# A New Feature Optimization Method Based on Two-directional 2DLDA For Handwritten Chinese Character Recognition

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***Abstract*—LDA transformation is one of the popular feature dimension reduction techniques for the feature extraction in most handwritten Chinese characters recognition systems. The integration of the feature extraction and LDA transformation can be viewed as a two-directional feature transformation procedure, one is the pixel-level feature transformation by the summing up or blurring, another is by the LDA matrix, and the transformation coefficients are set empirically in the former. In this paper, we proposed a feature optimization method based on the gradient feature extraction by using the two-directional 2DLDA, which can find the optimal transformation coefficients in two directions. A series of experiments on the randomly selected 15 groups of the similar Chinese character samples from HCL2000 have indicated that, our method can effectively improve the recognition performance, the error rate reduction reaches 45.02% comparing to the traditional method, showing the effectiveness of the proposed approach.**

***Keywords- character recognition; gradient feature optimization; linear discriminant analysis; handwritten Chinese character recognition***

## I. INTRODUCTION

The recognition of handwritten Chinese characters (HCC) has been a very active research area in pattern recognition for a few decades. Although tremendous advances and successful applications have been achieved, it still remains a challenge problem, especially for unconstraint handwriting [1]. The public recognition contest organized in CCPR2010 [2] indicated that, the best system can only achieve 89.99% recognition accuracy for offline handwritten Chinese characters of the GB2312-80 level-1 set. The difficulties mainly come from the existence of the similar characters and the handwriting deformation in unconstraint Chinese handwriting. And the differences for some similar characters can be very small and are more difficult to identify, for examples, the characters “千” and “于”, “大” and “太”,etc. To attack the problems, much effort is needed to refine every aspect of HCC recognition systems, among which the feature extraction is one of most important issues. In this paper, a new feature optimization method is proposed for handwritten Chinese character recognition.

Different from the Latin family of languages, Chinese character is a kind of pictograph, where most of the strokes are composed of vertical, horizontal or two diagonal line segments. In terms of the directional characteristics of Chinese character strokes, many feature extraction methods have been proposed and proven to be effective for handwritten Chinese character recognition [3-8]. In the following, we will review some of the typical feature extraction methods for handwritten Chinese character recognition. Jin et al. [3] proposed a directional decomposition cellular feature extraction method in which each stroke pixel is decomposed into four directional sub-images according to the directional property of the pixels. In [4], Huo et al. presented a kind of Gabor features of handwritten Chinese character by using a set of 2D Gabor filters with $M$ different orientations. As a result, $M$ Gabor features are derived as the amplitudes of the filter outputs corresponding to the different orientations for each pixel of the character image. The gradient feature is another typical and widely used handwritten Chinese character feature with very promising recognition performance, which was first proposed by Liu et al. for handwritten digit recognition [5] and later applied in handwritten Chinese character recognition [6]. The Sobel operators are first used to obtain the horizontal and vertical gradient at each image pixel, and then the gradient vector is decomposed into $L$ directions. Thus $L$ directional sub-patterns are created for each character image. The directional feature, one of most effective feature in online handwritten Chinese character recognition, shares the similar idea. For example, 8 directional sub-patterns are obtained for each character image [7]. To extract the character feature vector, the character images are usually divided into several sub-blocks by elastic meshing or uniformly grid generation, and the sub-blocks partition is applied on each directional sub-patterns, respectively. Then, in one sub-block of each sub-pattern, one feature is computed by either summing up [3, 6] or Gaussian blurring [5, 7-8]. As for the Gabor feature extraction, the amplitude of

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the filter outputs at the center sampling point of each sub-block is adopted as its feature. However, for the aforementioned feature extraction methods, one of the drawbacks is that the extracted features may lose the discriminant information embedded in the sub-blocks, especially for the similar Chinese characters. One intuitive idea to this problem is that the resolution of sub-blocks is set high enough, for example, to the pixel level, that is, each pixel is viewed as a sub-block. However, this will lead to very high dimension of the feature vector, such as $64 \times 64 \times 8 = 32768$ for $64 \times 64$ character image using 8-directional decomposition, the commonly used character image size. When the subsequent linear discriminant analysis (LDA) [9] is applied for feature dimension reduction, which is a normal case in most of current handwritten Chinese recognition methods, it is too time-consuming and thus not practical. On the other hand, the storage of LDA transformation matrix will become very large.

Motivated by the successes of the two-dimensional LDA (2DLDA) [10] and the two-directional 2DLDA ((2D)$^2$LDA) [11] for face recognition, which are the extended versions of traditional LDA but very time-efficient in computing the LDA transformation matrix, we propose to extract the pixel-level character raw features using the existing feature extraction methods and then apply the two-directional 2DLDA to optimize the raw features. As used in face recognition, the pixel-level character raw features are first converted into the character feature matrix, and then, the row- and column-directional feature dimension reduction are completed by using 2DLDA. Since LDA can find a projection matrix that maximizes the trace of the between-class scatter matrix and minimizes the trace of the within-class scatter matrix in the projected subspace. Compared with the existing feature extraction method, the optimized features will have better discriminant ability. The experimental results indicate that the optimized gradient feature by our method can outperform greatly the traditional gradient features in handwritten Chinese character recognition.

The rest of this paper is organized as follows. We first review the two-directional 2DLDA approach in section 2. The gradient feature extraction and the optimization method are discussed in detail in section 3. In section 4, a series of experiments are given to verify the effectiveness of proposed method. Section 5 concludes the paper.

## II. TWO-DIRECTIONAL 2DLDA

LDA-based dimension reduction method is first proposed by Fisher [9] for binary classification and extended by Rao [12] to multi-class classification, which transforms the pattern feature vectors to a lower dimensional space by an optimal linear projection matrix such that the between-class scatter is maximized while the within-class scatter is minimized. Since the discriminant information between different pattern classes is considered, the transformed feature vectors can not only have the lower dimension but also the better discriminant ability. Two-directional 2DLDA is an extended version of LDA [11, 13-14], which treats the input pattern as the 2D pattern matrix instead of the 1D pattern vector. As a result, the between-class scatter matrix and the within-class scatter matrix can have the lower dimensions and the optimization of the linear projection matrix can be computationally time efficient.

For a $C$ -class classification problem, suppose that the training pattern samples consist of the $m \times n$ pattern matrices $X \in \{X_{ij} \mid i = 1, \cdots, C; j = 1, \cdots, N_i\}$ , $N_i$ and $N = \Sigma_{i=1}^{C} N_i$ are the training sample numbers of the $i$th class and the whole training set respectively, the two-directional 2DLDA aims at seeking two projection matrices $Z$ and $U$ such that

$$Y = Z^T X U \tag{1}$$

where $Y$ is the transformed pattern matrix with the lower dimensions $q \times d$ .

Due to the difficulty of computing the optimal $Z$ and $U$ simultaneously in Fisher criterion, the optimization procedure is decomposed into two parts: the optimization of matrices $Z$ and $U$ , respectively. The optimal projection matrices $Z^*$ and $U^*$ are defined as follows:

$$Z^* = \arg\max_{Z} tr\, ax((Z^T S_w^Z Z)^{-1}(Z^T S_b^Z Z)) \tag{2}$$

$$S_b^Z = \frac{1}{N} \sum_{i=1}^{C} (\overline{X}_i - \overline{X}) U U^T (\overline{X}_i - \overline{X})^T \tag{3}$$

$$S_w^Z = \frac{1}{N} \sum_{i=1}^{C} \sum_{j=1}^{N_i} (X_{ij} - \overline{X}_i) U U^T (X_{ij} - \overline{X}_i)^T \tag{4}$$

$$U^* = \arg\max_{U} tr((U^T S_w^U U)^{-1}(U^T S_b^U U)) \tag{5}$$

$$S_b^U = \frac{1}{N} \sum_{i=1}^{C} (\overline{X}_i - \overline{X})^T Z Z^T (\overline{X}_i - \overline{X}) \tag{6}$$

$$S_w^U = \frac{1}{N} \sum_{i=1}^{C} \sum_{j=1}^{N_i} (X_{ij} - \overline{X}_i)^T Z Z^T (X_{ij} - \overline{X}_i) \tag{7}$$

The column vectors of $Z^*$ and $U^*$ are composed of eigenvectors of $(S_w^Z)^{-1} S_b^Z$ and $(S_w^U)^{-1} S_b^U$ corresponding to the largest $q$ and $d$ eigenvalues, respectively.

For the computation of the optimal projection matrices $Z^*$ and $U^*$ , Ye et al. [13] gave an iterative algorithm where $U$ is fixed in calculation of $Z$ according to (2-4), and vice versa for the computation of $U$ . Yang et al. [14] suggested another algorithm that assumes the matrix $Z$ to be the unit matrix in computing the optimal projection matrix $U^*$, and then calculate the optimal projection matrix $Z^*$ using $U^*$ in terms of (2-4). However, those two algorithms are quite time-consuming in the search for the best subspace dimensions $q$ and $d$. Comparatively, Noushath et al. [11] suggested a simple and effective way to compute the projection matrices, that is, let $U$ to be the unit matrix in calculation of $Z^*$, and vice versa. In this paper, we adopt Noushath's strategy in our proposed feature optimization method.

## III. Gradient Feature Optimization

The gradient feature is one of the most effective and frequently used features in handwritten Chinese character recognition. In the following, we will base the gradient feature [6] to describe our proposed feature optimization method. The optimization of some other frequently used features such as the Gabor feature etc. can also follow the similar procedure.

To extract the gradient features, a $3\times3$ Sobel operator (as shown in Fig. 1) is used to obtain the horizontal and vertical gradient at each pixel of the character image, respectively. The character image is then decomposed into a number of regions corresponding to $L$ directions with an equal interval $2\pi/L$ (8 directions are most frequently used in the references, we also use this setting in our experiments), and the gradient vector of each pixel is decomposed into its two nearest directions in a parallelogram manner, as illustrated in Fig.1. In this way, $L$ directional sub-pattern images can be derived from each character image.

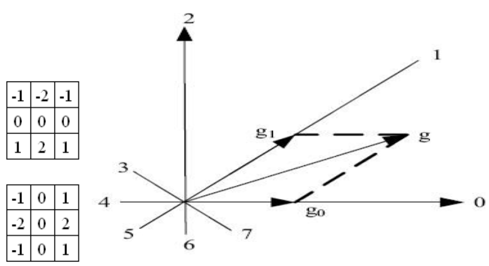


Figure 1. Sobel operators and the decomposing of the gradient vector.

To extract the gradient feature vector of handwritten Chinese characters, the character images are usually divided into several sub-blocks by elastic meshing or uniformly grid generation and the sub-blocks partition is applied on the $L$ directional sub-patterns. And then, in one sub-block of each directional sub-pattern, one feature is computed by either summing up or Gaussian blurring. Assume that $D\times D$ sub-blocks are partitioned, and then a $D\times D\times L$ dimensional gradient feature vector can be formed for each character image.

Take as an example the computing of the gradient feature vectors using the summing up and the uniformly grid partition. Suppose that $x_i (i=1,\cdots,D\times D\times L)$ be the pixel-level gradient feature vectors formed in the $k$th $(k=1,\cdots,D\times D)$ sub-block and the $l$th $(l=1,\cdots,L)$ direction after the gradient vector decomposition. For each character image, it can be represented by a pattern matrix of the gradient features as $X=[x_1,\cdots,x_{D\times D\times L}]$. Let $v$ be the gradient feature vectors of $D\times D\times L$ dimensions obtained by the traditional gradient feature extraction method [6], $W$ be the classical LDA transformation matrix obtained on $v$, and $y$ be the transformed feature vectors, that is, $y=W^T v$, then we have,

$$v^T=[1,\cdots,1]X \tag{8}$$

$$y^T=[1,\cdots,1]XW=QXW \tag{9}$$

It can be seen that the classical computation of the gradient feature vector takes the similar form as the 2DLDA transformation (as shown in equation (1)), the only difference is that the column directional transformation matrix $Q$ is set empirically in (9). By using the two-directional 2DLDA method, our proposed method can learn the optimal matrix Q from the training samples, thus produces better recognition performance. In addition, we don't limit the row number of matrix $Q$ to one in order to find the best parameters setting for character recognition.

It should be noted that, as a preprocessing step, the nonlinear shape normalization method by line interval [15] is also applied on each character image to adapt the deformation of handwritten Chinese characters. After the nonlinear shape normalization, the character images are divided into $8\times8=64$ sub-blocks and 8-directional gradient vector decomposition is adopted since those parameters settings are widely used to obtain the better recognition accuracy for $64\times64$ handwritten Chinese character images.

## IV. Experimental Results

To evaluate the performance of our proposed feature optimization method for handwritten Chinese character recognition, a series of experiments were carried out on China 863 National Handwriting Database HCL2000. HCL2000 contains 1000 sets of isolated handwritten Chinese characters from different writers, which are scanned with the resolution of 300 DPI and normalized into 64×64 binary images. In our experiments, we selected randomly 100 sets as the training data and 100 sets as the testing data.

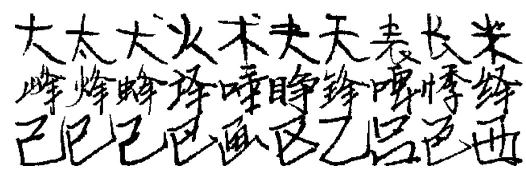

Figure 2. Some samples of the selected similar Chinese character sets.

We chose 15 groups of the similar Chinese characters from the GB2312-80 level-1 set as the testing character sets, each group containing 10 similar Chinese characters. The similar character sets are selected from the top candidates given by another recognition engine. Fig.2 shows some samples of the selected character sets. In the experiments, we repeated the recognition test on each group respectively, and the feature match technique based on the minimum Euclidean distance was used to give the recognition results.

As a basis for comparison, we implemented the gradient feature extraction methods according to the following 3 cases: (1) the elastic meshing and the summing up are used in feature computation (denoted as ***M1***); (2) the uniformly grid partition and the summing up are adopted (denoted as ***M2***); (3) the uniformly grid partition and the Gaussian blurring are used (denoted as ***M3***). In all 3 cases, $8\times8$ sub-blocks are divided. When using the uniformly grid partition, the nonlinear shape normalization method by line interval [15] is applied. For the Gaussian blurring, the recommended setting of the wavelength in [7] is used. The test results are listed in Fig.3 and Table 1.

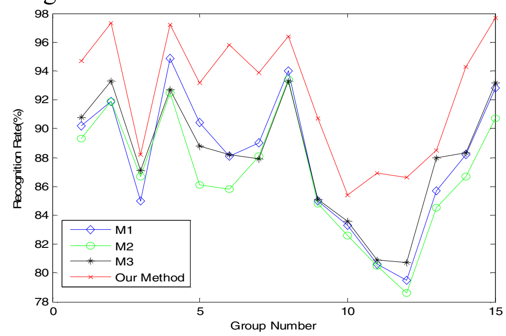


Figure 3. The recognition performance comparison on each group of similar Chinese characters (The feature dimension is reduced to 9 in all methods)

TABLE I. AVERAGE RECOGNITION PERFORMANCE COMPARISON WITH DIFFERENT GRADIENT FEATURE EXTRACTION METHODS

| ***Method*** | ***M1*** | ***M2*** | ***M3*** | ***Our method*** | ***Our method (best result)*** |
|---|---|---|---|---|---|
| Feature dimension after reduction | 9 | 9 | 9 | $1\times9$ | $1\times13$ |
| Average Recognition Rate (%) | 87.92 | 86.93 | 88.16 | 92.45 | **93.49** |

From the Fig.3, we can see that our method always gives the highest recognition rates in all groups of the tested similar Chinese characters. In Table 1, we computed the average recognition rate on all 15 groups of testing samples, it can be seen that, our proposed feature optimization method gives the best recognition rate and the error rate reduction reaches 36.23% (Feature dimension is reduced to $1\times9$ ) and 45.02% (the best result) comparing to M3, showing the effectiveness of our proposed method.

## V. CONCLUSIONS

LDA transformation is one of the most frequently used feature dimension reduction algorithms in handwritten Chinese character recognition, which can maximize the between-class scatter and minimize the within-class scatter. The transformed features can not only have the lower dimension but also the better recognition performance. By using an extended version of LDA, two-directional 2DLDA, we proposed a feature optimization method based on the gradient feature in this paper. A series of experiments on HCL2000 have shown that our method can effectively improve the recognition performance, and the error rate reduction reaches 36.23% and 45.02% (our best result) comparing to the best gradient features. It is worthwhile to note that our method can also be used in the other feature extraction methods.

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## REFERENCES


[1] C. L. Liu and H. Fujisawa, "Classification and learning for character recognition: comparison of methods and remaining problems," Machine Learning in Document Analysis and Recognition, Springer Berlin, 2008, pp.139-161.

[2] C. L. Liu, F. Yin, D. H. Wang, and Q. F Wang, "Chinese handwriting recognition contest 2010," Proc. Chinese Conference on Pattern Recognition 2010, 2010, pp.1-5.

[3] L. W. Jin and G. Wei, "Handwritten Chinese character recognition with directional decomposition cellular features," Journal of Circuits, System, and Computers, vol. 8, 1998, pp. 517-524.

[4] Q. Huo, Y. Ge, and Z.D. Feng, "High performance Chinese OCR based on Gabor features,discriminative feature extraction and model training," Proc. IEEE Int'l Conf. Acoustics, Speech, and Signal Processing, 2001, pp. 1517-1520.

[5] C. L. Liu, K. Nakashima, H. Sako, and H.Fujisawa, "Handwritten digit recognition: investigation of normalization and feature extraction techniques," Pattern Recognition, vol. 37, 2004, pp. 265-279.

[6] H. Liu and X. Ding, "Handwritten character recognition using gradient feature and quadratic classifier with multiple discrimination schemes," Proc. 8th Int'l Conf. Document Analysis and Recognition, 2005, pp. 19-23.

[7] Z. L. Bai and Q. Huo, "A study on the use of 8-directional features for online handwritten Chinese character recognition," Proc. 8th Int'l Conf. Document Analysis and Recognition, 2005, pp. 262-266.

[8] C. L. Liu, "Normalization-Cooperated Gradient Feature Extraction for Handwritten Character Recognition," IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 29, Aug. 2007, pp. 1465-1469.

[9] R. A. Fisher, "The use of multiple measurements in taxonomic problems," Annals of Eugenics, vol. 7, 1936, pp. 179-188.

[10] L. Ming and B. Yuan, "2D-LDA: a statistical linear discriminant analysis for image matrix," Pattern Recognition Letters, vol. 26, 2005, pp. 527-532.

[11] S. Noushath, G. Hemantha Kumar, P. Shivakumara, "(2D)2LDA: An efficient approach for face recognition," Pattern Recognition, vol. 39, 2006, pp. 1396-1400.

[12] C. R. Rao, "The Utilization of multiple measurements in problems of biological classification," J. Royal Statistical Soc. B: Methodological, vol. 10, Oct. 1948, pp. 159-203.

[13] J. Ye, R. Janardan, and Q. Li, "Two-Dimensional Linear Discriminant Analysis," Neural Information Processing Systems, 2005, pp. 1569-1576.

[14] J. Yang, D. Zhang, X. Yong, and J. Y. Yang, "Two-dimensional discriminant transform for face recognition," Pattern Recognition, vol. 38, 2005, pp. 1125-1129.

[15] S. W. Lee and J. S. Park, "Nonlinear shape normalization methods for the recognition of large set handwritten character," Pattern Recognition, vol. 27, 1994, pp. 895-902.