Multi-resolution Character Recognition by Adaptive Classification

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Abstract. The quality of character image plays an important role for the performance of character recognition system. However there is no good way to measure the recognition difficulty of a given character image. For the given character image with unknown quality, it is improper that apply the single character database to recognize it by the same feature and the same classifier. This paper proposed a novel approach for multi-resolution character recognition whose feature is extracted directly from gray-scale image and classification is adaptive classification which adaptively selects the appropriate character database and classifiers by evaluating the image quality of the input character. A resolution evaluation algorithm based on gray distribution feature was proposed to decide the adaptive classification weights for the classifiers, which make the classification have the higher probability of being the correct decision. Experiment results demonstrate the proposed approach highly improved the performance of character recognition system.

1 Introduction

With the rapid progress of digital imaging technology, there are more and more requirements for character recognition. As the variety of acquisition conditions, there are a lot of defects in the images. The degraded character recognition makes the recognition task not easy to solve, and is a bottleneck for enhancing rate of the character recognition. If it is successfully resolved, it can be applied in many ways such as name card recognition, ID card recognition, car number recognition, camera-based character recognition, and so on.

During the past decades, the great success has been achieved in document image analysis and recognition. However, for degraded character images, traditional OCR methods do not provide satisfactory recognition performance because it is very difficult for conventional methods to get clear binary character images from the degraded ones. So the new method is required to resolve the problem of the degraded character recognition.

In recent decades, some research has been concentrated on degraded character recognition, which can be divided into two categories. One is according to traditional method, which extracts the character feature from the binary character image by

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degradation recovery and advanced binarization [1,2]. It focuses on how to remove the degradation and get ideal binary patterns. However, the character degradation is much more complicated. Single recovery and simple binarization based method can not solve all the problems because these processes will inevitably result in information loss and will generate a lot of broken strokes or connected strokes and noise into the binarized image. In order to avoid the information loss the other one is proposed by directly extracting the feature from the gray scale image. It can be further divided into two categories: structural features and frequency features. Structural features include direction feature, skeleton feature, topological feature and so on [3,4]. Structural features can precisely describe the structure of a character and succeed in the characters recognition. But they are vulnerable to the recognition of low resolution gray characters. It is difficult to extract invariable structural features because of deform and variation existing in low resolution gray characters. Frequency features are very effective for the recognition of low resolution gray character, such as Fourier transform and wavelet transform.

Gabor filter is a kind of frequency filter which has good quality in character recognition. Xuewen Wang, etl. [5] utilized Gabor filters to extract the basic structures of character, and modified the non-linear function to regulate the outputs of Gabor filters adaptively to improve the performance for low quality images. Peifeng Hu, etl. [6] used Gabor Dominant orientation matrix as recognition feature by response outputs of 18 Gabor filters with different orientation. Hamamoto and Uchimura, etl. [7] proposed a Gabor filter-based feature extraction method for handwritten numeral character recognition. Yoshimura and Etoh [9] used Gabor jets projection to form a feature vector for recognizing low resolution gray-scale character. These applications show that the Gabor filter-based feature extraction methods are very effective in recognizing degraded characters.

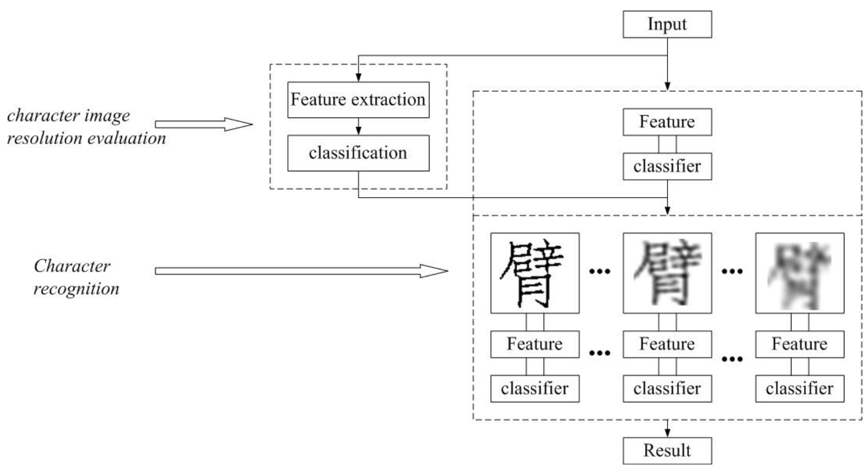

Fig. 1. Diagram of the proposed approach, which is composed of two major stems: character image resolution evaluation, character recognition

Although these approaches made some considerable success in the degraded character recognition, they only consider the feature extraction and neglect the information of the input image quality. The quality of character image plays an important role for the performance of character recognition system, but there is no measure which tells us the recognition difficulty of a given character image. For the given character image with different quality, it is improper that apply the single character database to recognize it by the same feature and the same classifier. This paper proposed a novel approach by adaptive classification which adaptively selects the appropriate character database and classifiers by evaluating the image quality of the given character image. In this paper we propose a degraded character recognition method whose feature is gray scale feature and classification is adaptive classification which selects the appropriate classifiers by evaluating character image qualities. Fig.1 shows the structure of the proposed approach. The recognition systems are composed of the following two major stem: character image quality evaluation, character recognition.

In the part of character image quality evaluation, to overcome the simplification of training data set, we ranked the training sets into several data sets according to the image quality, and select the corresponding suitable classifier for every rank training set, which can form several character recognition subsystems. For the input character image, we try to select the training **d**ata set with the most similar quality to join the recognition. In this paper, a kind of degradation source, low resolution, is taken into account. A resolution evaluation algorithm based on gray distribution feature is proposed to evaluate the character image quality in order to select the appropriate training data set.

After the input image quality is identified by the resolution evaluation algorithm, the character recognition is carried out by two stages. In the first stage, the classifier is trained by the whole character sets including all rank qualities. For the given degraded character image, a group of candidates can be generated by the first classifier. In the second stage, the given degraded image is recognized by the adaptive classifiers in these candidates. The adaptive classification is based on the quality of the given character image to decide the adaptive classification weight of every classifier's action. The adaptive classification weight is smaller for the classifier by training the character set whose quality is more different with the input character image quality, and inversely is larger for the classifier by training the character set which has more similar quality with the input image quality. The resolution evaluation algorithm was used for adaptive classification to decide the adaptive classification weights for the classifiers, which make classification have the higher probability of being the correct decision. Experiment results demonstrate the proposed approach highly improved the performance of the degraded character recognition system.

The paper is organized as follows. In section 2, the resolution evaluation method is presented to determine the adaptive classification weights. Section 3 describes the adaptive character recognition. Section 4 discussed the experiment results. In the final section conclusions are provided.

2 Character Image Resolution Evaluation

It is improper that the character recognition system only applies the single training set to recognize the character images with various degraded degree, because the single training set is only matched well to the character images with several limited kinds of image qualities. To overcome the simplification of training data set, we ranked the training sets into several data sets according to their image quality, which respectively represent good, moderate, bad data and other quality rank data. At the same time we select the corresponding classifiers according to the rank of the image quality of training sets. For the degraded input image, it is ideal to match the appropriate classifier by training the character set with the similar image quality. By the experiment we find that gray distribution feature [13] can perfectly fulfill the work of the quality rank identification of the input character image. The algorithm is performed by 2 steps: (1) Quality evaluation of Character image resolution; (3) Adaptive classification weights.

2.1 Quality Evaluation of Character Image Resolution

According to these gray distribution characteristic, the gray distribution feature (GDF) [13] is used to evaluate the resolution quality of the character image. Firstly, each character image is preprocessed to form a 64x64 uniform image. Secondly, the gray distribution feature is extracted by computing the gray histogram of the normalized image as followed:

$$h_d(i) = \begin{cases} 1, & h(i) > t_0 \\ 0, & h(i) \le t_0 \end{cases} . \tag{1}$$

Here, h is the gray histogram of the input image, i is the gray value in the range [0,255], t_0 is the threshold of h and h_d is the gray distribution feature which display the gray distribution characteristic.

After feature extraction, we apply the neural net classifier to identify the rank of character image quality. Thus it is evaluated that the input character image is good or not by the identification of the character image quality rank.

2.2 Adaptive Classification Weight

In order to avoid the mistake of image quality identification and improve the effect of adaptive classification, every classifier is required to appropriately operate during the adaptive classification. We define the adaptive classification weights (W) which are used to adaptively adjust every classifier's action according to the result of the character image quality identification. It is defined as $W = (w_1, ...w_i, ...w_n)$, where n is the rank number of character image quality, w_i is the weight of the ith classifier's operation. If the input character image quality is closer to the image quality of the ith training set, we set the weight w_i larger. Inversely the weight is smaller for the classifier by training data set with more different image quality. Thus the adaptive classification can be accomplished by adjusting the adaptive classification weights based on the input image quality.

3 Adaptive Classification

The adaptive classification for multi-resolution character recognition is specified in this section. We respectively design the corresponding feature and appropriate classifier for the recognition sub-system of every image quality rank of training sets (seen from Fig.1). In this paper, for the comparison of experiment all recognition sub-systems apply Gabor filter-based feature and the minimum distance classifier.

For multi-resolution character recognition, the output of individual classifier is not enough because the recognition of low resolution image is more difficult than high resolution image's. It is a good way that a set of special appropriate classifiers are combined to recognize the degraded character image. There are several methods of combing the classifiers that have been proved to be effective in improving the classifier performance [11,12]. So the problem focuses on how to adaptively select classifier and combine classifier in the classifier's output space. The adaptive classification weights (*W*) provide a way to compute the weighted averaging of every classifier's output, which make the given image resolution information join in the classification.

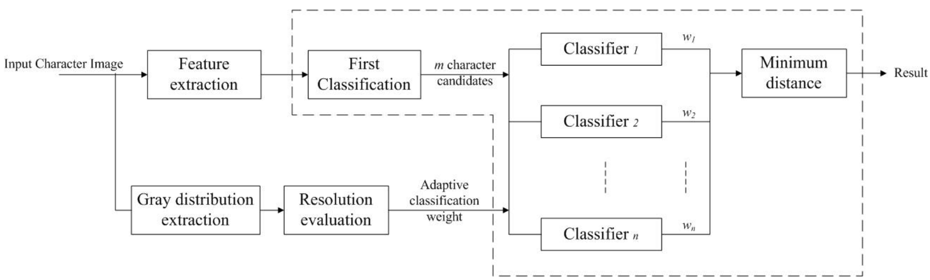

Fig. 2. Flow chart of the proposed approach

3.1 Feature Extraction

We extract the gray scale feature by Gabor filter from the input image as the recognition feature because it is proved to be effective for OCR in low-quality images. It is combined with adaptive classification to recognize the low quality character image.

Gabor filter-based feature extraction is processed by three steps. (1) Normalize the input image into the standard size *64x64*; (2) Extract the features from the outputs of Gabor filters separately; (3) Divide the input image into several blocks, and apply PCA to compress the features on every block, and concatenate the features of every block into the final powerful feature vector.

3.2 Adaptive Classification

The adaptive classification mainly consists of two steps: the first classification, the second classification (seen from Fig.3).

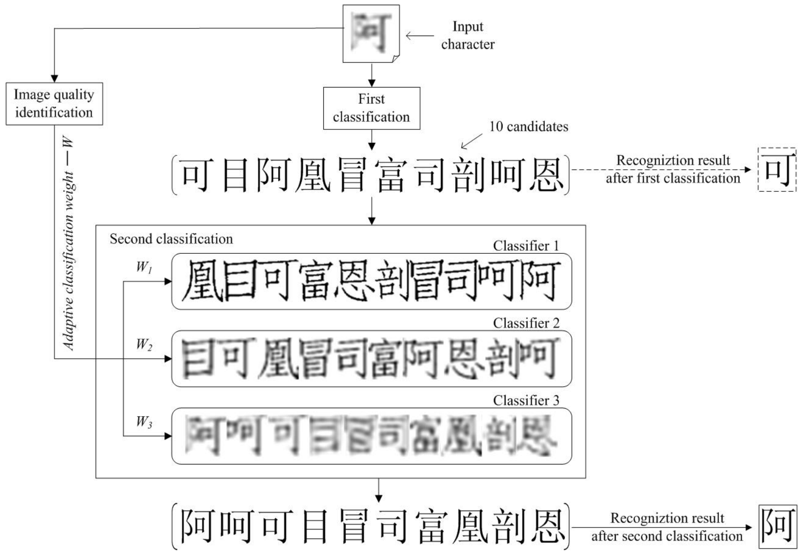

Fig. 3. The adaptive classification consists of two steps: the first classification, the second classification. In this example, according to the image quality the training set is ranked into three levels {GOOD, MODERATE, BAD}. For the input character image, its' quality is identified as 'BAD' by image quality identification. So the adaptive classification weight is adaptively set down, *w=[0, 0, 1]*. At the same time, after the first classification we get 10 candidates. In the second classification the input image respectively is recognized by three classifiers in the 10 candidates scope. The weighted averaging of three classifiers' outputs is computed by the adaptive classification weight. Then we correct the fault result in the first classification and get the correct recognition result.

The first classifier is achieved by training the whole character sets including all rank qualities. We compute the average template by all training data sets as the first classification template. For the given degraded character image, it is assumed that m candidates can be generated by the first classifier. It is the most possible to get the correct recognition result in these m candidates. So in the second classification, the given image is recognized only in the candidates by the adaptive classifiers. The adaptive classification is based on the quality of the given character image to decide the adaptive weight of every rank classifier's action. Here we rank the training set into n data sets according to their image quality. The n classifiers are generated by training these n character sets with n rank image qualities. Thus after the first classification for m character candidates we can get mxn sets of templates. The input image was respectively compared with these templates of character candidates. The final recognized result was achieved by the adaptive weighted averaging of every classifier. The detailed computation is performed as formula (2).

$$r = \arg\min_{i=1,2,\ldots m}(d_{ij}) = \arg\min_{i=1,2,\ldots m}\left(\sum_{j=1}^{n} w_j \left|f - t_{ij}\right|\right). \quad (2)$$

Here, t_{ij} is the ith character candidate template by training data set with the *jth* rank image quality in the range [*1,n*]. f is the feature vector of the input character image. w_j is the adaptive classification weight of the *jth* classifier, which can be adjusted according to the resolution evaluation algorithm. r is the final recognized result in m candidates. Fig.3 give a example to show the whole recognition process.

4 Experiment

In this section, in order to evaluate the effectiveness of the proposed method several experiments are carried out on printed Chinese character images, which include 3755 character categories, five frequent Chinese fonts (Fangsong, Heiti, Kaiti, Songti, Youyuan). For convenience, we use a scaling degradation model [12] to generate the character dictionary, which represents the samples under various resolutions. We use n different scaling rates to form n kinds of multi-resolution character sets by down-sampling, which are respectively used as training set and testing set.

4.1 Resolution Evaluation Experiment

In the character dictionary, the size of character varies from *10*10~64*64* pixels. Three kinds of resolution character sets are selected as three levels {GOOD, MODERATE, BAD} image quality, whose character size is respectively *50x50*, *20x20*, *12x12* pixels. We randomly select 1000 character images respectively from GOOD, MODERATE, BAD images in Fangsong character sets as training set. Namely the total of training images is *1000*x*3*. The other 53,325 character images (*2755*x*3*x*1+3755*x*3*x*4*, which respectively come from 3 kinds of resolution, and 5 kinds of fonts) are used as testing data to evaluate the effectiveness of resolution identification. Seen from Table1, the experiment result demonstrates the proposed algorithm can get above 97.82% recognition rates of resolution evaluation, which can effectively evaluate the image quality resolution.

Above experiment is carried out only on the character sets which character size is respectively 50x50, 20x20, 12x12 pixels. Following above experiment, we perform another experiment to evaluate the effect on the character sets with other resolutions. Firstly the same way as above experiment is conducted that 1000 character images are randomly selected respectively from GOOD, MODERATE, BAD images in character sets as training set, which character size is respectively *50x50*, *20x20*, *12x12* pixels. Then other character sets are used as testing data, which character size varies from *10x10* to *60x60*pixels. The final result is shown in Fig.4, which is the distribution of character sets with different resolution in three image quality ranks. The images with high resolution mostly locate at GOOD quality scope. And most of the images with low resolution distribute in BAD quality scope, namely round character size 12x12 pixels. The character images which character size varies from 30x30 to 15x15 pixels mostly locate in MODERATE scope. Experiment result demonstrates the proposed algorithm of resolution evaluation can be applied on the adaptive character recognition.

Table 1. Recognition rates of resolution evaluation

	GOOD	*MODERATE*	*BAD*	*Average*
Fongsong	100	99.09	99.23	99.44
Heiti	100	97.76	95.69	97.82
Kaiti	100	99.41	99.68	99.70
Songti	100	96.67	99.87	98.85
Youyuan	100	97.76	98.40	98.72

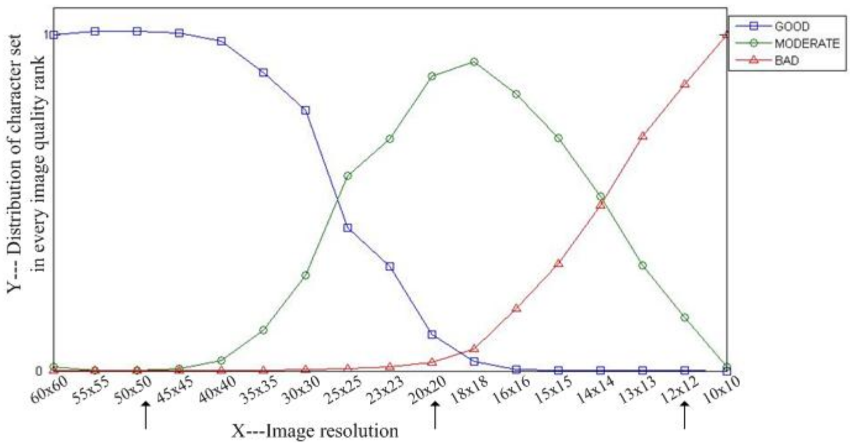

Fig. 4 Distribution of character sets with different resolution in three image quality ranks. X axis is the image resolution, character size. Y axis is the ratio of character set distribution in every three image quality ranks. Here, we select the datasets, whose character size is respectively 50x50, 20x20, 12x12, as training datasets. The other character sets is evaluated as testing datasets.

4.2 Experiment on Low Resolution Character Recognition

There are 95 sample sets with different resolution, and every sample set includes 3755 Chinese characters. We use 75 sample sets as training data, and the other 20 sample sets as testing data. These training data is divided into 3 classes which are regarded as different resolution level of image {GOOD, MODERATE, BAD}. Every level training sets includes 25 sample sets. The small size is to 9x8 pixels.

In this experiment, the process of character image resolution evaluation is performed by the way of the first experiment. The candidate number after first classification is 100, and the adaptive classification weights are respectively equal to [1, 0, 0], [0, 1, 0], [0, 0, 1], which respectively corresponding to the image quality {GOOD, MODERATE, BAD}. In Table 2, the result of the proposed method is compared with the single template method. ST is the single template method that computes the template by using the whole training sets without distinguishing the character image resolution quality. ACT is the proposed method that applies the adaptive classification template. Experiment result demonstrates the proposed method highly improved the performance of the low resolution character recognition system.

Table 2. Recognition rates of printed Chinese characters in different resolution

	ST	*ACT*
Fangsong	86.0971	92.72
Heiti	92.2475	96.16
Kaiti	89.6307	95.01
Songti	88.3229	91.18
Youyuan	92.7914	95.46

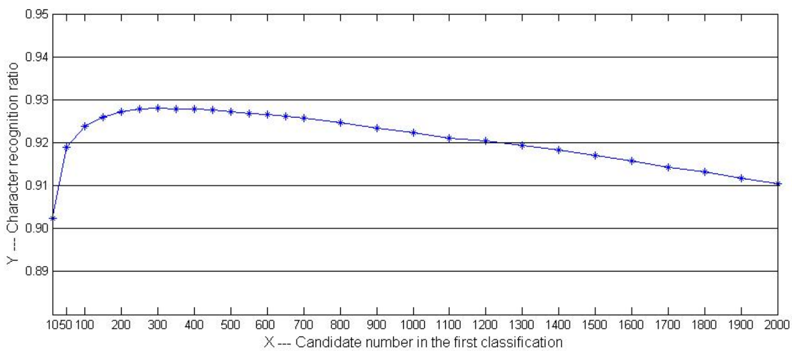

Fig. 5. Recognition rate by the different candidate number in the first classification. X axis is the candidate number in the first classification. Y axis is character recognition ratio by the different candidate number.

The above experiment is performed under the selection that the candidate number in the first classification is 100. The different candidate number will influence the final recognition result. Fig.5 shows the recognition results by the different candidate number after first classification. It can be seen that the recognition result is unideal if the candidate number is very small or very large. The reason is that the correct candidate can not be selected in the candidates during the first classification if the candidate number is very small. If the candidate number is very large, it increases the recognition disturbance during the second classification. Furthermore, the large candidate number will increase the computation.

5 Conclusions

In this paper, we have proposed an approach for the multi-resolution character recognition. It applies the adaptive classification method which adaptively selects appropriate character database and classifiers by evaluating character image qualities. A resolution evaluation algorithm based on gray distribution feature is proposed to decide the adaptive classification weight for the classifier, which is independent of the image content. It is no-reference objective method with low computational complexity and time and with anti-noise ability. The adaptive classification weight provides a way to compute the weighted averaging of every classifier's output, which make the given image resolution information join in the classification. The experiment shows that the proposed approach highly improved the performance of the multi-resolution character recognition system.

In the future research, two problem need to be tackled. One is the selection of the appropriate feature and classifier for character recognition subsystem of every resolution level, which can improve the performance of every recognition subsystem. The other is the integration of every recognition sub-system by the proposed approach which can lead to the improved performance of the whole recognition system.

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