modest increase in extraction time under illumination and pose variations.

Table 3: Comparison of Average Feature Extraction Time of Three Algorithms

Dataset	Gabor Amplitude	Gabor Amplitude+Phase	Proposed Algorithm
Yale	0.85s	1.24s	1.47s
Yale B	1.32s	1.89s	2.15s
CMU-PIE	1.68s	2.34s	2.67s

Conclusion

To address the high dimensionality issue caused by concatenated feature fusion in Gabor wavelet amplitude and phase-based face feature extraction methods, this paper proposes an improved Gabor wavelet transform feature extraction algorithm. By computing local amplitude and phase features, the algorithm enhances feature correlation. Weighted fusion of local amplitude and phase features reduces dimensionality and improves representational capability compared to concatenation. Experimental results demonstrate that the proposed algorithm extracts features with high representational capability and low dimensionality, albeit with relatively higher average extraction time. Future work will focus on reducing algorithmic time complexity and decreasing average feature extraction time.

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