Optical Chinese Character Recognition using Probabilistic Neural Networks

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Abstract

Building on previous work in Chinese character recognition, we describe an advanced system of classification using probabilistic neural networks. Training of the classifier starts with the use of distortion modeled characters from four fonts. Statistical measures are taken on a set of features computed from the distorted character. Based on these measures, the space of feature vectors is transformed to the optimal discriminant space for a nearest neighbor classifier. In the discriminant space, a probabilistic neural network classifier is trained. For classification, we present some modifications to the standard approach implied by the probabilistic neural network structure which yield significant speed improvements. We then compare this approach to using discriminant analysis and Geva and Sitte's Decision Surface Mapping classifiers. All methods are tested using 39,644 characters in three different fonts.

1 Introduction

1.1 Factors in Optical Chinese Character Recognition

Optical character recognition for Chinese texts poses new and interesting pattern recognition problems when compared to recognition of Latin or other Western scripts. The size of the corpus is daunting: Chinese fonts contain several thousand characters, including the few hundred English letters and symbols. Since Chinese does not use an alphabet, one can not employ the use of a dictionary to improve accuracy.

From a pattern recognition standpoint, Chinese characters are of widely varying complexity, consisting of one to thirty or more distinct strokes. Differences between individual characters can be quite small, as can be seen in **Figure 1**. In contrast, the differences between fonts can be significant, as shown in **Figure 2**. Both of these factors together are a potential problem for some methods of omnifont recognition techniques. Specifically, for a given feature, two characters may have only a small between-class variance and a large within-class variance, implying an overlapping of their distributions.

Proposing font detection then font-specific recognition causes a separate set of problems. Accurate font detection is difficult as small variations on a font often occur, which in Western typesetting would be considered a separate font. However, because of the size of the character set, it is not feasible to store separately all the variations a single font family may have. As we will show later, omnifont recognition seems to be a viable method of

Figure 1 Examples of visually similar characters in the *songti* font.

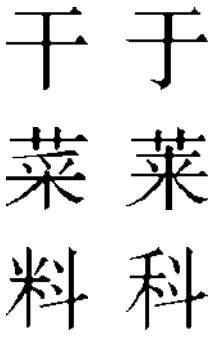
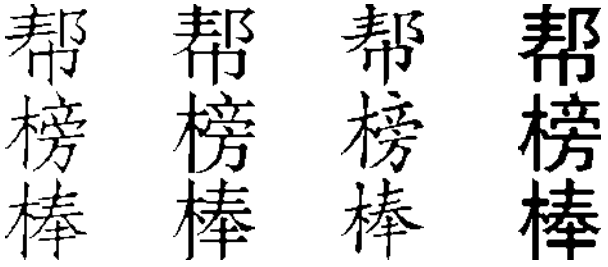


Figure 2 Examples of characters in the four main fonts. Left to right, they are: *fangsongti*, *songti*, *kaiti*, and *heiti*.



classification.

Finally, because of the complexity of the entire Chinese character set, our work uses a large set of features. Because of the size of the entire feature vector, heuristics and optimizations are needed to effectively prune it down to a more manageable size, pointing to the need for some type of feature selection or combination.

1.2 Previous Work

The backbone of this work is the actual features which are computed on the characters. The features which we use were originally developed specifically for printed Chinese texts. The most complete description of the entire feature set can be found in [Suchenwirth *et al.* 89,] a study done by the Institutes of Measurement and Control Techniques, Communications, and Linguistics at the Technical University of Berlin. Their work includes a survey of Chinese character recognition methods and their relative performance. A table of the feature types and their sizes is given in **Table 1**, and **Appendix A** describes all of the features in more detail. These features are computed on a normalized 64×64 image.

Our previous work, described in [Romero *et al.* 95,] consisted of two main pieces: statistical analysis of the features to create a nearest-neighbor classifier, and an additional post-processing step of neural network training. The statistical analysis was performed on a collection of 37,000 characters in the *songti* font, scanned from Chinese texts and subsequently ground-truthed. Based on these measurements, multiple discriminant analysis was performed to combine all of the features into a reduced-dimension space while scaling the dimensions to uniform within-class variance. Applying the discriminant transform to a set of reference characters rendered from a TrueType font generated the class means for the nearest neighbor classifier.

Additionally, we applied two methods of neural network training, LVQ (Learning Vector Quantization) and DSM (Decision Surface Mapping,) to further modify the nearest neighbor classifier. The training was performed using a subset of the ground-truthed character data. In those tests, the LVQ training resulted in the better performance.

1.3 Ground Truth Data

We have generated a set of ground truth data from various printed sources that represent characters in three fonts: *songti*, *fangsongti*, and *kaiti*. The one font we do not have represented is *heiti*, which is a “headline” style font. Of these fonts, the distribution of characters

Name	Dimensions
Stroke Width	1
Total Stroke Length	1
Horizontal Projection	64
Vertical Projection	64
Number of Horizontal Transitions (white-to-black)	1
Number of Vertical Transitions (white-to-black)	1
First Order Peripheral Features	32
Second Order Peripheral Features	32
Stroke Density at 0° and 90°	16
Local Direction Contributivity with four regions and four directions	64
Maximum Local Direction Contributivity	64
Stroke Proportion	32
Black Jump Distribution in Balanced Subvectors	32
Total Feature Dimensions	404

Table 1 Brief summary of the features extracted.

and sources is given in **Table 2**. The vast majority of characters are from the *songti* font. The document quality and font sizes vary widely between the various sources. The document set was selected as a representative sample of publications one could expect to see from the People's Republic of China by a native of the country.

1.4 Current Work

The previous tests were all done on a single font and the scanned data was used in all of the steps when creating the classifier. By not performing font detection, one potential source of error has been omitted. By using our scanned data to create the classifier, our results were optimistically biased. It is unclear how much of a factor either of these omissions comes in to play, but the downward impact on the generalizing capability of the resulting classifier is assured.

We have since advanced this work, using distortion modeled data to create omnifont recognition capabilities. By using distortion modeled data, we also lessen the impact seen when characters with low occurrence rates need to be classified. From our set of 39,644 ground-truthed characters, only 1948 unique characters were represented, and 463 characters appear exactly once. The total font size is 6992 characters.[1] In another study of character

Table 2 Ground Truth Character Information

Font	Characters	Unique Characters	Number of Source Pages	Number of Source Documents
songti	37 021	1 850	68	13
kaiti	1 816	500	2	1
fangsongti	807	357	5	1

frequency [Xiandai 86], a collection of 1.8 million characters contained 4574 unique characters, 425 of which occurred only once. By using distortion modeling, we can generate exemplars of all of the characters.

In addition, we have extended our work to provide probability measures on the result of a classification. Previously, using forms of nearest neighbor classification, there was no absolute measure of confidence which could be extracted from the classification results. We have implemented a new method of training and classification using PNN's (Probabilistic Neural Networks) to directly model the probability distributions of the individual character classes.

2 Discriminant Transformation

2.1 Multiple Discriminant Analysis

By computing the features outlined in **Table 1** and described in **Appendix A**, we can apply multiple discriminant analysis (MDA) techniques to create a nearest-neighbor, omnifont classifier. A brief summary of the computations involved is given here, but for a full discussion see [Duda and Hart 73]. The goal of multiple discriminant analysis is to maximize

$$\frac{|\tilde{S}_b|}{|\tilde{S}_w|} = \frac{|W^t S_b W|}{|W^t S_w W|} \qquad \text{(EQ 1)}$$

In this equation, s_b is the between-class scatter matrix, s_w is the within-class scatter matrix, and w is the transformation we are searching for in order to form the optimal discriminant space. We can define the following, with χ_i being the set of exemplars in class i, and x a feature vector for a particular exemplar:

$$\boldsymbol{m_i} = \left(\frac{1}{n_i}\right) \sum_{x \in \chi_i} \boldsymbol{x} \qquad \text{(EQ 2)}$$

$$\boldsymbol{m} = \left(\frac{1}{n}\right) \sum_i n_i \boldsymbol{m_i} \qquad \text{(EQ 3)}$$

$$S_i = \sum_{x \in \chi_i} (\boldsymbol{x} - \boldsymbol{m_i})(\boldsymbol{x} - \boldsymbol{m_i})^t \qquad \text{(EQ 4)}$$

$$S_w = \sum_i S_i \qquad \text{(EQ 5)}$$

$$S_b = \sum_i n_i (\boldsymbol{m_i} - \boldsymbol{m})(\boldsymbol{m_i} - \boldsymbol{m})^t \qquad \text{(EQ 6)}$$

Equation 2 computes the class means based on the set of exemplars. Both the within-class scatter s_w and the between-class scatter s_b are analogous to their respective covariance matrices. In looking for w we can define:

$$\boldsymbol{y} = W^t \boldsymbol{x} \qquad \text{(EQ 7)}$$

$$\psi_i \equiv \left\{ \boldsymbol{y_i} \middle| (\boldsymbol{x_i} \in \chi_i, y_i = W^t \boldsymbol{x_i}) \right\} \qquad \text{(EQ 8)}$$

$$\tilde{\boldsymbol{m}}_i = \left(\frac{1}{n_i}\right) \sum_{y \in \psi_i} \boldsymbol{y} \qquad \text{(EQ 9)}$$

$$\tilde{\boldsymbol{m}} = \left(\frac{1}{n}\right) \sum_i n_i \boldsymbol{m_i} \qquad \text{(EQ 10)}$$

$$\tilde{S}_w = \sum_i \sum_{y \in \psi_i} (\boldsymbol{y} - \tilde{\boldsymbol{m}}_i)(\boldsymbol{y} - \tilde{\boldsymbol{m}}_i)^t \qquad \text{(EQ 11)}$$

$$\tilde{S}_b = \sum_i n_i (\tilde{\boldsymbol{m}}_i - \tilde{\boldsymbol{m}})(\tilde{\boldsymbol{m}}_i - \tilde{\boldsymbol{m}})^t \qquad \text{(EQ 12)}$$

And it follows from this that

$$\tilde{S}_w = W^t S_w W \qquad \text{(EQ 13)}$$

$$\tilde{S}_b = W^t S_b W \qquad \text{(EQ 14)}$$

Taking the determinant of a scatter matrix is equivalent to finding the product of the eigenvalues, which corresponds to the product of the variances. Looking back at Equation 1, by maximizing this ratio, we are looking for a transform w that maximizes the between-class

1. This font size is for the simplified character sets, as distributed in the Apple Chinese Language Kit, which includes the Latin alphabet, Arabic numerals, standard punctuations, and symbols.

variance with respect to the within-class variance. The solution of Equation 1 can be shown to correspond to the generalized eigenvectors of the equation:

$$S_b \boldsymbol{w_i} = \lambda_i S_w \boldsymbol{w_i} \qquad \text{(EQ 15)}$$

where the vectors $\boldsymbol{w_i}$ then form the columns of the matrix W.

In addition, the individual dimensions of the discriminant space created by each eigenvector $\boldsymbol{w_i}$ are now ordered. The between-class variance in dimension i is proportional to the eigenvalue λ_i. Assuming a constant within-class variance, the higher the between-class variance of a dimension, the better discriminant capacity of that dimension. This fact will aid later in improving classification speed.

One additional step can be taken to scale all the within-class variances to uniform size in the discriminant space. The variance in dimension i can be computed as:

$$\boldsymbol{w_i}^t S_w \boldsymbol{w_i} \qquad \text{(EQ 16)}$$

and each dimension can be scaled by replacing $\boldsymbol{w_i}$ with

$$\hat{\boldsymbol{w_i}} = \frac{\boldsymbol{w_i}}{\sqrt{\boldsymbol{w_i}^t S_w \boldsymbol{w_i}}} \qquad \text{(EQ 17)}$$

giving each new dimension uniform variance. This should be done if the classifier being used does not account for differing variances between dimensions, as is the case in DSM and LVQ.

2.2 Computation

The computation of the discriminant transform was obtained by first computing s_w, s_b, and $\boldsymbol{m_i}$ based on the features from all of the distortion modeled characters. However, because some of the feature elements are linearly dependent on other features, s_w and s_b are not of full rank, and the linearly dependent dimensions need to be removed. To determine these dependencies, the correlation matrix was computed from the total covariance matrix, $\left(\frac{1}{n}\right)(S_w + S_b)$. Linear dependence between dimensions can be determined using variance inflation factors, the diagonals of the inverse correlation matrix. A high variance inflation factor signifies that a particular dimension is a linear combination of others. (For a discussion on variance inflation factors, see [Myers 90] or another statistical textbook on regression.) Dimensions are iteratively removed, always removing the dimension with the highest variance inflation factor, until the maximum variance inflation falls below a threshold. Using a threshold of 1000, we removed 9 dimensions, for a total feature vector of 395 dimensions.

All that remains is a straightforward calculation of the eigenvalues and eigenvectors. The transformation matrix is formed with eigenvectors in the order of their increasing eigenvalues. To obtain an initial set of class means, compute $\tilde{\boldsymbol{m}}_i$ as shown in Equation 9.

3 Probabilistic Neural Networks

In our past experience with classification using the DSM (Decision Surface Mapping [Geva and Sitte 91]) and LVQ (Learning Vector Quantization [Kohonen 88]) algorithms, we found the lack of a confidence measure on classification results somewhat disconcerting. The result of the classification in these systems is a distance measure between an exemplar and a class, which provides an ordering for the results, but the actual distance is of little use for computing confidence measures.

As a result, we have chosen to implement a PNN (Probabilistic Neural Network [Specht 88]) classifier. The PNN implementation attempts to model the actual probability distributions of classes with mixtures of Gaussians, allowing the computation of the posterior probability associated with each exemplar classification.

Standard PNN methods require the storage of all of the exemplars in order to compute the final probability of class membership. Instead, we have used Mixture Gaussian PNN's [Streit and Luginbuhl 94] which create probability distributions using a fixed number of Gaussian components. The resulting distribution formed through Generalized Fisher iterative training is the local maximum likelihood estimate for the class. **Appendix B** contains a short description of the training algorithm. See [Streit and Luginbuhl 94] for details, discussion, and a derivation.

The training computes three sets of values: the means for the components of each class, the mixing proportions to use for the individual components, and the final within-class covariance matrix. We will let μ_{ij} be the i^{th} component mean for class j, π_{ij} be its mixing proportion, and Σ be the final within-class covariance matrix. Then, the probability density function associated with classifying exemplar x as a member of class j is given by:

$$g_j(\boldsymbol{x}) = \sum_{i=1}^{G_j} \pi_{ij} p_{ij}(\boldsymbol{x}) \qquad \text{(EQ 18)}$$

where G_j is the number of Gaussian components used to model class j and $p_{ij}(\boldsymbol{x})$ is defined as:

$$p_{ij}(\boldsymbol{x}) = (2\pi)^{-N/2}|\Sigma|^{-1/2}\exp\left[-\frac{1}{2}(\boldsymbol{x}-\mu_{ij})^t\Sigma^{-1}(\boldsymbol{x}-\mu_{ij})\right] \qquad \text{(EQ 19)}$$

We assume that the costs associated with choosing any of the characters incorrectly is the same. By choosing the class with the highest-valued probability density function, the Bayes minimum risk decision can be made. Alternatively, a priori character occurrence probabilities can be embedded into this system. The ability to improve classification, though, is dependent on the character occurrence rates for the particular document set. If the rates embedded into the classification system do not correlate well with the observed character occurrences, recognition results could be hindered.

4 Classification Modifications

Examining Equation 19 shows that in order to compute the probability density function of an exemplar belonging to a single class, a vector-matrix multiply must be computed. The dimension of the matrix Σ is $n \times n$, where n is the dimension of the feature vector. Considering the size of the initial feature vector at about 400 dimensions, this vector-matrix multiply is a serious bottleneck in computation. With two Gaussian components per character class, it would take approximately 320,000 multiply-adds to compute a single $g_j(x)$, and over 2 billion multiply-adds to classify a single character.

One simple proposal is to ignore all of the covariances as if they were zero and just consider the dimension variances. This may seem like a drastic measure, but on closer inspection, it has some credibility. When performing an initial multiple discriminant analysis step, one of the results is that the discriminant feature space is created using an orthogonal basis, the eigenvectors. As such, all within-class and between-class covariance is removed. However, that is with respect to the initial covariance matrices. The PNN Generalized Fisher training introduces a new set of covariance matrices based on classes made of Gaussian mixtures. The question is, how much covariance is introduced by this training.

Another method is to reduce the dimensionality of the feature vectors. Again, multiple discriminant analysis helps in performing this task by ordering the transformed dimensions based on their discriminant capacity. All that needs to be done is to pick the top n eigenvectors which will make up the columns of the transformation matrix. We used this method in [Romero *et al.* 95] when doing just

a single font. This step can done before PNN training takes place. However, choosing a reasonably sized n of 100, classifying a single character still requires a very large number of floating point computations. With two component means per class, approximately 140 million multiply-adds would be required for each classification.

Taking the cues up to this point, one should see that before any exemplar is given to the classifier, a vector-matrix multiply is applied to transform it into the discriminant space. It is feasible to modify the initial discriminant transform so that instead of orthogonalizing the initial within-class covariance, it orthogonalizes the feature space after PNN training occurs. In order to do this, we simply apply multiple discriminant analysis again to the covariance space generated from the PNN training.

This can be done by computing the eigenvectors and eigenvalues corresponding to the within-class covariance matrix, Σ in Equation 19, and the new between-class covariance matrix, C_b. C_b can be computed as follows:

$$\tilde{S}_T = \tilde{S}_w + \tilde{S}_b \qquad \text{(EQ 20)}$$

$$C_b = \frac{1}{n}(\tilde{S}_T) - \Sigma \qquad \text{(EQ 21)}$$

The generalized eigenvectors of Σ and C_b can be used to create the transform matrix V as before, and we have:

$$\hat{\boldsymbol{y}} = V^t\boldsymbol{y} = V^t(W^t\boldsymbol{x}) = (V^tW^t)\boldsymbol{x} \qquad \text{(EQ 22)}$$

$$\hat{\Sigma} = V^t\Sigma V \qquad \text{(EQ 23)}$$

The resulting $\hat{\Sigma}$ will be a diagonal matrix and the vector-matrix multiply is now an $O(n)$ operation instead of $O(n^2)$. The exemplar's feature vector must still have a transform applied to it, but this is only done once. The vector-matrix multiply in Equation 19 is done for every component of every character class. Using n equal to 100 and using two components per class, we now have an initial vector-matrix multiply of about 40,000 multiply-add's to compute the transformed exemplar, then an additional 1.4 million multiply-adds to compute the probability density functions.

Note that the initial transformation generated using MDA was based on covariance estimates using a single component mean. The final transformation is based on covariance estimates using more complex multiple-component distributions. However, any information loss generated in the first transformation will be propagated through the entire system. We currently have not examined the effects on performance which may be caused by this initial information loss. (See **Section 6.5** for a discussion of the relevant results.)

Also note that the final post-processing MDA step does not affect classification performance. All of the information which was contained in the space before this step is retained. Specifically, the Mahalonobis distances, used in computing the probability density functions, are preserved. We have simply removed the existing covariances from the new space.

Lastly, an iterative pruning method can be used in conjunction with the above orthogonalization step. Since the dimensions of the final transform are ordered according to their discriminant capacity, one can use a small subset of the dimensions to form a candidate pool, then iteratively increase the number of dimensions to reduce the size of the candidate pool. While heuristic in nature, this optimization can be safely done if one avoids over-zealous candidate pruning.

5 Distortion Modeling

All of our classification methods reported here used distortion modeling to generate sets of exemplars. The initial set of "clean" characters was generated by rendering scalable TrueType fonts into a 64×64 bitmap, using all of the *songti*, *fangsongti*, *kaiti*, and *heiti* simplified

Figure 3 Example of distortion effects on a single character in the *songti* font.

variations. The distortion program we used was originally developed by Mitek Systems, Inc. While the program offers additional types of noise effects, we used it to generate blurring and scaling effects. We augmented their distortion types to also perform thinning. **Table 3** describes the types of distortion and their parameters.

The blurring and thinning effects are controlled by one parameter, the probability that a single (foreground) pixel will be blurred or thinned. A very high probability, ($p > 0.95$,) of blurring causes a uniform thickening of the image. A moderate probability, ($0.1 > p > 0.5$,) causes the edges to become increasingly jagged with each iteration. Low probabilities, ($0.1 > p$,) cause fine distortions around the edges of the character.

The scaling effects are simulated by a virtual discretization of the full resolution bitmap into a lower resolution. The actual image size is not changed, but the effect is the same as first scaling the image down, applying an appropriate thresholding parameter, and then scaling the image back to the original size. The scale we used was $2{:}1$, making the 64×64 bitmaps appear as if they were scaled up from a 32×32 bitmap. Thresholding was done at three different levels of 1, 2, and 3 pixels out of a possible 4.

6 Results

We have tested the following sets of classification schemes, all of which resulted in omnifont classifiers:

- Multiple Discriminant Analysis using 100, 150, and 200 dimensions
- DSM training applied after MDA, using fixed training data
- PNN training applied after MDA using fixed training data, and classification without covariances
- PNN training applied after MDA, with covariances eliminated by a second MDA, using dynamically generated training data
- PNN training applied after MDA, using dynamically generated training data, and classification without covariances.

The first three methods all used training data generated from a single set of distortion models. The models used blurring and scaling distortions combined in various ways to arrive at 16 different noise models. The models are summarized in **Table 4**. No thinning operations were done in these runs. The effects of the distortion can be seen in the images shown in **Figure 3**. The number of characters being

Table 3 Description of Distortion Specification Format

Command	Description
(b *p*)	Blur foreground pixels with probability *p*
(s *d*)	Scale apparent resolution 50%, using *d* foreground pixels as the threshold. (1 <= *d* <= 4)
(t *p*)	Thin foreground pixels with probability *p*. (Blur the inverse image.)

Table 4 Distortion models used for MDA, DSM and PNN training using a static set of exemplars.

Lists of Distortions Applied	
((b 0.99) (b 0.05) (b 0.05))	((b 0.05) (b 0.05))
((b 0.2) (b 0.2))	((b 0.99) (b 0.2) (b 0.2) (s 3))
((b 0.05))	((b 0.2))
((b 0.1))	((s 1) (b 0.25) (b 0.25) (s 2) (b 0.05))
((b 0.99) (b 0.99) (b 0.05) (b 0.05))	((b 0.99) (b 0.99) (b 0.2) (b 0.05) (b 0.05))
((b 0.99) (b 0.2) (b 0.1) (b 0.1) (b 0.05) (b 0.05) (s 3))	((s 2) (b 0.2) (b 0.1) (b 0.1) (b 0.05) (s 3))
((b 0.99) (b 0.2) (b 0.1) (b 0.1) (b 0.05) (b 0.05) (s 2))	((b 0.99) (b 0.4) (b 0.1) (b 0.1) (b 0.05) (b 0.05) (s 2))
((b 0.99) (b 0.4) (s 2))	((b 0.99) (b 0.4) (s 3) (b 0.125))

Table 5 Distortions used for dynamically generated exemplars used during PNN training

Lists of Distortions Applied	
((b 0.99) (b 0.05) (b 0.05))	((t 0.5) (b 0.05))
((b 0.2) (b 0.2))	((b 0.99) (t 0.2) (b 0.2) (s 3))
((b 0.9) (b 0.9) (t 0.2) (b 0.05))	((b 0.05))
((s 1) (b 0.25) (b 0.25) (s 2) (t 0.05))	((b 0.9) (b 0.05) (t 0.7) (b 0.05))

used in the training set totaled 447,488, with 6992 characters per font and 64 exemplars per character class, generated using 16 noise models applied to each of the 4 fonts.

Another set of distortion models was used in dynamically training a full PNN model with covariances. The actual steps taken in this experiment differ from all other training methods in that all of the exemplars were dynamically generated. The set of distortion models for this run are given in **Table 5**. A summary for all the results is given in **Table 6**.

6.1 MDA Classifiers

Using just multiple discriminant analysis, we generated three nearest-neighbor classifiers. Each classifier used the dimension reduction properties of multiple discriminant analysis to a varying degree. The transformation matrix was modified so that the final dimensions were all scaled to uniform variance. The final number of dimensions used was reduced from the initial feature size of 404 dimensions to each of 100, 150, and 200 dimensions. The classification results on the ground truth set is given in **Table 6**, rows one through three.

The difference between using 100 versus 200 dimensions in the resulting classifier is small, only about 0.15%. Note that the results obtained using just MDA are equivalent to LVQ with a single prototype per class and also to PNN with a single component per class. Using just this method, we obtain a very respectable 97% recognition rate using a 100 dimensional space.

6.2 DSM Classifier

For details on our version of the DSM algorithm, please refer to [Romero et al. 95]. We included a new feature in which additional components could be added to a class during the training phase. The modified DSM training algorithm was applied on the nearest-neighbor classifier of 100 dimensions generated with MDA. Our parameter settings were:

$\alpha_0 = 0.2$, the initial learning rate.

$\beta = 0.01$, the linear decrease applied to the learning rate each epoch.

$\gamma = 1.75$, the threshold used to determine if a new component should be added to a class.

These parameters are fully described in

Table 6 Performance results of various training algorithms.

Algorithm	Dimensions	Number of Components	Recognition Rate
MDA	100	6 992	97.07
MDA	150	6 992	97.13
MDA	200	6 992	97.22
MDA+DSM	100	7 026	97.61
MDA+PNN (without covariances)	100	13 984	97.43
MDA+PNN+MDA	100	20 885	97.32
MDA+PNN (without covariances)	100	20 885	97.04

Figure 4 Absolute values of correlations corresponding to the within-class covariance matrix after

[Romero et al. 95]. The classifier was presented each of the 447,104 distorted characters four times. The order of exemplar presentation was pseudo-random: first, the distortion model and font were randomly picked, then the ordering of the exemplars was permuted. Since each character class occurred only once per distortion model and font pair, all of the character classes will be presented exactly once before any of the character classes are repeated. The resulting classification performance is given in **Table 6**, row four.

The improvement in classification is quite good, considering the low level of additional overhead involved in classification. The results for the individual fonts are:

songti -	97.70%
kaiti -	95.76%
fangsongti -	97.15%

The modifications to the classifier during DSM training have a tendency to target the more troublesome areas of classification. By adding additional prototypes where needed, a significant improvement can be made with minimal costs. However, there is still the remaining problem of obtaining confidence intervals. One aspect of DSM training is that class prototypes are moved to form decision boundaries, not to model actual character distributions. Because of this, the prototypes tend to move towards the actual boundaries in order to make finer boundary modifications, rendering the distance information useless for computing confidence intervals.

6.3 PNN Without Covariances

We have also tested the PNN training algorithm while disregarding the covariance measures during classification, but not training, considering only the dimensional variances. For this test, we used two component means per class, for a total of 13,972 individual components. The training was performed in the first 100 dimensions of the discriminant space, which were not rescaled to uniform variance. The PNN training forms its own estimates of variances, making the re-scaling unnecessary. The training was allowed to run for 25 iterations through the data. The fourth row of **Table 6** outlines these results. The results on a per-font basis are:

songti -	97.53%
kaiti -	95.70%
fangsongti -	96.78%

The results for the MDA and DSM algorithms are quite encouraging, however the PNN training using no covariance measures is surprisingly unspectacular. Using twice the number of component means, it performs slightly worse than using just multiple discriminant analysis alone.

One possible explanation is that the aggregate affects of disregarding covariances is quite damaging. In examining this issue, we can look at the within-class correlation matrix obtained after the PNN classifier has been trained. The first 25 dimensions of the within-class correlation matrix are given in **Figure 4**. The dimensions have previously been ordered according to their discriminant capability, making the first 25 dimensions relatively more descriptive and relevant than later dimensions. **Figure 4** seems to indicate that there is quite a bit of covariance information which we are throwing out.

Another possible problem, mentioned briefly before, is that the initial MDA step caused irreparable loss of some information which carried through to the PNN training. If this occurred, we could expect that the PNN classifier would perform only about as well as MDA techniques alone, even though it contained twice as many components per class.

It could also be the case that the training set is too small to accurately estimate the component means. For each class, we are using 64 exemplars to estimate two component means and their mixing proportions. The next test addresses this particular issue. The other objections raised will be considered in light of the additional results.

6.4 PNN with Covariances and Dynamic Distortion Models

The final classifier we have built uses all of the covariance information throughout training, a dynamically generated set of exemplars, and an additional post-processing MDA step to create an orthogonal space. The set of distortion models used is given in **Table 5**. In this run, the following steps were done all using the same distortion models, but freshly generated data. Each set of distortion data consisted of 32 exemplars per class, 8 distortion models applied to 4 fonts:

- Generate initial estimates for the within-class and between-class covariance matrices based on single component class means.
- From this, form a transformation matrix that results in a 100-dimensional space.
- In the transformed space, create estimates for the component means using the moving-averages algorithm (as described in **Appendix B**) on a fixed set of distortion exemplars.
- Create an initial estimate of the within-class covariance matrix using a new set of distortion exemplars.
- Perform PNN training for 20 epochs, generating a new set of distortion data for each epoch.
- Using the initial and final covariance estimates, as outlined in **Section 4**, create a new transformation matrix which orthogonalizes the transformed space.

The total number of exemplars generated for the entire process was over five million, 23 sets of 32 exemplars per class. For this classifier, we have increased the initial number of component means per class to 3. During training, some of these are pruned out because their mixing proportion becomes negligible, and the final classifier contained 20,885 component means. The results are shown in row 4 of **Table 6**. Again, performance is only slightly better than just MDA techniques alone, and still not as good as the DSM classifier. The total performance rate was 97.32, and the performance for the three fonts came out as:

songti -	97.32%
kaiti -	95.15%
fangsongti -	96.03%

Even more interesting, the performance of this classifier, which used all the covariance information, is only comparable to the previous classifier which completely ignored that information during classification.

As a final test of the importance of the covariances, this classifier was used to generate another model that disregarded the covariances. Instead of performing the final MDA step, the off-diagonals of the covariance matrix compute up to that point were set to zero, and the initial transformation matrix was kept intact.

The results for that run were in the last row of **Table 6**, with recognition rates of 97.04%. The breakdown is:

songti -	97.16%
kaiti -	95.29%
fangsongti -	95.43%

These rates are surprisingly comparable to what we obtained using the covariance information.

6.5 Discussion

The most telling of all the results given above is the comparison between PNN classification with and without covariances. There is a possible confounding of factors here, since the distortion models and the number of component means changed. After examining these factors, it seems that the critical process is in the distortion modelling step.

It was mentioned earlier that there was some inevitable information loss when applying MDA to reduce dimensionality. This, however, can not be the sole cause of the problems seen when using PNN training. If it were, it could be remedied by not performing any dimension reduction. MDA can still be used to generate the discriminant functions, while keeping the full dimensionality of the feature vector without loss of information. We have attempted just this, applying PNN training on a non-reduced space, with no better performance than already reported.

One possible scenario which could sidestep the initial loss is as follows:

- Compute the MDA transformation matrix using all available dimensions
- Train the PNN classifier in the full discriminant space
- Reduce the dimensionality of the final classifier using a post-processing MDA step

In this process, no information loss is incurred until the final MDA step, and keeping around all information for PNN training may be beneficial. However, as was said in **Section 4**, classification performance is not affected by any additional MDA post-processing if all of the dimensions are retained. In order for this method to perform better than the other PNN methods, two things need to be true:

- The MDA transforms we applied to reduce dimensionality prior to PNN training caused significant information loss.
- The same loss won't occur with an MDA transform applied after PNN training.

We have strong reason to believe that the first item is true, but the second item is more dubious. The reason for doubt is that the same distortion models are used throughout the entire process. Information deemed irrelevant with an initial MDA dimension-reduction will likely still be irrelevant after PNN training.

Further evidence of this comes when looking at the empirical within-class scatter matrix generated from the ground truth data, compared to the within-class scatter matrix computed on the distorted exemplars. We computed the within-class covariance matrix of the ground-truth data using all of the characters which had ten or more instances. The total number of character instances used was 35,899 out of a total 39,644 characters in our corpus.

PNN training has occurred.

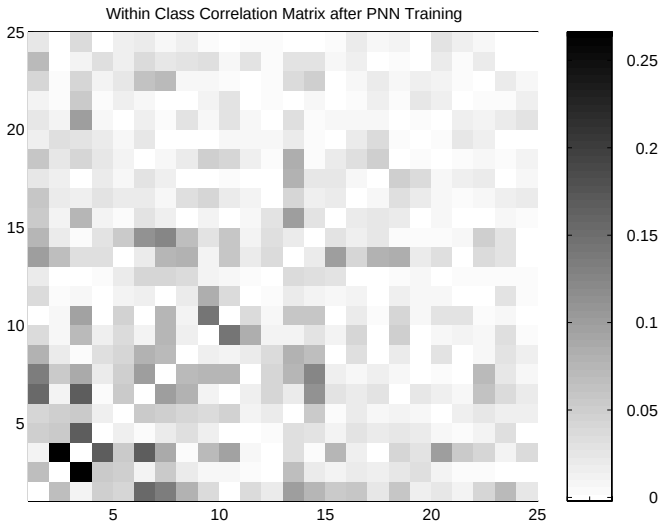


Figure 5 Absolute values of correlations from the transformed within-class covariance matrix generated from the ground-truth data.

We then computed the covariance as it would exist in the discriminant space using the same transformation matrix generated for creating the MDA classifier. If the covariance estimates from the distorted characters are accurate, the transformed covariance matrix should be nearly diagonal. **Figure 5** shows the absolute values for the first 25 dimensions of the transformed, within-class correlation matrix with the diagonals removed. It is quite evident that we have not created an orthogonal basis for the true distribution of characters because of the prominence of correlations between dimensions.

Since the covariance estimates were inaccurate, PNN training hindered the final performance more than helping through trying to include the covariances as additional and useful information. This is further shown by the relative performance of the PNN classifiers with and without the use of the covariances. While somewhat disconcerting, these results do show us where work still needs to be done.

7 Summary

Given the available information, we have identified a crucial area which needs additional attention: distortion modeling. We believe that the greatest gain in recognition performance will come from additional work in creating more accurate distortion modelling techniques. In addition, we have shown methods which can be used to verify a distortion set's validity.

We have developed and demonstrated several classification models for Chinese character recognition. In addition, we have generated a large corpus of ground truth data used for classification verification. Of our existing implementations, the best recognition performance was attained using multiple discriminant analysis combined with decision surface mapping post-processing. However, this system does not provide estimates for posterior probabilities on the classification results.

We have developed a class of recognition methods that utilize both multiple discriminant analysis and probabilistic neural networks. In

addition, we have presented methods of improving the classification speed without loss of precision. We have shown a viable method for an omnifont Chinese character recognition scheme that allows posterior probabilities to be computed on the classification results. What remains to be done is an extensive examination of iterative pruning methods to further increase classification speed.

Appendix A : Description of the Feature Set

Stroke Width

To compute the average stroke width, three bitmap masks are convolved with the image:

Each match in the image with at least one of these masks counts as a single hit. A single location in the image that matches multiple masks is only counted once. If b, blackness, is the number of foreground pixels, and h is the number of hits, the average stroke width is then $b/(b-h)$.

Notice that if there are no hits, then the stroke width is one. If there are half as many hits as foreground pixels, the stroke width is two. The result is a single valued feature of dimension one.

Total Stroke Length

An estimate for the total stroke length can be obtained by taking the number of foreground pixels, b, divided by the average stroke width, w. This can be simplified, substituting from the equation for average stroke width to $b/w = b/(b/(b-h)) = b-h$.

Horizontal and Vertical Histograms

Two histograms are computed, one horizontal and one vertical. Each histogram is a feature vector of dimension 64. The value for the feature in dimension n is the number of foreground pixels in row n for horizontal histograms, or in column n for vertical histograms.

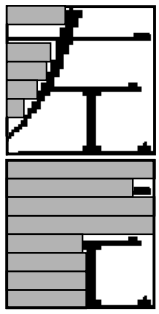
Transitions

Similar to the histograms, transitions are computed along horizontal and vertical scan-lines. The value for scan-line n is the number of transitions from background to foreground pixels. The feature value is the sum of all the transitions in the given direction, resulting in two values, one for the horizontal scan and one for vertical scan.

Peripheral Features

Peripheral features are computed on an image sub-divided into “stripes” in both the horizontal and vertical directions. The first order peripheral feature for a particular stripe is the distance from the edge of the strip to the first background to foreground transition. The second order peripheral feature is the distance from the edge of the strip to the closest second background to foreground transition along a single scan-line.

The second order peripheral feature is not necessarily the second transition in the stripe. Instead, we look for the second transition within a scan-line and report the closest of these within each stripe. Below is an example of the first and second order peripheral features in the “East” direction.



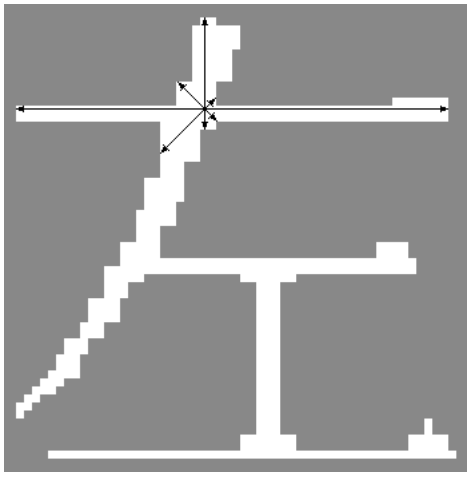
First and second order peripheral features are computed for each of the four main directions, North, South, East and West. The image is divided into eight stripes. This results in 32-dimensional features for both first and second order peripheral features.

Stroke Density

To compute stroke density, first divide the image into eight stripes for both horizontal and vertical directions. Within each stripe, count the number of background to foreground transitions. The result is a 16-dimensional feature.

Local Direction Contributivity

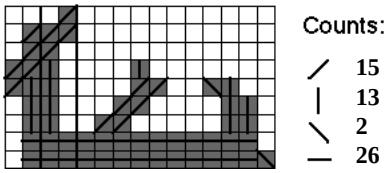
Local direction contributivity locally measures the size of strokes in the four major orientations. For each foreground pixel, we compute the length of four lines that pass through the pixel, one for each of $0°$, $45°$, $90°$, and $135°$. The line segment spans only foreground pixels, giving it endpoints next to the furthest background pixel. An example of these four lines is given below:



The image is then divided into regions using a four-by-four grid. For each region, the average length of the lines for each of the four orientations is computed. This results in a 64-dimensional feature.

Stroke Proportion

Stroke proportion is a proportional measure of stroke directions. To start, for each foreground pixel, determine the orientation of the longest continuous line of foreground pixels that passes through this pixel. Orientations are limited to $0°$, $45°$, $90°$, and $135°$. The pixel is then labeled as a member of a stroke in that orientation. The figure below shows such a labeling for a sub-image.



The image is divided into four stripes for both horizontal and vertical directions. Within each stripe, the fraction of pixels labeled with each orientation is computed. For the above stripe, with a total of 56 foreground pixels, the stroke proportions would be:

$0° \Rightarrow 26/56$

$45° \Rightarrow 15/56$

$90° \Rightarrow 13/56$

$135° \Rightarrow 2/56$

Each of these is reported for a single stripe, and there are four horizontal and four vertical stripes, resulting in a 32-dimensional feature.

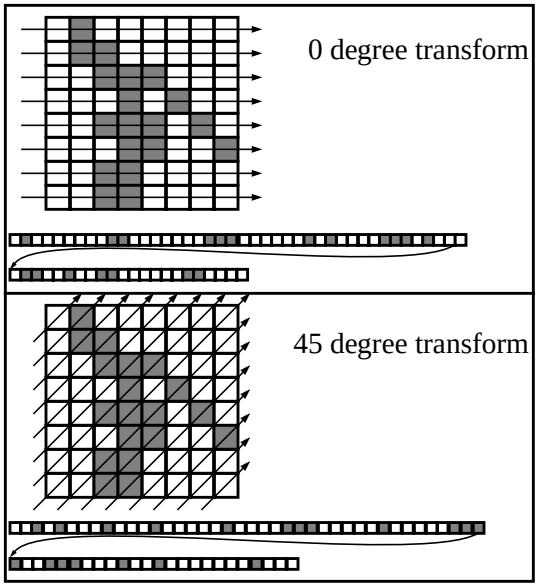
Maximum Local Direction Contributivity

This feature is closely related to local direction contributivity and stroke proportion. Each foreground pixel is assigned an orientation based on the same computation as in stroke proportion. The image is divided into a grid as in local direction contributivity. Within each block, report the number of foreground pixels which belong to each orientation. The result is a 64-dimensional feature.

Black Jump Distribution in Balanced Subvectors

This feature treats an image as a single long vector instead of a two-dimensional object. The transformation into a single vector is done four separate ways to represent the four orientations. Below is an image of how an image would be transformed into a vector for

the $0°$ and $45°$ orientations:



Each long vector is then sub-divided into k sub-vectors each with approximately the same number of foreground pixels. Within each sub-vector, the number of background to foreground transitions is computed and divided by the total number of transitions for the entire vector. We used k equal to 8, yielding a 32-dimensional feature.

Appendix B : PNN Training

Training for the maximum likelihood probabilistic neural network is achieved through the following steps. First, initial estimates are made for the component means, $\mu_{ij}^{(0)}$, the mean for class j and component i. This is done using a moving averages algorithm applied for each class. Initial estimates for components are randomly selected from the set of exemplar data. All exemplars are classified as members of their closest component. Then, each $\mu_{ij}^{(0)}$ is recomputed as the mean of all exemplars which are members of this component. The algorithm stops iterating when no changes are made to any of the $\mu_{ij}^{(0)}$'s.

Mixing proportions, $\pi_{ij}^{(0)}$, for each component are initially computed as the number of exemplars which are members of component i divided by the total number of exemplars for class j. Let N be the total number of classes, x_{jk} be the k'th exemplar for class j, G_j be the number of components for class j, and T_j be the number of exemplars for class j. The within-class covariance matrix is initially estimated using the following:

$$\Sigma^{(0)} = \frac{\sum_{j=1}^{N}\sum_{i=1}^{G_j}\sum_{k=1}^{T_j}(\pi_{ij}^{(0)})^2(\boldsymbol{x}_{jk}-\mu_{ij}^{(0)})(\boldsymbol{x}_{jk}-\mu_{ij}^{(0)})^t}{\sum_{j=1}^{N}T_j} \quad \text{(EQ 24)}$$

For our work, we began training with $G_j = G$ and $T_j = T$, a constant number of exemplars and components means for all classes.

For PNN training iteration n, we start by computing the following:

$$w_{ij}^{(n)}(\boldsymbol{x}_{jk}) = \frac{\pi_{ij}^{(n)}\exp\left[-\frac{1}{2}(\boldsymbol{x}_{jk}-\mu_{ij}^{(n)})^t(\Sigma^{(n)})^{-1}(\boldsymbol{x}_{jk}-\mu_{ij}^{(n)})\right]}{\sum_{l=1}^{G_j}\pi_{lj}^{(n)}\exp\left[-\frac{1}{2}(\boldsymbol{x}_{jk}-\mu_{lj}^{(n)})^t(\Sigma^{(n)})^{-1}(\boldsymbol{x}_{jk}-\mu_{lj}^{(n)})\right]} \quad \text{(EQ 25)}$$

Then, we update the mixing proportions using:

$$\pi_{ij}^{(n+1)} = \frac{1}{T_j}\sum_{k=1}^{T_j} w_{ij}^{(n)}(\boldsymbol{x}_{jk}) \quad \text{(EQ 26)}$$

And the new component means are:

$$\mu_{ij}^{(n+1)} = \frac{\sum_{k=1}^{T_j} w_{ij}^{(n)}(\boldsymbol{x}_{jk})(\boldsymbol{x}_{jk})}{\sum_{k=1}^{T_j} w_{ij}^{(n)}(\boldsymbol{x}_{jk})} \quad \text{(EQ 27)}$$

The new covariance matrix is estimated as:

$$\Sigma^{(n+1)} = \frac{1}{\sum_{j=1}^{N}T_j}\cdot\sum_{j=1}^{N}\sum_{i=1}^{G_j}\sum_{k=1}^{T_j} w_{ij}^{(n)}(\boldsymbol{x}_{jk})\cdot (\boldsymbol{x}_{jk}-\mu_{ij}^{(n+1)})(\boldsymbol{x}_{jk}-\mu_{ij}^{(n+1)})^t \quad \text{(EQ 28)}$$

Care needs to be taken at some points of this computation. For instance, it is possible for

one of the mixing proportions, π_{ij}, to become small. In Equation 27, there is an implicit division by π_{ij}, which can cause problems if π_{ij} approaches zero. Our implementation checked for small π_{ij}, on the order of 10^{-5}, and removed the corresponding component mean from that class. The assumption is that removing components that have little or no influence on the final computation for $g_j(x)$ in Equation 18 is safe.

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