Modified Quadratic Classifier and Directional Features for Handwritten Malayalam Character Recognition

Bindu S Moni
School of Computer Sciences
Mahatma Gandhi University
Kerala, INDIA

G Raju
Department of Information Technology
Kannur University
Kerala, INDIA

ABSTRACT

Gradient of images is an effective discriminative feature, widely used in pattern recognition applications. In this work the twelve directional codes depending on the gradient direction is coupled with a statistical classifier for designing an offline recognition system for handwritten isolated Malayalam characters. Preprocessed character images are decomposed into sub-images using the Fixed Meshing strategy and the twelve directional codes are extracted to form the feature vector. Classification has been carried out by implementing the Modified Quadratic Discriminant function (MQDF), a successful statistical approach for Handwritten Character Recognition. We obtained 95.42% accuracy, and the experimental result shows that the approach provides better results. Compared to QDF, MQDF improves the classification performance by more than 10%, reduces the computation cost and also provides dimensionality reduction to a larger extent. A database of 19,800 handwritten Malayalam character samples was used for the experiment.

Keywords

Fixed Meshing, Gradient Features, Handwritten Character Recognition, Quadratic Classifiers.

1. INTRODUCTION

Handwritten character recognition being a challenging problem in pattern recognition area, widely captures the attention of researchers. The large variation of individual writing style adds to the complexity. The discriminative power of the feature is showing beneficial impact on the HCR system. The combination of feature – classifier pair contributes to the performance of the system. Feature extraction methods are generally based on statistical and structural features of the characters. The directions of character strokes contain important information for character recognition. If we can precisely describe that strokes in certain directions occur at certain positions in the character image, the character can be easily categorized. The gradient feature provides higher resolution on both magnitude and angle of the directional stokes, which leads to improvement on the character recognition rate [17]. The gradient feature represents local characteristic of a character image. In [21], the features of directions of pixels of the characters with respect to their neighboring pixels are extracted to form the feature vector. The direction is divided into 12 regions with each region covering angle of 30 degree, hence direction value of any pixel can have only 12 values assigned from 1 to 12. This approach increases the information content and gives better recognition rate with reduced recognition time.

Statistical techniques and neural networks are the widely used classification methods in various pattern recognition problems. The robust characteristic and simple training schemes of statistical approaches owes to fit in practical applications. Offline HCR systems are matured only in few languages like English and Chinese [4] [5] [12] [13].

The performance of an HCR system generally depends on the character set. In Malayalam language, characters of the alphabet are rich in shape and they are subjected to many variations in terms of handwriting styles. Malayalam characters are isolated in nature; there is no cursive writing and no upper and lower case difference. Only few works are reported in Malayalam HCR [1] [7] [8] [9] [10] [11] [14] [16] [18] [19] [22]. Most of the above works used the same database or its extension.

This work focuses on offline recognition of unconstrained, isolated Handwritten Malayalam Characters. Methods which decompose the character images in blocks (zones) are very popular in HCR. We have implemented Fixed Meshing for blocking the character images. The features of directions of pixels of the characters with respect to their neighboring pixels are extracted to form the feature vector. For classification, we implemented a MQDF classifier [17].

The rest of the paper is organized as follows. In section 2, feature extraction method is described. The classifier is presented in section 3. The experiment and results are included in section 4. Finally, section 5 concludes the paper.

2. CHARACTER FEATURE

2.1 Meshing Techniques

The feature extraction methods for handwritten character recognition are based on two types of features: statistical and structural. The statistical features are derived from the statistical distributions of pixels, such as zoning, moments, projection histograms or direction histograms. Structural features are based on the topological and geometrical properties of the character, like strokes and their directions, end-points or intersection of segments and loops. Integration of the structural and statistical information is a better solution to accommodate the large variations observed on the handwritten character images and highlight different character properties. Since these two types of features can be considered complementary in nature, the features representing the structural properties of different regions of the character image extracted with the aid of partial decomposition (blocking or zoning) should work efficiently for the Malayalam scripts.

2.1.1 Fixed Meshing

Fixed meshes are constructed by dividing the image into N equal sized blocks. For example, a 27 X 27 image can be divided into nine 3 X 3 blocks (Fig. 1).

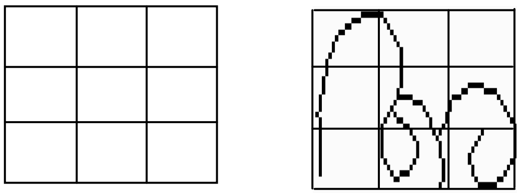

Fig. 1. Fixed Meshing

2.2 Directional Features

Gradient direction feature is flexible for application to machine print/handwriting, binary/gray scale, and low-resolution images. Specifying a number of standard directions, a gradient vector of arbitrary direction is decomposed into two components coincident with the two neighboring standard directions (Fig. 2). The components are assigned to the corresponding direction planes. On decomposing all the gradient vectors, a number of feature values are extracted from each direction plane. Conventionally, the gradient is computed on each pixel of the normalized image [3]. The gradient feature represents local characteristic of a character image properly, but it is sensitive to the deformation of handwritten character [20].

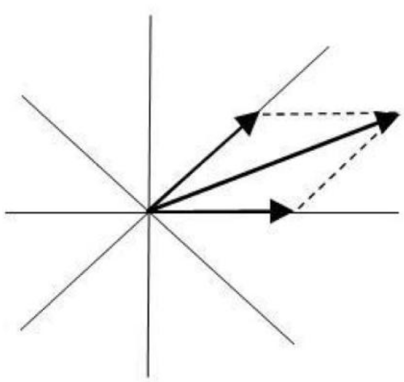

Fig. 2. Direction decomposition of gradient vector

In this work, the gradient feature is extracted from grayscale image. Each image of character is normalized into 72×72 size and thinned. To extract gradient feature, 3×3 Sobel operators are used. It uses two templates to compute the gradient components in horizontal and vertical directions, respectively. The templates are shown in Fig. 3 and two gradient components at location (i, j) are calculated by:

$$\begin{aligned} g_v(i,j) = {} & f(i-1,j+1)+2f(i,j+1)+f(i+1,j+1) \\ & -f(i-1,j-1)-2f(i,j-1)-f(i+1,j-1) \end{aligned} \tag{1}$$

$$\begin{aligned} g_h(i,j) = {} & f(i-1,j-1)+2f(i-1,j)+f(i-1,j+1) \\ & -f(i+1,j-1)-2f(i+1,j)-f(i+1,j+1) \end{aligned} \tag{2}$$

The gradient direction is computed as,

$$\theta = \arctan[gv(i,j) / gh(i,j)] \tag{3}$$

-1	0	1
-2	0	2
-1	0	1

Vertical Template

1	2	1
0	0	0
-1	-2	-1

Horizontal Template

Fig. 3. Sobel operator templates

At each pixel of the image, the gradient direction is mapped on to 12 direction codes with an equal angle span (30 degree) between the directions. Fig. 4 shows the 12 directions.

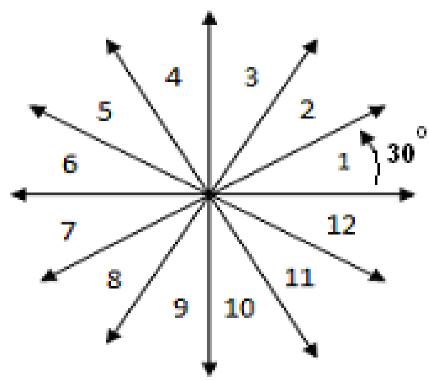

Fig. 4. 12 Directions

3. THE CLASSIFIER

The statistical classifiers typically construct generative probabilistic model or learn prototypes for each character class. Here, the parameters of one class are estimated from the samples of its own class only. The training time is linear with the number of classes and is easy to add a new class to an existing classifier. For many statistical pattern recognition methods, distributions of sample vectors are assumed to be normal, and the quadratic discriminant function (QDF) derived from the probability density function of multivariate normal distribution is used for classification. The multivariate normal distribution is usually used as the density function because it is easy to handle and in many cases the distribution of sample vectors can be regarded as normal if there are enough samples. If there are not enough training samples, accurate estimation of the covariance matrix is not possible. Also, for the higher dimensions, the estimation error increases in eigen value expansion. To achieve high recognition accuracy in statistical pattern recognition, the distribution of patterns must be precisely estimated. For the precise estimation, a great number of sample patterns are required, especially when the feature vector is high dimensional. Since the estimation error of the covariance matrix is critical when the training samples are limited, Kimura et al. proposed the modified quadratic discriminant function (MQDF), which has been successful in character recognition [17].

3.1 MQDF Classifier

For a d- dimensional feature vector x, the QDF distance can be represented as follows,

$$g_i(x) = (x-\mu_i)^T \Sigma_i^{-1}(x-\mu_i) + \log|\Sigma_i| \qquad (4)$$

$$i = 1,2\ldots C$$

Where C is the number of the total character classes. μ_i and Σ_i denote the mean vector and the covariance matrix of a given class ω_i, respectively.

Using orthogonal decomposition on Σ_i, and replace the minor eigen values with a constant σ^2 (combined variance) to compensate for the estimation error caused by small training set, the MQDF distance is derived as

$$g_i(x) = \frac{1}{\sigma^2}\{\| x-\mu_i \|^2 - \sum_{j=1}^{k}(1-\frac{\sigma^2}{\lambda_{ij}})[\varphi_{ij}^T(x-\mu_i)]^2\} + \sum_{j=1}^{k}\log\lambda_{ij} + (d-k)\log\sigma^2$$

$$i = 1,2\ldots.C \qquad (5)$$

Where λ_{ij} and φ_{ij} denote the jth eigenvalue (in descending order) and the corresponding eigenvector of Σ_i respectively. k (k < d) denotes the number of dominant principal axes.

Compared to QDF, MQDF improves the classification performance and reduces the computation and storage cost from O (d^2) to O (kd). The classification rule then becomes

$$\omega(x) = \underset{1 \le i \le C}{\arg\min}\; g_i(x) \qquad (6)$$

4. EXPERIMENT

4.1 Dataset

A database containing real samples of handwritten characters with different size, shape variation, thickness etc is important to evaluate the performance of any HCR system. In the present study we considered only isolated characters of vowels and consonants. Four hundred and fifty handwritten pages containing the selected 44 characters are collected from different persons belonging to different age groups, qualification, and profession. Each page is scanned at 300 DPI. The characters are segmented, cropped to fit the minimum sized window and stored. The resultant data base consists of 450 samples each of the 44 selected character classes. It includes broken and distorted characters.

4.2 Preprocessing

The characters are resized to 72x72 images and thinned.

4.3 Feature Extraction Algorithm

For each image in the database, apply the following method. Find and record the feature values.

1. Find the horizontal gradient gh at each pixel
2. Find the vertical gradient gv at each pixel
3. Find the gradient direction, at each pixel
4. Map the gradient direction into 12 directions
5. Apply Fixed Meshing: Divide the image into 36 (6 x 6) equal sized blocks.
6. For each block, find the sum of each directional codes.

Extracted features (432) are stored into files which are used for subsequent experiments. Fig. 5 shows the gradient codes assigned to a block.

1	1	1	1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	1	11
1	1	1	1	1	1	1	1	1	1	11	11
1	1	1	1	1	1	1	1	1	11	11	2
1	1	1	1	1	1	1	1	1	10	11	10
1	1	1	1	1	1	1	1	11	10	11	10
1	1	1	1	1	1	1	11	11	2	11	11

Fig. 5 Gradient Codes of a block

4.4 Training and Testing

The training and testing was carried out with 4 different data sets. In all the experiments, 70% of the samples are selected randomly for training and the remaining 30% for testing. Among the 19800 samples in the database, 13860 samples are used in the training phase and the remaining 5940 in the testing phase. For the creation of next data set, another combination of the same character samples (19800) are considered, and the selected 70% (13860) training data & 30% (5940) testing data will be different from the first. The formation of the four different data sets ensures the distribution of all variations of characters across training and testing phases.

4.5 Result and Discussion

The results are tabulated in table 1. The experiment was done with different number of blocks. The best results were obtained with 36 blocks. The 12 directional codes for 36 blocks forms the feature vector of size 432. We got a recognition rate of 85.16 % with QDF for 432 features. For improving the recognition rate and reducing the dimensionality, we experimented with MQDF for various K values. The dominant principal axes K has been reduced nearly to $1/4^{th}$ of D. The best classification performance, 95.42%, was obtained for a value of K = 118. The testing time is also reduced to 40% of time required for QDF.

Table 1. Classification Performance

Data Set	**Classification Accuracy (%)**					
	QDF	MQDF (D = 432)				
	D = 432	K = 120	K = 119	K = 118	K = 117	K = 116
1	84.29	94.81	94.83	94.88	94.95	94.81
2	85.35	95.59	95.49	95.81	95.86	95.77
3	86.08	95.86	95.79	95.82	95.79	95.81
4	84.92	95.19	95.2	95.17	94.88	94.9
AVG	**85.16**	**95.36**	**95.33**	**95.42**	**95.37**	**95.32**
Testing Time (min)	**25.21**	**10.66**	**10.61**	**10.5**	**10.6**	**10.48**

In the paper [17], the authors take L directional code for each pixel. The L directional codes are summed up in each block to get the features. The dimensionality depends on the value of L. We have added the directional codes of pixels in each block, which results in dimensionality reduction. Further reduction is done by experimenting with MQDF. Selection of number of dominant principal axes for reducing the estimation error caused by small training set is experimentally found. We have tested with the different values of K. A higher recognition rate is attained by a relatively small value of K. The computation cost is also reduced to a higher extent. Fig. 6 shows the performance of MQDF with the promising values of K.

In comparison to the previous works mentioned in section 1, we have used more number of characters and samples per character. Hence outcome of the study is significant.

5. CONCLUSION

In this work, we implemented Fixed Meshing for the offline recognition of handwritten isolated Malayalam characters. The feature values for classification are formed by the twelve directional features of the blocks. QDF and MQDF classifier is used for classification. From the results obtained, it is found that the classifier gives better result with K (dominant principal axes) as 118 from a total of 432 features. Also, computational efficiency is achieved. MLP network requires considerable amount of time for training and a fraction of seconds for testing. The training time for statistical classifier is very small and testing time is larger. In comparison with MLP, the overall time for MQDF is much smaller.

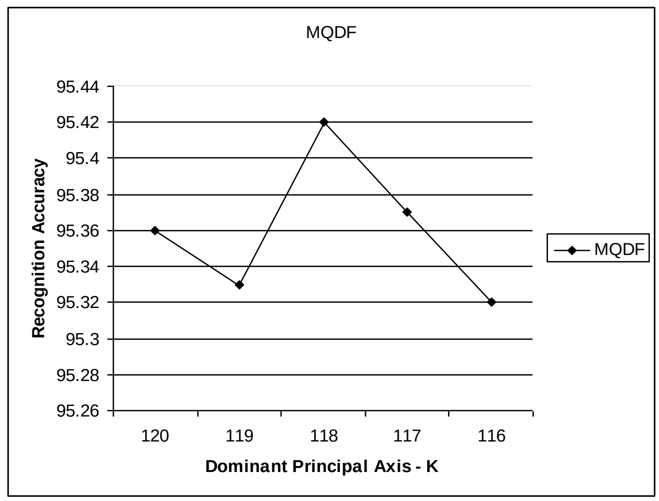

Fig. 6. Performance of MQDF with different values of K.

REFERENCES

[1] Bindu S Moni, Raju G, "Meshing and Normalized Vector Distance from Centroid for Handwritten Malayalam Character Recognition", 2nd Int. National Conference on Signal and Image Processing (ICSIP – 2009), Mysore, 2009, pp 398 – 403, Aug 12 – 14.

[2] Bunke H., Wang P.S.P., Handbook of Character Recognition and Document Analysis, World Scientific, 1997.

[3] Cheng-Lin Liu, "Normalization-Cooperated Gradient Feature Extraction for Handwritten Character Recognition", IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 29, no. 8, August 2007.

[4] Nagy G, "Twenty Years of Document Analysis in PAMI", IEEE Trans. On PAMI, Vol 22(1), pp 38 – 61, 2000.

[5] Plamondan R., Srihari S.N., "Online and Offline Handwriting Recognition: A comprehensive Survey", IEEE Trans. On PAMI, Vol 22(1) pp 63 – 84, 2000.

[6] Rajasekharadhya S.V., Vanaja Rajan P., "Efficient Zone Based Feature Extraction Algorithm for Handwritten numeral Recognition of four Popular South Indian Scripts", J. of Theoretical and applied Information technology, pp1171 – 1181, 2008.

[7] Raju G,"Recognition of Unconstrained Handwritten Malayalam Characters Using Zero-crossing of Wavelet Coefficients", Proc. of 14th International Conference on Advanced Computing and Communications, 2006, pp 217 – 221.

[8] Raju G, "Wavelet Transform and Projection Profiles in Handwritten Character Recognition – A Performance Analysis", Proc. 16th International Conference on Advanced computing and Communication (ADCOM)*), 2008, pp 309-313.

[9] Raju G, Bindu S Moni., "Global Elastic Meshing for Handwritten Malayalam Character Recognition", Proc. of the National Conference on Computational Science and Engineering - NCCSE 2009, Cochin, Kerala, February, 2009, pp 10 – 14.

[10] Raju G, Bindu S. Moni, "Global and Local Elastic Meshing for Handwritten Malayalam character Recognition", Int. J. of Computers, Information Technology and Engineering, Vol. 3, No. 1, January - June 2009, pp. 149 – 153.

[11] Renju John, Raju G and Guru D. S., "1D Wavelet Transform of Projection Profiles for Isolated Handwritten Character Recognition", Proc. of ICCIMA07, Sivakasi, 2007, Vol 2, 481-485, Dec 13-15.

[12] Srihari S.N., Yang X. and Ball G.R., "Offline Chinese Handwriting Recognition: an assessment of current Technology", Front. Comput. Sci, China, Vol. 1(2), pp. 137-155, 2007.

[13] Trier D, Jain A.K. and Taxt T, "Feature Extraction Methods for Character Recognition - A survey", Pattern Recognition, Vol 29, 4, pp 641 – 662, 1996.

[14] Bindu S Moni, G Raju, "Multiple MLP Classifiers for Handwritten Malayalam Character Recognition", Proc. of the Int. National Conference on Mathematical and Computational Models: Recent Trends- ICMCM-09, Coimbatore, 2009, pp 349-354, Dec 21-23.

[15] Binu P. Chacko, Babu Anto P., "Discrete curve Evolution Based Skeleton pruning for character recognition", Proc. of IEEE International Conf. in Pattern Recognition, 402 – 405, Feb 2009.

[16] Bindu S Moni, G Raju, "Quadratic Classifier for Handwritten Malayalam Character Recognition", Proc. of the U G C sponsored National Conference on Soft Computing, organized by Dept. of Computer Applications, Marian College Kuttikkanam, Kerala, Jan 20 – 22, 2010, pp. 59 – 68, ISBN: 978-81-908520-1-2.

[17] Hailong Liu and Xiaoqing Ding, "Handwritten Character Recognition Using Gradient Feature and Quadratic Classifier with Multiple Discrimination Schemes", Proc. of the 2005 Eight Int. Conference on Document Analysis and Recognition (ICDAR'05).

[18] Bindu S Moni, G Raju, "Study on different Meshing Techniques and Normalized Vector Distances for Handwritten Malayalam Character Recognition", Int. Journal of Engineering Research and Industrial Applications (IJERIA), Vol. 3, No.1 (Feb 2010), pp 181 – 195, ISSN 0974-1518.

[19] Bindu S Moni, G Raju, " Runlength Counting for Handwritten Malayalam Character Recognition", Proc. of the AICTE sponsored Int. National Conference, ICMCM 2010, organized by MACFAST, Thiruvalla June 17-19, 2010.

[20] Weipeng Zhang, Yuan Yan Tang, Yun Xue, "Handwritten Character Recognition Using Combined Gradient and Wavelet Feature",1-4244-0605-6/06/$20.00 ©2006 IEEE.

[21] Dayashankar Singh, Sanjay Kr. Singh, Dr. (Mrs.) Maitreyee Dutta, "Hand Written Character Recognition Using Twelve Directional Feature Input and Neural Network", ©2010 International Journal of Computer Applications (0975 – 8887) Volume 1 – No. 3.

[22] Bindu S Moni, G Raju " Modified Quadratic Classifier And Normalised Vector Distance For Handwrittan Malayalam Character Recognition", Proc. of the Int. National Conference on Emerging Trends in Mathematics and Computer Applications – ICETMCA 2010, organized by MEPCO Schlenk Engg. College, Sivakasi, , Dec 16-18, 2010, pp 356 – 360, ISBN : 978 – 81 – 8424 – 649 - 0.