Journal of Software Engineering

ISSN 1819-4311

Academic Journals Inc.

www.academicjournals.com

Journal of Software Engineering 8 (3): 211-218, 2014
ISSN 1819-4311 / DOI: 10.3923/jse.2014.211.218

Feature Extraction by Wavelet and Gabor Transform with MMC for a Single Training Sample

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ABSTRACT

Face feature extraction is a key technology for face recognition. A new framework of feature extraction is proposed in this study. Use wavelet and Gabor transformation with maximum margin criterion to extract face features for a single training sample. The less data of face features make it possible to transmit those data to servers as quickly as possible. The results conducted on ORL database show that the proposed method improves the performance, simultaneously obtains less data to transmit.

Key words: Feature extraction, Gabor transformation, maximum margin criterion, single training sample

INTRODUCTION

Face recognition plays an important role in homeland security, social security, anti-terrorism, etc. In general, image acquisition, image segmentation, feature extraction and classification compose a face recognition system. Obviously, face feature extraction is a very significant link for a face recognition system.

So far, in most cases the face images collected by intelligent terminals are uploaded to the servers directly. Besides, another option is that the images can be processed in the intelligent terminals (Oh *et al*., 2013) which is conducive to combat terrorism and safeguard stability in real time. Although, as we know, the dual or quad core CPU makes the mobile intelligent terminals have strong processing power, the upstream bandwidth is deficient. So, we can only upload the data of face feature. The less data we get the greater efficiency we have if we can guarantee the recognition rate little change. One clear priority for this study is to get the less data of face feature.

There is one bareheaded photo of every person in public security bureau. If people upload a suspect by the mobile intelligent terminal to servers, the public security bureau can use the face system to identify. This goes to the problem of a single training sample. It is very meaningful to study feature extraction for a single training sample (Tan *et al*., 2006). This is another priority for this study.

At present, face feature extraction technology has made a certain progress but face images are prone to affected by illumination, expression, posture, occlusion and so on. Especially a big change among the images of the same person will bring great difficulties to extract face features. Therefore, how to extract face feature in a simpler and more effective way is one of the difficulties of the application of face recognition.

Eigenface (Turk and Pentland, 1991a, b) is a very classical algorithm. It looks for a low dimensional space to describe the human face. The low dimensional space is called eigenspace which maximize the differences among the different face images. Then the image is projected into the eigenspace to identify. The eigenface method is easy to use and has a low computational cost. There is also an impressive recognition rate when the training samples are huge. But the recognition rate will decline sharply with one training sample. Linear Discriminant Analysis (LDA) (Khoukhi and Ahmed, 2010) is a reducing the eigen dimension method. Its main idea is to build a subspace which consist of all of the projection axis. In this space, it tries to minimize the within-class variance and maximize the between-class variance. But the obtained characteristics are not optimal discriminant. Belhumeur *et al.* (1997) further presented fisherface on that basis. But it is very sensitive to small sample sets and the recognition rate is not ideal. Particularly it does not work for a single training sample. To avoid getting the inversion of within-class scatter matrix, Maximum Margin Criterion (MMC) (Cui and Fan, 2012) was presented. But it overemphasizes the categories with big between-class distances and ignores the categories with small within-class distances. So, it can easily separate the categories with big between-class distances and make the categories with small within-class distances overlapped (Yang *et al.*, 2011). Wavelet transformation (Burrus *et al.*, 2008) is another choice to extract the face features. Due to the characteristics of wavelet base, the function after projected to the wavelet transform domain is beneficial to extract its essence. It also can remove some noise. Gabor transformation (Yang *et al.*, 2013; Zhang and Liu, 2013) being used to analyze human face achieves good results as well. Nonetheless, heavy computation is a disadvantage of the algorithms based on multi-scale and multi-direction wavelet.

Many of those methods have good performance but the results are not excellent for small sample sets. Song *et al.* (2012) presented a method that reconstruct a 3-D face model from a single 2-D face image for small sample sets. A uniform pursuit approach for a single training sample is proposed in (Deng *et al.*, 2010). Above two methods achieved good results but that's not enough. We think there might be other methods for a single training sample. A new framework is proposed here. Use wavelet and Gabor transformation with MMC to extract face features. The contributions of this study is that (1) Proposed a novel framework for feature extraction and (2) Found a way to solve the problem that there is no within-class scatter matrix for a single training sample in MMC.

FRAMEWORK OF FEATURE EXTRACTION

In this section, we design a novel face representation with Gabor transformation and MMC for a single training sample.

Gabor representation: A Gabor filter is gained by modulating a sinusoid with a Gaussian function (Tahmasebi and Pourghassem, 2013). Let $g(x, y, \theta, \varphi)$ be the function defining a Gabor filter with center frequency and orientation of φ and θ, respectively. We can view Gabor filters as (Eq. 1):

$$g(x,y,\theta,\varphi) = \exp\left(-\frac{x^2+y^2}{\sigma^2}\right) \times \exp(2\pi\theta i(x\cos\varphi + y\sin\varphi)) \tag{1}$$

where, the spatial coordinates (x, y) indicate the centroid localization of the Gabor window. The parameter σ, denoting the standard deviation of the Gaussian kernel, depends on the spatial frequency. The response of a Gabor filter to an image is obtained by a 2D convolution operation. Let I(x, y) denote the face image and G(x, y, θ, φ) denote the response of a Gabor filter with frequency θ and orientation φ to an image at point (x, y) on the image plane. G(.) is obtained as follows (Eq. 2):

$$G(x,y,\theta,\varphi)=\iint I(p,q)g(x-p,y-q,\theta,\varphi)dpdq \tag{2}$$

where, G denotes the filtered image. More than three different frequencies and three different orientations are often selected (Xu *et al.*, 2013). However, after a great deal of experiments, it is proved that eight frequencies and one orientations total 8 filters is the best choice.

Improved maximum margin criterion: Suppose there are N training samples $\{x_1, x_2,\dots, x_N\}$ belonging to c classes $\{X_1, X_2,\dots, X_c\}$. Let S_b and S_w be the between-class scatter matrix and within-class scatter matrix, respectively:

$$S_w=\frac{1}{N}\sum_{i=1}^{c}\sum_{x_k\in X_i}(x_k-\mu_i)(x_k-\mu_i)^T \tag{3}$$

$$S_b=\frac{1}{N}\sum_{i=1}^{c}N_i(\mu_i-\mu)(\mu_i-\mu)^T \tag{4}$$

where, μ_i is mean value of X_i, μ is the mean value of all training sample, N_i is the number of X_i.

Because, as we know, LDA cannot handle a single training sample, (Li *et al.*, 2006) put forward the maximum margin criterion function, defined as follows (Eq. 5-6):

$$\max J_m(W)=tr(\bar{S}_b-\bar{S}_w) \tag{5}$$

$$\bar{S}_b=W^TS_bW,\quad \bar{S}_w=W^TS_wW \tag{6}$$

where, $W=[\varphi_1, \varphi_2,\dots \varphi_d]\in R^{n\times d}$ is projection matrix made up of the optimal discriminant vector $\varphi\in R^n$. W can be the top d eigenvectors corresponding to the largest values of generalized eigenmatrix as in Eq. 7:

$$(S_b\text{-}S_w)X=\lambda X \tag{7}$$

For a single training sample, $S_w = 0$, that means we cannot use the information of within-class variance. We propose a method that we can employ the Gabor features of each image to acquire S_w. As in Eq. 8 and 9, S_w^g is the expansion of S_w. Where y_k is a Gabor feature of one image, μ_i^g is mean value of $y_k\in X_i$ and M is the number of Gabor features of one image. As previous section, we can know that when one image do convolution operation with 8 Gabor filters, we can get the 8 Gabor features. Then, as show in Fig. 1, with the 8 Gabor features we can obtain S_w^g:

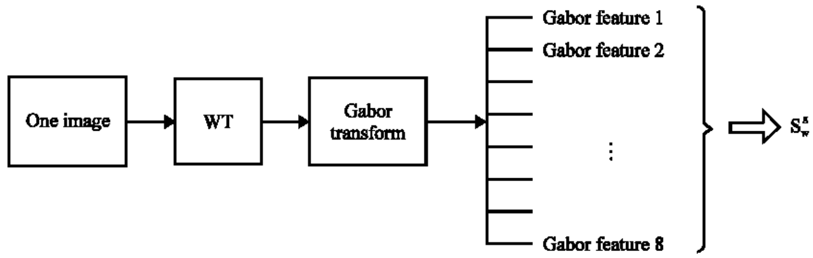

Fig. 1: Get S_w^g with gabor features

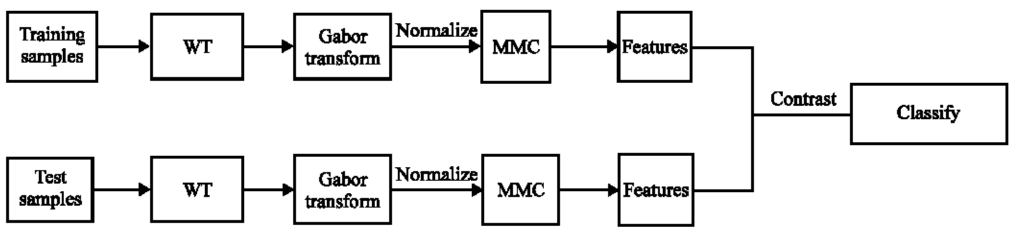

Fig. 2: Framework of the proposed method

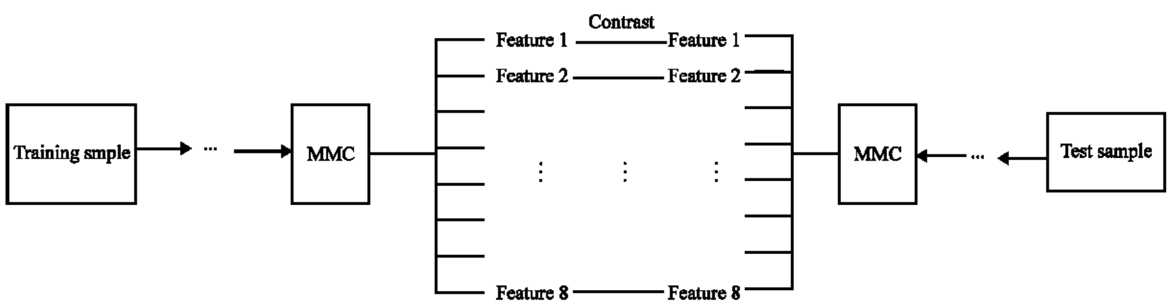

Fig. 3: Contrast method of training sample and test sample

$$S_w^g = \frac{1}{N}\sum_{i=1}^{c}\sum_{y_k \in X_i}(y_k - \mu_i^g)(y_k - \mu_i^g)^T \tag{8}$$

$$\mu_i^g = \frac{1}{M}\sum_{i=1}^{M} y_i \tag{9}$$

Novel framework: In the proposed method, as shown in Fig. 2, training samples are firstly processed by wavelet transformation. Secondly, Gabor transformation is employed to handle the processed samples. Next, normalize them. Then use the maximum margin criterion to get the face features to transmit.

Figure 3 shows that there are eight different features of one training sample after processed by MMC, the same as test samples. The point is we compare the corresponding features. Because the classifier is out of the research of this study, we use the Euclidean distance to discriminate the features.

EXPERIMENT AND ANALYSIS

To test the proposed method, ORL face database (http://www.cl.cam.ac.uk/research/dtg/attarchive/facedatabase.html) consisting of 400 images of 40 subjects has been used. Figure 4 shows some samples of the database. Images are of frontal faces with different postures, facial expressions. The image size is 92×112. We resize all the images to 64×64 in order to get the recognition rate, we simulate it with MATLAB.

Select one image of each of 40 subjects randomly as the training samples and the rest as test samples. Wavelet transformation is used in the proposed method. We just take the approximate coefficients as the inputs of Gabor transformation. In order to prove the superiority of the method, we compare it with other algorithms as follows: WT+Gabor, WT+Gabor+PCA and WT+Gabor+LDA.

Analysis of the number of features: With a larger number of experiments, we choose eight frequencies and one orientation in Gabor transformation and $\sigma = \pi\sqrt{2}$. With eight filters, we can acquire eight Gabor features of one image, by which we can get the within-class scatter matrix S_w^g. Euclidean distance is used to discriminate the training features and the test features.

We did the experiment about the relationship between the number of MMC's feature and recognition rate. As shown in Fig. 5, the curve with circles represents one of 10 times randomized trials of MMC and the curve with triangles is one of 10 times randomized trials of LDA. The curve with plus signs is the average of 10 times trials of MMC and the curve without anything is the average of 10 times trials of LDA. We are glad to see that no matter the number of the MMC's features are 2 or 20, there is a little change for the recognition rate. That is to say, we can use less

Fig. 4: Samples of ORL database

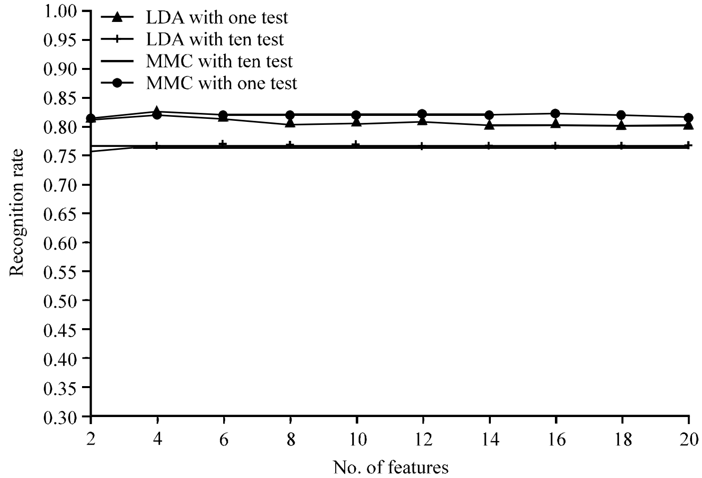

Fig. 5: Relationship between recognition rate and No. of features

Table 1: Comparison of different algorithms

Algorithms	Average recognition rate (%)	Maximum recognition rate (%)
WT+Gabor	74.19	75.50
WT+Gabor+PCA	73.58	77.50
WT+Gabor+LDA	75.63	81.11
Proposed method	76.58	81.94

Table 2: Comparison of the No. of bytes

Transmitting form	No. of bytes
Original image	10304
WT+Gabor features	12168
WT+Gabor+MMC feature	624

features to represent the face image. Here, we take 2 eigenvectors as the projection matrix. The size of an original face image is 92×112 and suppose each pixel takes 1 byte (8 bits) of storage. Table 1 shows us that if transmit the image to the servers directly, there need to transmit 10304 bytes. And if we use the WT+Gabore features, 12168 bytes are needed to transmit. Because after processed by wavelet transformation, the size of the image becomes to 39×39. And with eight Gabor filters, there will generate eight Gabor features for one image. Then, the number of WT+Gabor features are 39×39×8 = 12168. In the same way, the number of features of the proposed method are 39×2×8 = 624. Obviously, less data to be transmitted for the proposed method.

Comprison of recognition rate: For this part, we will study on the recognition rate of different algorithms for the same training samples and the same test samples. Take one face image of each of subjects randomly as training sample and the rest as test samples. We did the experiment 10 times. Because the within-class scatter matrix S_w^g both in LDA and MMC need to be calculated, we can do the same way to get the S_w^g in LDA. As shown in Fig. 5, the recognition rate of MMC already reach more than 80%. It's a good result for present. We also can get that the results of MMC are a little better than that of LDA. As shown in Table 2, in the case of taking the number of features 2, we can view that the proposed method has a better performance than other methods. The highest recognition rate can reach 81.94%. If we choose proper images rather than pick images randomly to train, the results will be better.

In general, some noise could be removed from a face image by using wavelet transformation. And after Gabor transformation one image can be represented from the different frequencies and orientations, with which also can make the within-class scatter matrix meaningful in MMC or LDA for a single training sample so that we can improve the discriminant ability of projection matrix.

CONCLUSION

In this study, we described a novel framework for face feature extraction and use the eight Gabor features of one image to obtain the within-class scatter matrix which make the MMC more powerful. The experimental results demonstrate that we can get the less face features to transmit and acquire good recognition rate.

ACKNOWLEDGMENT

This study is supported by National Natural Science Foundation of China (61261036). The authors are grateful to our colleagues, teachers and classmates for their help.

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