Biometric Personal Identification Based on Handwriting +

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Abstract

In this paper, we describe a new method to identify the writer of Chinese handwriting documents. There are many methods for signature verification or writer identification, but most of them require segmentation or connected component analysis. They are the kinds of content dependent identification methods as signature verification requires the writer to write the same text (e.g. his name). In our new method, we take the handwriting as an image containing some special texture, and writer identification is regarded as texture identification. This is a content independent method. We apply the well-established 2-D Gabor filtering technique to extract features of such textures and a Weighted Euclidean Distance classifier to fulfil the identification task. Experiments are made using Chinese handwritings from 17 different people and very promising results were achieved.

1. Introduction

Biometric personal identification is an important research area aiming at automatic identity recognition and is receiving growing interest from both academia and industry [1]. There are two types of biometric features: physiological (e.g. face, iris pattern and fingerprint) and behavioral (e.g. voice and handwriting). Personal identification based on handwriting is a behavioral biometric identification approach. Handwriting is easy to obtain and different people have different handwritings. Handwriting based personal identification has a wide variety of potential applications, from security, forensics, financial activities to archeology (e.g. to identify ancient document writers).

Automatic handwriting based personal identification (HBPI) is an active research topic in the computer vision and pattern recognition filed [2-6]. However, most existing HBPI methods assume that the text is fixed (e.g. in signature verification). These methods extract such features as writing speed, direction, duration, height, width, slant angle, black pixels etc. They rely on the interactive localization and segmentation of the relevant text information which remains to be difficult and far from being solved.

Since the purpose of HBPI is to identify the writer of a specific handwriting, one does not need to know what the written text is. In this paper, we describe a new HBPI algorithm. The key point is using texture analysis to extract features. Each person's handwriting is seen as having a specific texture. The spatial frequency and orientation contents represent the features of each texture. It is these texture features that we use to identify writers of handwritings. This is a content independent method and requires no segmentation or connected component analysis. We use the well-established multi-channel Gabor filters to extract these features. It has demonstrated good performance in texture discrimination and segmentation [7-11].

The new algorithm has been proven to have good performance in English HBPI [13]. This paper is to explore its efficiency in Chinese HBPI.

The problem of HBPI is a typical problem of pattern recognition. It can be described as the following flow chart.

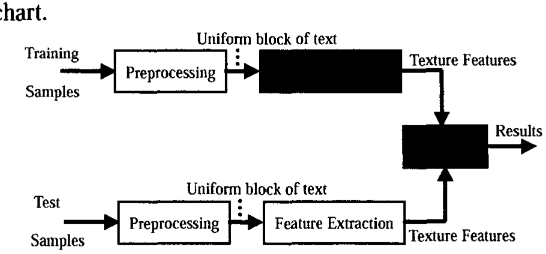

Figure 1. The flow chart of the HBPI system.

The original image is preprocessed to form a uniform block of text. The multi-channel Gabor filtering technique is used to extract features from the uniform text blocks (i.e. the texture images). A Weighted Euclidean Classifier is used to identify the writers.

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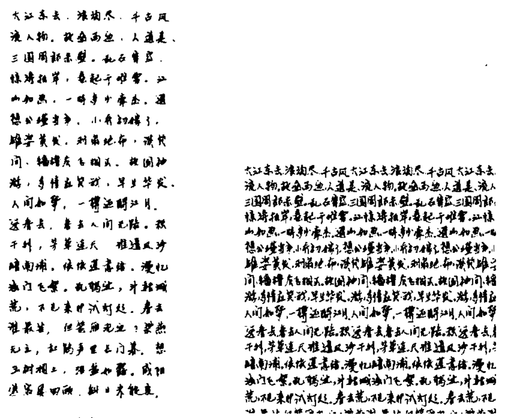
In Section 2, we will discuss pre-processing in detail. Section 3 will introduce the multi-channel Gabor filters for texture feature extraction. Section 4 is about the classifier. Experiments and results will be discussed in Section 5. Conclusions will be drawn in Section 6.

2. Preprocessing: creating a uniform block of text

The original input is a binary image. It may contain characters of different sizes and spaces between text lines. For the purpose of texture feature extraction, the input documents need to be normalized to create a uniform block of text. Figure 2 shows an original handwriting image and the resultant uniform block of text. This procedure can be accomplished in the following four steps.



(a) (b)

Figure 2. Example of preprocessing. (a) The original handwriting image. It may contain different spaces between characters. (b) The preprocessed image.

2.1 Locate text lines

The horizontal projection profile (HPP) of the document is computed. The valley between peaks corresponds to the blank between text lines. The distance between two valleys corresponds to the height of each text line.

2.2 Normalize height of text lines

Since the size of each text line may differ greatly in the handwriting documents, it is necessary to resize each character to the similar size. Given that the height of each text line can be obtained from step 2.1, they can easily be normalized.

2.3 Normalize spacing

The handwriting image may contain different spaces between characters, words and text lines. Different spacing may influence the texture of the images, so the normalization of spaces is necessary. After text line localization in step 2.1, the vertical projection profile (VPP) is computed. The same strategy as in step 2.1 is employed to determine spacing between characters or words.

2.4 Form a uniform texture image by text padding

The input image may contain incomplete or partially justified text lines. The blank spaces are filled up by means of text padding. Padding may also be applied if the handwriting document contains only a small number of characters. In our case, the text is padded to create a block of a predefined size.

3. Feature extraction: multi-channel Gabor filtering

In fact, any type of texture analysis methods such as the multi-channel Gabor filtering or the gray level co-occurrence technique can be employed here. Experiments showed that the former has better performance [12-13]. So we chose the multi-channel Gabor filtering approach to extract texture features.

Klement *et al.* [14] have summarized that the features selected for writer identification must meet the following requirements: (1) writer specificity (small intra-class variability, large inter-class variability); (2) completeness (any writer should be distinguishable); and (3) environment invariance (against the writing material and utensil used). In our new method, we take a handwriting image as having a specific texture. By using the multi-channel Gabor filtering technique, we can fully analyze handwriting texture in different scales. Both the inter-class variability and intra-class similarity are included in these texture features.

3.1 Gabor filter

The multi-channel Gabor filtering approach has been shown to be practically useful for analyzing textured images [9].

In our application, we use pairs of isotropic Gabor filters with quadrature phase relationship [10]. The computational models of such 2-D Gabor filters are (h_e and h_o denote the even- and odd- symmetrical Gabor filters respectively):

$$\begin{aligned} h_e(x,y) &= g(x,y)\cdot\cos[2\pi f(x\cos\theta + y\sin\theta)] \\ h_o(x,y) &= g(x,y)\cdot\sin[2\pi f(x\cos\theta + y\sin\theta)] \end{aligned} \quad (1)$$

where

$$g(x, y) = \frac{1}{2\pi\sigma^2} \cdot \exp\left[-\frac{x^2 + y^2}{2\sigma^2}\right] \qquad (2)$$

The spatial frequency responses of the Gabor functions (1) are:

$$H_e(u, v) = \frac{[H_1(u, v) + H_2(u, v)]}{2}$$
$$H_o(u, v) = \frac{[H_1(u, v) - H_2(u, v)]}{2j} \qquad (3)$$

where ($j = \sqrt{-1}$) and

$$H_1(u, v) = \exp\{-2\pi^2\sigma^2[(u - f\cos\theta)^2 + (v - f\sin\theta)^2]\} \qquad (4)$$
$$H_2(u, v) = \exp\{-2\pi^2\sigma^2[(u + f\cos\theta)^2 + (v + f\sin\theta)^2]\}$$

f, θ and σ are spatial frequency, orientation and space constant of the Gabor envelope.

3.2 Filter design

Each pair of the Gabor filters is tuned to a specific band of spatial frequency and orientation. There are some important guides in selecting the channel parameters. Texture feature extraction requires both the radial frequency and orientation. Experiments show that there is no need to uniformly cover the entire frequency plane so far as texture recognition is concerned [10].

Since the Gabor filters we use are of central symmetry in the frequency domain, only half of the frequency plane is needed. Four values of orientation θ are used: $0^\circ, 45^\circ, 90^\circ, 135^\circ$. For each orientation, central frequencies are chosen so that they are 1 octave apart. In order to achieve good results, for an image of size $N \times N$, central frequencies are chosen within $f \leq N/2$ cycles/image. Filters with low radial frequencies are not very useful here because these filters capture spatial variation that are too large to explain textural variation in an image. In our experiments, the input image is of size 128×128. For each orientation θ, we select 2, 4, 8, 16, 32, 64 as spatial frequencies. This gives a total of 24 Gabor channels. Later we will show some channels are not necessary. The spatial constants σ of these channels, which determine the channel bandwidths, are chosen to be inversely proportional to the central frequencies of the channels.

The mean values and the standard deviations of the channel output images are chosen to represent texture features. Thus a total of 48 features is extracted from a given image. They form a 48 dimensional feature vector.

4. Classifier: writer identification

The identification of writers based on given feature vectors is a typical pattern recognition problem. In principle, we can use any type of classifiers here. For simplicity, we use the Weighted Euclidean Distance (WED) classifier to identify the writer.

Features of unknown testing writers are compared with those of a set of known writers. The writer of a handwriting document is identified as writer k *iff* the following weighted Euclidean distance is a minimum at k:

$$WED(k) = \sum_{i=1}^{N} \frac{(f_i - f_i^{(k)})^2}{(\delta_i^{(k)})^2} \qquad (5)$$

where f_i denotes the ith feature of an unknown handwriting, $f_i^{(k)}$ and δ_i^k denotes the ith feature and its standard deviation of handwriting by writer k, N denotes the total number of features extracted from a single writer.

5. Experiments and results

A number of experiments have been carried out to test our new algorithm. 17 persons' handwritings were trained and tested. The handwriting script containing 400 Chinese characters was scanned from A4 papers to a 2-colored bitmap image with the resolution of 100 dpi. We divided this image to two non-overlapped sub-images. One is for training, the other for testing. Each sub-image was preprocessed to form a 640×640 uniform block of text. It was divided into 25 128×128 non-overlapping blocks.

Figure 3 shows some samples of different handwriting images by different people.

Figure 3. Samples of the preprocessed handwriting images by 6 different people.

Different combinations of features were tested. Experiment results are shown in Table 1. The results show that the new method has good performance in Chinese HBPI. Good results are achieved when all the features are used. It is also suggested that Gabor channels with lower central frequency such as 2 cycles/image are not critical in HBPI. The highest accuracy (95.7%) is achieved at f=4, 8, 16, 32, 64. Even when only 4 central frequencies (f=8, 16, 32, 64) are used, it can achieve the identification accuracy as high as 94.2%.

Table 1. Chinese handwriting identification accuracy of the multi-channel Gabor filtering technique under WED. Mean: only the mean values; STD: only the standard deviations; All: both Mean and STD. Default is All. f is the central frequency of the Gabor channel. Default is f=2, 4, 8, 16, 32, 64.

Features	Accuracy (%)	Features	Accuracy (%)
All	94.5	f=32	40.3
Mean	87.4	f=64	73.5
STD	91.1	f=4,8,16,32,64	95.7
f=2	56.0	f=4,8,16,32	91.4
f=4	57.9	f=8,16,32,64	94.2
f=8	62.8	f=2,4,8,16,32	88.6
f=16	63.4	f=16,32,64	87.4

6. Conclusions

We have presented a new algorithm for HBPI. Different to most existing methods, our algorithm is text independent. In this paper, we have investigated the feasibility of this method in Chinese HBPI. Compared with other techniques, the method proposed in this paper has the following important advantages:

- Unlike signature verification, this method is content independent. The content of training handwriting samples is not required to be the same as testing samples. The method needs neither segmentation nor connected component analysis.
- In theory, any texture classification and analysis technique (such as Gabor filtering and GLCM) can be applied in our method.
- Because of preprocessing, the new method can function well even if the input image contains a small amount of text.
- Because of the small size variations between Chinese characters, character size normalization of handwritten Chinese documents is easier to perform than Latin Languages. The method is therefore particularly suitable for Chinese HBPI.
- The method needs no complex computing. It may easily be applied in practical applications.

All of these demonstrate that the new method is able to handle writer identification tasks efficiently. It is a promising technique for biometric personal identification.

7. Acknowledgement

Aspects of the work described in this paper have been filed for patent, Chinese Patent Application No. 99105851.8, 1999.

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