Compact MQDF classifiers using sparse coding for handwritten Chinese character recognition

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**A B S T R A C T**

The modified quadratic discriminant function (MQDF) is an effective classifier for handwritten Chinese character recognition (HCCR). However, it suffers from high memory requirement for the storage of its parameters, which makes it impractical to be embedded in memory limited hand-held devices. In this paper, we explore the applicability of sparse coding to build compact MQDF classifiers. To be specific, we use sparse coding to compact the parameters of MQDF. Two methods of sparse coding, viz., the maximum likelihood-based method and the K-SVD method, are adopted to build two compact MQDF classifiers, namely, MQDF-ML classifier and MQDF-KSVD classifier. Furthermore, we learn multiple dictionaries rather than single dictionary for sparse coding, because the multiple dictionary learning is capable of not only greatly reducing the computational complexity, but also alleviating the degradation of recognition accuracy, compared to the single dictionary learning. Experiments and comparison with the existing method have demonstrated the effectiveness of our proposed method for the issue of unconstrained handwritten Chinese character recognition.

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1. Introduction

The performance of handwritten Chinese character recognition (HCCR) has been improved by many effective approaches [1–4]. Among these traditional methods, the modified quadratic discriminant function (MQDF) has been extremely successful and widely used for HCCR due to its high performance with low computation complexity [5]. And many methods have been proposed for improving the accuracy of MQDF in the past two decades. For instance, Liu et al. [6] proposed to use the minimum classification error (MCE) criterion for discriminative training of MQDF. The re-training of MQDF based on instance importance weighting [7] and instance selection [8] can be also viewed as some kinds of discriminative training. MQDF and its discriminative learning version, namely discriminative learning quadratic discriminant function (DLQDF), once yielded the highest performance [6]. Zhang et al. [9] proposed a method called locally smoothed modified quadratic discriminant function (LSMQDF) to avoid over-fitting of the training data by smoothing the covariance matrix of each class with its nearest neighbor classes. The accuracy of recent MQDF on unconstrained handwritten Chinese character database CASIA-HWDB 1.1 is over 90.2% [9,10]. Nowadays, deep learning based methods are getting more and more popular. With the impact from the success of deep learning in different domains, the solution for HCCR has been changed from traditional methods to convolutional neural networks (CNN) [11–13]. The difference on features and classification mechanisms between MQDF and CNN are significantly. MQDF is implemented with hand designed features such as directional feature, Gabor feature, or stroke distribution feature. And it assumes that the features satisfy Gaussian distribution. The maximum likelihood estimates are usually used as the parameters in MQDF. Unlike MQDF, CNN operates on raw image pixels directly, and learns feature extraction, dimensionality reduction and classifier parameters at the same time in a supervised manner. Therefore CNN can provide end-to-end solutions for many pattern recognition problems. But the computation complexity of CNN is extremely high for large scale classification and training a robust CNN needs a large amount of samples. Wang et al. [14] suppose that these significant differences between MQDF and CNN may complement each other. Based on this idea, they proposed an MQDF-CNN hybrid model for HCCR and the experimental results demonstrated that the combination of MQDF and CNN outperformed either of them alone. Furthermore,
by integrating the traditional normalization-cooperated direction-decomposed feature map (this feature map was used by MQDF before and made the MQDF achieved the best accuracy for HCCR) with the CNN, Liu et al. [13] have obtained the highest accuracies for both online and offline HCCR on the ICDAR-2013 competition dataset. Hence, it is reasonable to believe that the improvement of MQDF related methods is still an important issue since it can help to boost the performance of HCCR. In this paper, the main objective of our study is to build a compact MQDF classifier. Although CNN can achieve the higher performance than MQDF and can be designed very compact (e.g. the method of [13] achieved 97.373% by a single network of 23.5 MB for ICDAR-2013 offline HCCR competition), a compact MQDF with lower computation and time complexity is more suitable to be embedded in memory limited handheld devices.

There are many related work to build compact classifier and they have been successfully applied to some hand-held devices [15–18]. Wang and Huo [15] proposed a approach to modeling the inverse covariance matrices by expansion of some tied basis matrices. Furthermore, they extended their work to simultaneously compress the parameters and improve the accuracy through vector quantization (VQ) technique and minimum classification error (MCE) training [16]. Zhu et al. [17,18] built a compact online Markov random field (MRF) recognizer for large handwritten Japanese character set using structured dictionary representation and VQ technique. However, there is little study on memory reduction of MQDF except Long and Jin’s work [19,20]. They compressed the principal eigenvectors of MQDF classifier by subspace distribution sharing which combined VQ technique and clustering algorithm. Their method greatly compressed the storage of the MQDF classifier with a small accuracy loss when tested on the dataset of HCL2000 [21]. And their compact MQDF classifier was integrated in a handwritten Japanese text recognizer by Gao et al. [22].

The storage requirement of MQDF classifier is usually very large (e.g. 140 MB for a 3755-class, 160-dimension and 60 principal eigenvectors problem [23]). And the storage mainly depends on the number of principal eigenvectors of MQDF classifier. An intuitive way to reduce the memory space of MQDF is storing only a small number of principal eigenvectors. However, this strategy may result in tremendous accuracy loss as demonstrated in our experiments. To reduce the memory space of MQDF and prevent the loss of accuracy, in this paper, we use sparse coding [24] to represent the principal eigenvectors in sparsity. Sparse coding has emerged as a successful tool for analyzing a large class of signals [25–27]. Many signals can be efficiently represented with a linear superposition of a few properly chosen basis functions. Such compact representation of signals is desired and has been widely used in applications such as signal compression and denoising [28,29].

We apply the sparse coding to train a compact MQDF classifier for HCCR. The diagram of the recognition system is given in Fig. 1. As shown in the figure, the discriminative features are extracted from the pre-processed handwritten Chinese character images and then are used to train the MQDF parameters including mean vectors, principal eigenvalues, and eigenvectors of the covariance matrix. For storage compressing, the parameters can be stored in a form of sparsity via sparse coding. We focus on compressing the parameter of eigenvectors because they take the most storage space in MQDF. To be specific, the D-dimension eigenvectors are used to learn an overcomplete dictionary $\Theta = \{\theta_{j}\}_{j=1}^{\infty}$ ($\theta_{j} \in \mathbb{R}^{D}$, $d \geq D$) that contains $d$ basis functions (also called atoms) for columns. Then the eigenvectors are encoded by the learned dictionary to generate a new sparse representation, i.e., each eigenvector is represented by some linear combination of a small number of dictionary elements. In this way, a compact MQDF can be derived. In testing phase, the eigenvectors are reconstructed by sparse linear combination of the atoms to recognize the input character image.

The remainder of this paper is organized as follows: Section 2 describes the compact MQDF via sparse coding. Section 3 shows the experimental results and Section 4 concludes the paper.

## 2. Compact MQDF via sparse coding

MQDF proposed by Kimura et al. [5] makes a modification to the quadratic discriminant function (QDF) by K-L transform and smoothing the minor eigenvalues to improve the computation efficiency and classification performance. Although MQDF classifier has been extremely successful in recognizing unconstrained handwritten Chinese characters, it still has a parameter complexity problem for large category classification. Therefore, we aim to build a compact MQDF classifier in this study.

### 2.1. MQDF classifier

MQDF is derived from the QDF classifier, which is a Bayesian classifier assuming samples of each class satisfying Gaussian distribution. A QDF of an $D$-dimension feature vector ($x$) is given as

$$f_{QDF}(x, i) = (x - \mu_{i})^{T} \Sigma_{i}^{-1} (x - \mu_{i}) + \log |\Sigma_{i}|,$$

where $\mu_{i}$ and $\Sigma_{i}$ denote the mean vector and the covariance matrix of class $i$, respectively. QDF is actually a distance metric of the input pattern with the classes and the class with minimum QDF is assigned to the input pattern.

By K-L transform, the covariance matrix can be diagonalized as

$$\Sigma_{i} = \Phi_{i} \Lambda_{i} \Phi_{i}^{T},$$

where $\Lambda_{i} = \text{diag}(\lambda_{i1}, \ldots, \lambda_{ij}, \ldots, \lambda_{iD})(j = 1, \ldots, D)$ denotes the eigenvalues (sorted in decreasing order) of $\Sigma_{i}$, and $\Phi_{i} = [\phi_{i1}, \ldots, \phi_{ij}, \ldots, \phi_{iD}]^{T}$ ($\phi_{ij} \in \mathbb{R}^{D}$, $j = 1, \ldots, D$) stands for the sorted eigenvectors. $\Phi_{i}$ is orthonormal (unitary) such that $\Phi_{i}^{T} \Phi_{i}$ is $I$.

Inserting Eqs. (2) to (1), the QDF can be rewritten in the form of eigenvectors and eigenvalues:

$$f_{QDF}(x, i) = \sum_{j=1}^{D} \frac{1}{\lambda_{ij}} |\phi_{ij}^{T} (x - \mu_{i})|^{2} + \sum_{j=1}^{D} \log \lambda_{ij}.$$  

By replacing the minor eigenvalues with an appropriate constant $h^{2}$, then the MQDF is derived as

$$f_{MQDF}(x, i) = \log (h^{2(D-k)} \prod_{j=1}^{K} \lambda_{ij})$$

$$+ \frac{1}{h^{2}} \|x - \mu_{i}\|^{2} - \sum_{j=1}^{K} (1 - \frac{h^{2}}{\lambda_{ij}}) |\phi_{ij}^{T} (x - \mu_{i})|^{2},$$

where $K$ is the number of principal eigenvalues per class. The value of $K$ should be judiciously selected, in order to avoid large estimation error of $\lambda_{ij}$ and $\phi_{ij}$ ($j = 1, \ldots, K$). Compared with QDF, MQDF has multifold advantages. Firstly, the bias of minor eigenvalues is overcome by replacing them with a constant. Secondly, only the principal eigenvectors and eigenvalues of covariance matrices are to be stored so that the memory space is reduced. Thirdly, the computation effort is largely saved because the projections to minor axes are eliminated.

As analyzed above, we can find that the classifier needs to train and store the parameters for each class such as mean feature vector $\mu_{i}$, principal eigenvalues $\lambda_{i}$ and eigenvectors $\Phi_{i}$ of the covariance matrix $\Sigma_{i}$. The size of parameters $\mu_{i}$, $\lambda_{i}$, and $\Phi_{i}$ for each
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</tr>
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<tbody>
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</tr>
<tr>
<td>امکان دانلود نسخه ترجمه شده مقالات</td>
</tr>
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<td>پذیرش سفارش ترجمه تخصصی</td>
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<tr>
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