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Writer identification using global wavelet-based features

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Abstract

In the human society, it is very important to find out the true writer of an unknown handwriting document. Therefore handwriting-based writer identification has been a hot research topic in pattern recognition field since several decades before. In our research, we find that the global styles of different people's handwritings are obviously distinctive and the histogram of the wavelet coefficients of preprocessed handwriting image can be well characterized by the generalized Gaussian model (GGD) in wavelet domain. As a consequence, in this paper, we propose a new method by combining wavelet transform and GGD model for writer identification of Chinese handwriting document. Tested by our experiment, this method achieves a satisfied identification result and computational efficiency as well.

Keywords: Writer identification; Chinese document; Wavelet; Generalized Gaussian model; 2-D Gabor model

1. Introduction

Handwriting, which refers to the text document manually written by one person, plays an irreplaceable role in human's communications and records in the civilized society. A long history before, people has realized the importance of finding out the true writer of one unknown handwriting document. In fact, even in the modern society, writer identification of handwriting (for example, there are signatures, letters, notes) still has a wide application field: to confirm the document authenticity in the financial sphere, to solve the expert problems in criminology, etc.

As an individual act, the handwriting characterizes its writer by the reproduction of details and unconscious practices, and naturally regarded as a sign of the writer. The reason is very simple—the handwriting habit of one person is formed by a long time's practice in one's childhood and therefore very hardly to be changed when he/she grows up. The fundamental property of handwriting that there exist writer invariants makes writer identification possible. The writer's invariants, reflecting the writing style (in some papers, writing style of one person is called as writing individuality) of his/her handwriting, can be defined as the set of similar patterns or graphemes extracted from his/her handwriting using a particular extraction technique. It must be admitted, the existence of writer's comparative invariance does not deny the existence of writer's variance. In fact, two samples of a writer cannot be completely same. Generally, two types of handwriting variability are clearly defined as [24]:

- V_{w^i}: Intra-writer variability. It refers to the variation observed within different writing samples of one writer i. The collection of writing samples of writer i is denoted as (W^i).
- V_{w^i,w^j}: Inter-writer variability. It refers to differences between two genuine handwriting classes (W^i) and (W^j).

In theory, intra-writer variability V_{w^i} must be as low as possible and inter-writer variability V_{w^i,w^j} should be large enough for class separation.

In fact, all techniques of writer identification rest on such two hypothesis, which are proved in Ref. [27].

- Each individual has comparatively consistent handwriting which is distinct from the handwriting of another individual.

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- The intra-writer variation is less than the inter-writer variation.

In practice, some people often confuse writer identification and optical character recognition (OCR) because both of them are the classification problems based on handwritings. Though OCR and writer identification both are techniques of handwriting documents analysis, they are apparently dissimilar. OCR is to understand and identify the handwriting's content. It needs to overcome the variations of a same character written by different individuals as well as same writer at different time. On the other hand, writer identification focuses on distinguishing the difference between the writings of different writers and needs not to understand the content of handwriting. Simply put, OCR is desired to minimize as much as possible the distance within these variations for the same characters, on the contrary, writer identification maximizes as much as possible individuals' variations and extracts these variations as the writing features of writers [28].

Traditionally, writer identification is classified into on-line and off-line writer identifications [24,25]. In an on-line system, one transducer device is used to capture and convert writing motion of one writer into a sequence of signals and then send the signals into a connected computer. While in an off-line system, all available writing features are extracted from the handwriting images scanned by a scanner (some researches use the CCD camera). As a result, off-line writer identification is more challenging than on-line writer identification because it cannot extract the writing motion features.

Further, off-line writer identification can also be divided into two types: text-dependent and text-independent writer identification [24,25]. If any text may be used to establish the identity of the writer, the identification task is text-independent; otherwise, if a writer has to write a particular predefined text to identify himself/herself, the identification task is text-dependent. Text-independent approaches look at a feature set whose components describe global statistical features of one entire document image. While in text-dependent approaches, geometric or structure features of characters/words are extracted as the writing features for identification. In practice, the requirement of fixed text makes text-dependent writer identification inapplicable to many practical applications, such as, the identification of the writers of archived handwriting documents, crime suspect identification in forensic sciences, etc. The method proposed by us in this paper is for off-line, text-independent writer identification.

Because writer identification is an important and useful branch of personal identification, rich researches have been done in this field in the past several decades. However, most of these works are for on-line or/and text-dependent writer identification and only a small portion of them is for off-line and text-independent writer identification. This fact reflects that developing new method on off-line, text-independent writer identification is an urgent task. Here, we only introduce the relative, typical works for off-line, text-independent writer identification.

In Ref. [24], Plamondon pointed out that two general techniques had been proposed for the off-line, text-independent writer identification: transform techniques [9,10] and histogram descriptions [16,17,29,15]. More recently, inspired by the idea of multi-channel spatial filtering technique, Said et al. proposed a texture analysis approach [25]. In this method, they regarded the handwriting as an image containing some special textures and applied a well-established 2-D Gabor model to extract the features of such textures. In Ref. [13], we propose a hidden Markov tree model in wavelet domain to describe the handwriting image and this model is better than 2-D Gabor model.

Besides the methods based on global style features, some researchers also proposed approaches based on single word or text line, such as horizontal projection profiles of single words [32], text line features [14], edge-based directional probability distribution [3], etc. A new concept "writer invariants" is defined in Refs. [23,1,2]. In those papers, researchers suggested that each handwriting could be characterized by a set of writer invariant features, which could be detected by using an automatic grapheme clustering procedure. Except that, 11 innovative features extracted from handwritten digits are used by Leedham et al. in Ref. [18]. Certainly, multi-feature-based systems probably deliver better performance than any single constituent feature. Therefore, Cha et al. integrated several distance measures for many feature types: element, histogram, string, convex hull, etc. A satisfied result was achieved on their experiment database [4].

Though several types of methods have been developed for off-line, text-independent writer identification, strictly speaking, only the 2-D Gabor model based on the global style analysis is close to the principle of our method. So, in this paper, we only compare our method with the 2-D Gabor model.

The rest of the paper is organized as follows. In Section 2, we propose a wavelet-based GGD method, which well characterizes the writing styles of different writers, for off-line, text-independent writer identification. This method consists of three parts: preprocessing, feature extraction and similarity measurement, all of which are detailedly described in the subsections of Section 2, separately. In Section 3, we offer a brief introduction to 2-D Gabor model and compare our wavelet-based GGD method with this 2-D Gabor model. Some relative discussions are also offered in Section 3.

2. Our algorithm for writer identification

Our algorithm for writer identification consists of three main steps: preprocessing, feature extraction and similarity measurement, and we discuss these steps in detail in the following.

2.1. Preprocessing

Prior to the identification, original handwriting image is generally preprocessed to remove spurious noise, normalize the various aspects of the trace, and segment the text into meaningful units. In our system, the origin handwriting image contains characters with different sizes, spaces between text lines and even noises. So before extracting handwriting features, origin handwriting image should be preprocessed first.

Inspired by the work of [25], we propose a simple but whole procedure of automatic preprocessing.

(1) Locating text lines and empty spaces using the horizontal histogram profile. The valley between peaks corresponds to the empty space between two successive text lines.
(2) Computing the minimum, maximum and mean heights of each text lines.
(3) Removing the smallest 10% (in terms of height) to eliminate small blobs (such as punctuation, etc.), and then removing components with a height $>$(mean $\times$ 2.5) to eliminate components which are already connected across more than one text line.
(4) Normalizing the height of text lines.
(5) Normalizing the height of empty spaces between two successive text lines.
(6) If the image only contains a small number of characters which are not sufficient for writer identification, a text padding step can be added to combine several such images to form a qualified image.

Automatic preprocessing methods well deal with the handwriting documents with a regular layout but fails to deal with the handwriting documents with an irregular layout. In fact, most handwritings discussed in relative papers are written in some appropriate experimental protocols, such as writing within boxes, etc. Till now, automatic segmentation of irregular handwriting documents is far from being well solved and evasive in relative papers.

However, we cannot guarantee that all involved handwritings are written in a regular layout in practical applications. Therefore, we must develop an effective method to handle those irregular handwritings. In our research, we develop a software which can interactively localize, segment the characters manually and well process any irregular original handwriting to generate preprocessed handwriting images (PHI) with a high-quality for the later identification steps. For the details of our software, refer to Refs. [13,11].

2.2. Feature extraction based on wavelet

After obtaining PHIs, the next step is to extract prominent features from them, which can be used for the identification. Feature extraction phase is one of the crucial phases of writer identification system. The discriminative power of the features and their resilience to the variation within the query and reference handwritings of a writer play very important roles in the whole identification process.

Based on our discovery that the global styles of the people's PHIs are often visually distinctive, shown in Fig. 1, we propose a wavelet-based method to extract features from these PHIs. After feature extraction, we merge these features into a single feature vector for later similarity measurement.

2.2.1. Background of wavelet transform

Wavelets are mathematical functions that cut up data into different frequency components, and then study each component with a resolution matched to its scale [7]. Compared to the traditional Fourier methods, wavelets are more powerful to analyze such physical situations where the signals (1-D) and images (2-D) contain discontinuities and sharp spikes. Wavelets were developed independently in the fields of mathematics, quantum physics, electrical engineering, and seismic geology. Interchanges between these fields during the last 10 years have led to many new wavelet applications such as image compression, turbulence, human vision, radar and earthquake prediction.

An integrable function $\psi \subseteq L^2(R)$ is said to be a wavelet function if it satisfies the zero-moment condition [7,19]

$$\int_{-\infty}^{\infty} \psi(t)\,\mathrm{d}t = 0, \quad t \in R. \tag{1}$$

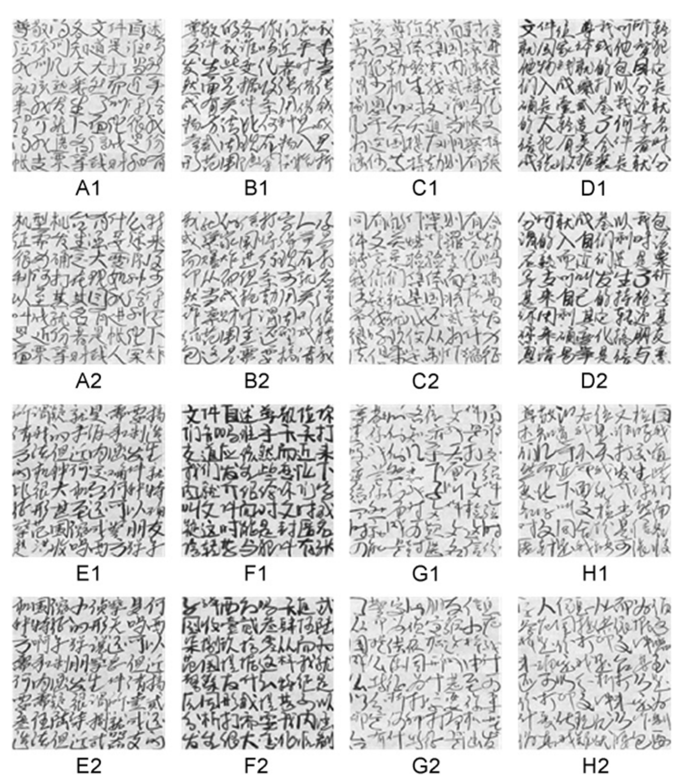

Fig. 1. Global styles of different writers apparently differ. (A1) and (A2) belong to the writer A, (B1) and (B2) belong to the writer B, and so on.

And the zero-moment condition is valid when

$$C_\psi = 2\pi \int_{-\infty}^{\infty} \frac{|\hat{\psi}(\xi)|^2}{|\xi|}\, d\xi < \infty, \quad t \in R. \tag{2}$$

Eq. (2) is called the "admissibility" condition. The continuous (or integrable) wavelet transform with kernel function ψ on $L^2(R)$ is defined by

$$W_\psi f(\mu, s) = \langle f, \psi_{\mu,s} \rangle = \int_{-\infty}^{-\infty} f(t)\psi^*_{\mu,s}\, dt, \quad t \in R, \tag{3}$$

where $\psi_{\mu,s}(t) = |s|^{-1/2}\psi((t-\mu)/s)$, with $\mu, s \in R, s \neq 0$. μ, s vary continuously over R and are named dilation parameter and translation parameter, respectively. ψ is called the mother wavelet and the $\psi_{\mu,s}$ are called wavelets [7].

The wavelets $\psi_{\mu,s}$ cover different frequency ranges when s changes. Large value of the dilation parameter $|s|$ responds to small frequencies (coarse scale) and small value of $|s|$ corresponds to high-frequency (fine scale). The time localization center can be moved by changing the translation parameter μ. Each $\psi_{\mu,s}(t)$ is localized around $t = \mu$. Therefore, the wavelet transform offers a perfect time–frequency description of function f.

Via Mallat algorithm [21,20], 2-D wavelet transform can be easily implemented by 1-D wavelet transform. In a certain scale, a 1-D wavelet filter is first used to convolute the rows of the input image, and one of every two columns is reserved. Then, another one-dimensional filter is applied to column convolution on the image, and one of every two rows is reserved.

By Mallat algorithm, we decompose the image into a series of wavelet subbands. What we should do next is to find out the features hidden in these wavelet subbands, based on which we can discriminate one writer from others.

2.2.2. The properties of wavelet coefficients of PHI

The simplest feature extraction method based on wavelet is to measure the energy or weighted energy signature of wavelet coefficients in each subband.

The basic assumption of these approaches is that the energy distribution in the frequency domain identifies an image. Generally, L^1-norm and L^2-norm are selected as measurement of energy. Sometimes, mean and standard derivation are also used as energy features.

The advantage of energy-based models is that only a few parameters are needed to describe an image. Unfortunately, the energy-based models are not sufficient to capture all image properties. It has already been shown that there may be perceptually very different images that have very similar energy features [26]. So we need to find out more effective features to replace the energy features.

By a lot of experiments, we find out that the marginal statistics of wavelet coefficients within each high-frequency wavelet subband of the PHI are highly non-Gaussian. That is, the margins tend to be much more sharply peaked at zero, with more extensive tails, when compared with a Gaussian of the same variance. This non-Gaussian marginal density can be well-modelled by a generalized Gaussian density (GGD) model. An example of our experimental discovery is given in Fig. 2.

The GGD model is given as

$$P(x|\{\alpha,\beta\}) = \frac{\beta}{2\alpha\Gamma(1/\beta)} e^{-1(|x|/\alpha)^\beta}, \tag{4}$$

where, $\Gamma(\cdot)$ is the Gamma function, i.e.,

$$\Gamma(\cdot) = \int_0^\infty e^{-t} t^{Z-1}\, dt, \quad Z > 0.$$

The normalization constant is $Z(\{\alpha,\beta\}) = 2(\alpha/\beta)\Gamma(1/\beta)$. An exponent of $\beta = 2$ corresponds to a Gaussian density, and $\beta = 1$ corresponds to the Laplacian density. The parameter $\alpha > 0$, called scale parameter, describes the standard deviation. α varies monotonically with the scale of the basis functions, with correspondingly higher variance for coarser scale components. The parameter $\beta > 0$, called shape parameter, is inversely proportional to the decreasing rate of the peak. In general, smaller values of β lead to a density that is both more concentrated at zero and has more expansive tails.

GGD model is completely determined by the marginal statistics of the wavelet coefficients with an assumption that the wavelet coefficients within a subband are independent and identically distributed (i.i.d). We must note that the low-frequency wavelet subband cannot be fitted by the GGD model, as shown in Fig. 2(c).

2.2.3. Estimate the parameters of GGD model

The basic idea of our wavelet-based GGD method is to establish corresponding wavelet-based GGD model for a handwriting image, and then the parameters of this model $\{\alpha,\beta\}$ can be regarded as the features of the handwriting. The most important work is to estimate the model parameters $\{\alpha,\beta\}$ according to the input PHI.

For a given wavelet subband Y, according to Bayes rule which is optimal in terms of identification error probability, the estimated parameters $\{\hat{\alpha},\hat{\beta}\}$ must maximize $P(\{\alpha,\beta\}|X)$. Similarly, Bayes theorem dictates that it is equivalent to setting $\{\hat{\alpha},\hat{\beta}\} = \operatorname{argmax}_{\{\alpha,\beta\}} P(\{\alpha,\beta\}|X)$. This is maximum likelihood estimation (MLE) rule.

Define $X = (x_1, \ldots, x_N)$ is an i.i.d sequence, which consists of wavelet coefficients in one wavelet subband Y. Then the likelihood function of the GGD model in Y can be defined as

$$L(X|\{\alpha,\beta\}) = \log \prod_{i=1}^{N} P(x_i|\{\alpha,\beta\}). \tag{5}$$

According to the Lagrange optimization, we get the following likelihood equations:

$$\frac{\partial L(x|\{\alpha,\beta\})}{\partial \alpha} = -\frac{N}{\alpha} + \sum_1^N \frac{\beta|x_i|^\beta a^{-\beta}}{\alpha}, \tag{6}$$

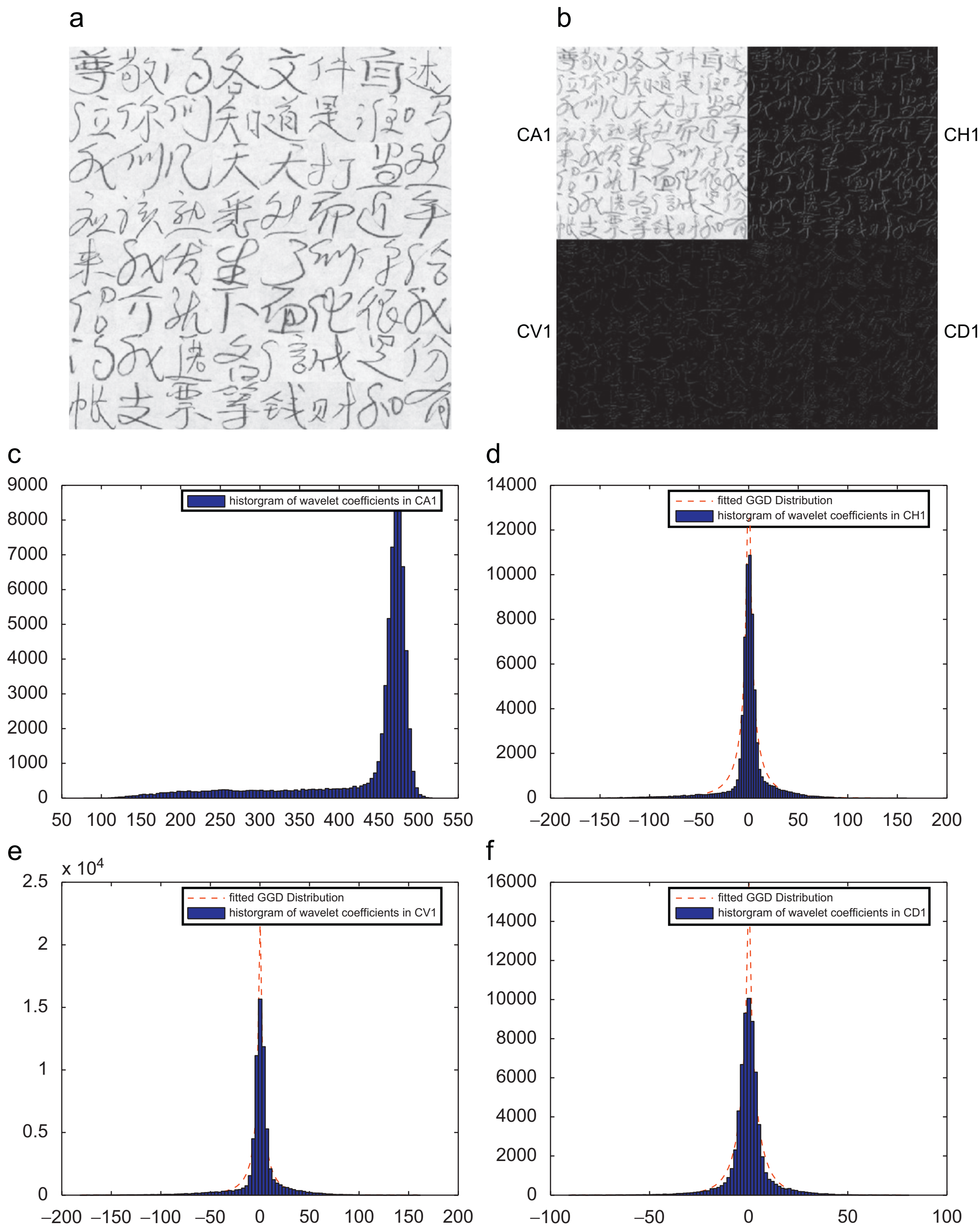

Fig. 2. The histograms of wavelet coefficients within all wavelet subbands (except for the subband CA1 at the lowest frequency) of the PHI satisfy the GGD distribution. (a) A PHI; (b) decomposition of the given PHI using db2 wavelet; (c) subband CA1; (d) subband CH1; (e) subband CV1; (f) Subband CD1.

$$\frac{\partial L(x|\{\alpha,\beta\})}{\partial\beta} = -\frac{N}{\beta} + \frac{N\Psi(1/\beta)}{\beta^2} - \sum_{i=1}^{N}\left(\frac{|x_i|}{\alpha}\right)\log\left(\frac{|x_i|}{\alpha}\right), \tag{7}$$

where $\Psi(z) = \Gamma'(z)/\Gamma(z)$.

Since $\beta > 0$ (In (4), it is obvious to know that $1/\beta > 0$ based on requirement of function Γ), the above equations have an unique root in probability. $\hat{\alpha}$, the solution of

$$\frac{\partial L(x|\{\alpha,\beta\})}{\partial\alpha} = 0,$$

can be obtained by

$$\hat{\alpha} = \left(\frac{\beta}{N}\sum_{i=1}^{N}|x_i|^{\beta}\right)^{1/\beta}. \quad (8)$$

Substituting the above equation into (7), we find that the estimation of β is the solution of the following equation:

$$1 + \frac{\Psi(1/\hat{\beta})}{\hat{\beta}} - \frac{\sum_{i=1}^{N}|x_i|^{\hat{\beta}}\log|x_i|}{\sum_{i=1}^{N}|x_i|^{\hat{\beta}}} + \frac{\log\left((\hat{\beta}/N)\sum_{i=1}^{N}|x_i|^{\hat{\beta}}\right)}{\hat{\beta}} = 0. \quad (9)$$

Eq. (9) can be numerically solved with a fast algorithm based on the Newton–Raphson iterative procedure and the initial value is given by the moment method [8]. After obtaining β, it is easy to get the estimate value of α from (8).

2.3. Similarity measurement

To some extent, writer identification is also a multiple hypothesis problem to find out N handwriting images maximizing $P(I_q|\theta_j)$, $1 \leqslant j \leqslant N$, I_q is the query handwriting image, θ_j is the hypothesis parameter set of training handwriting image I_j. This problem is equivalent to minimizing the Kullback–Leibler distance (KLD) between the two probability density functions (PDFs) $P(X|\theta_q)$ and $P(X|\theta_j)$, as is proved in [8,6]. The definition of the KLD between two PDFs is given as

$$D(P(X|\theta_q)\|P(X|\theta_j)) = \int P(x|\theta_q)\log\frac{P(x|\theta_q)}{P(x|\theta_i)}\,\mathrm{d}x. \quad (10)$$

In GGD model, the hypothesis parameter set $\theta = \{\alpha, \beta\}$. Substituting (4) into (10), after some simple calculations, we find that the KLD between two GGD models is explicitly given by

$$D(P(X|\{\alpha_1,\beta_1\})\|P(X|\{\alpha_2,\beta_2\})) = \log\left(\frac{\beta_1\alpha\Gamma(1/\beta_2)}{\beta_2\alpha_1\Gamma(1/\beta_1)}\right) + \left(\frac{\alpha_1}{\alpha_2}\right)^{\beta_2}\frac{\Gamma((\beta_2+1)/\beta_1)}{\Gamma(1/\beta_1)} - \frac{1}{\beta_1}. \quad (11)$$

And the KLD between two handwriting images I_1, I_2 is the sum of all the KLDs across all selected wavelet subbands

$$D(I_1, I_2) = \sum_{i=1}^{K} D(P(X|\alpha_1^{(i)},\beta_1^{(i)})\|P(X|\alpha_2^{(i)},\beta_2^{(i)})), \quad (12)$$

where K is the number of selected wavelet subbands.

We only consider the k-nearest neighbor classifier since it is a robust and efficient scheme. That is, identification results are to find the top N handwriting images which are most similar to the query handwriting. And from the name of found handwritings, we can know the corresponding writers. The similarity is measured by the KLD value. The smaller KLD value is, the large similarity it is.

3. Experiments

It must be noted that performance comparison between the existing systems and approaches are very difficult to be established because there does not exist an authoritative handwriting database which can act as a benchmark for performance evaluation and comparison. Most researchers built their own databases. We also have to create an Chinese handwriting database for our experiments. One thousand Chinese handwritings written by 500 persons are collected in our database, with one training handwriting and one query handwriting for each person. All handwritings are scanned into computer with a resolution of 300 dpi. We produce one PHI image from each original handwriting, and totally 1000 PHI images are obtained.

A criterion to evaluate the identification performance of a method is how many handwriting texts are required for identification. Most existing methods for off-line, text-independent writer identification required a full page of text, which generally consists of hundreds of characters or words. In our research, we design the size of PHI and the number of characters contained by PHI to achieve a good balance between the computation cost and the identification accuracy. In our system, each PHI consists of 64 Chinese characters with size 64×64 pixels, arranged in an 8×8 array. Our experiments show such a PHI image not only contains enough writing information to ensure a high-identification rate, but also let the identification processing be finished within an acceptable time. Next, before offering the experimental result, we first make a simple introduction to the 2-D Gabor model, which is compared with our method in the following experiments.

3.1. 2-D Gabor model

The multi-channel Gabor filtering technique is inspired by the psychophysical research that a set of parallel and quasi-independent mechanisms or cortical channels of human visual cortex, which receive and deal with the surrounding visual information, can be characterized by multiple bandpass filters. Generally, the Gabor model is a representative technique of multi-channel filtering and widely used in image processing, pattern recognition [25,31].

We use pairs of isotropic Gabor filters with quadrature phase relationship [25]. The Gabor filters are given as follows:

$$h_e(x,y) = g(x,y)\cos[2\pi f(x\cos\theta + y\sin\theta)], \quad (13)$$

$$h_o(x,y) = g(x,y)\sin[2\pi f(x\cos\theta + y\sin\theta)], \quad (14)$$

where h_e and h_o denote the so-called even and odd symmetric Gabor filters, and $g(x,y)$ is an isotropic Gaussian function.

The Gabor representation of a handwriting is the convolution of the image with the Gabor filters. Let $I(x,y)$ be a pixel of PHI, the convolution is defined below:

$$q_e^{f,\theta}(x,y) = h_e^{f,\theta} \star I(x,y), \tag{15}$$

$$q_o^{f,\theta}(x,y) = h_o^{f,\theta} \star I(x,y), \tag{16}$$

where $q_e^{f,\theta}(x,y)$ and $q_o^{f,\theta}(x,y)$ are even and odd Gabor-filtered outputs at orientation θ and frequency f, separatively. The notion $\star$ is the convolution operator.

Then we get the final Gabor-filtered output

$$q^{f,\theta}(x,y) = \sqrt{[q_e^{f,\theta}(x,y)]^2 + [q_o^{f,\theta}(x,y)]^2}. \tag{17}$$

Therefore, the set $Q = \{q^{f,\theta}(x,y) : f \in \{f_0, f_1 = f_0 * 2^1, \ldots, f_{M-1} = f_0 * 2^{M-1}\}, \theta \in \{\theta_0 = 0, \theta_1 = \theta_0 + \pi/N, \ldots, \theta_{N-1} = \theta_0 + (N-1)\pi/N\}\}$ forms the Gabor representation of the PHI I. M is the frequency level, generally $M = 4$. Tan et al. pointed out that for an image of size $N \times N$, the most significant Gabor frequency components were equal to or smaller than $N/4$ [30]. Therefore, for a PHI of size 512×512, the Gabor frequency should not be larger than 128 and accordingly the minimum frequency $f_0 = 16$. As for the orientation number N, usually we choose $N = 4$. Since the Gabor filter is symmetric, we only need to consider the orientation space $[0, \pi]$ rather than $[0, 2\pi]$. That is, $\theta \in \{0^\circ, 45^\circ, 90^\circ, 135^\circ\}$.

After filtering the handwriting image by Gabor filters, mean (M) and standard derivation (σ) of the multi-channel Gabor-filtered outputs are selected as writing features and weighted Euclidean distance (WED) is adopted for similarity measurement.

3.2. Experiment 1

In our experiments, we make a comparison between the wavelet-based GGD method and the 2-D Gabor model, not only on identification accuracy, but also on computational efficiency. Several combinations of different Gabor frequencies are tested, ranging from 16 to 128. For each spatial frequency, we select 0°, 45°, 90° and 135° as orientations.

For the wavelet-based GGD method, our experiments agree with [5] that the size of the smallest subimages should not be less than 16 pixels $\times$ 16 pixels so that estimated energy values or model parameters would be robust. Therefore, for a PHI of size 512×512, the number of wavelet decomposition levels should not be beyond five. According to our experiment records, three level decomposition is sufficient. All identification results shown in this paper are in the case of three level decomposition. We decompose the handwriting image via traditional discrete wavelet transform (DWT), and the used wavelets are Daubechies orthogonal wavelets. Of course, different wavelet filters may lead to different results. While testing all possible wavelet filters and finding which one is the best is out of the scope of this paper.

From a training PHI in the database, two GGD parameters $\{\alpha, \beta\}$ are estimated from each detailed wavelet subband using the MLE described in the previous section. Here we consider that these GGD parameters $\{\alpha, \beta\}$ are the writing features of the PHI, and can be used for the similarity measurement. Thus, in the case of three decomposition, totally 18 parameters are obtained, including 9 $\{\alpha\}$ and 9 $\{\beta\}$.

The evaluation criteria of identification are defined as follows: for each query handwriting, if the training handwriting belonging to the same writer is ranked at the top N matches, we say this is a correct identification, otherwise the identification fails. The identification rate is the percentage of the correct identification. The identification

Table 1
Writer identification rate 1 (%)

Number of top matches	Our method	Gabor, $f = 16$	Gabor, $f = 16, 32$	Gabor, $f = 16, 32, 64, 128$
1	39.2	13.4	18.2	32.8
2	45.8	24.6	31.8	39.0
3	54.6	33.8	43.2	49.4
5	62.4	41.4	51.6	56.2
7	69.6	47.2	58.4	64.8
10	77.2	55.0	64.2	71.4
15	84.8	64.6	71.6	79.8
20	92.6	70.8	79.4	85.2
25	97.8	76.2	84.2	91.2
30	100	80.6	87.8	95.6
40	100	86.6	92.8	100

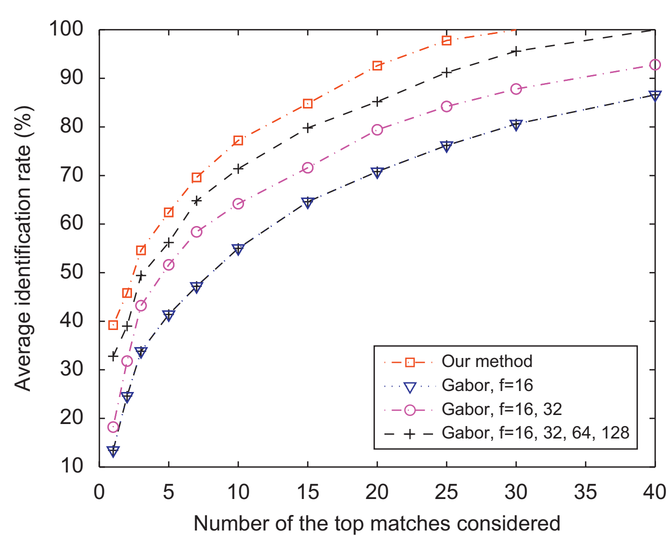

Fig. 3. Identification rate according to the number of top matches considered

rate certainly changes accordingly when the number of top matches varies. The identification results are recorded in Table 1 and Fig. 3.

The computational efficiency is measured by the elapsed time of each method. Our programs are implemented in the Matlab environment in PC computer. The software environment of our computer is: Window XP, Matlab 7.0; and the hardware environment is: Intel Pentium IV 2.4 GHZ CPU, 512 MB RAM. The record of average elapsed time is given in Table 2.

From Table 1, it is clear that in the Gabor method, the more frequencies are combined, the higher identification rate is achieved. Unfortunately, at the same time, the elapsed time also increases greatly. The identification rate of the Gabor model combing four frequencies $f = 16, 32, 64, 128$ is closest to that of wavelet-based GGD method, while its cost time is 24 times of that used in wavelet-based GGD method. The elapsed time of the Gabor model with $f = 16$ is the shortest in the different combinations of Gabor method, however, its identification rate is much lower than that of the wavelet-based GGD method. Comprehensively, the wavelet-based GGD method outperforms the Gabor model on both identification performance and the computational efficiency.

3.3. Experiment 2

We divide each PHI of 512×512 pixels into four non-overlapped sub-PHIs of 256×256 pixels to increase the writing samples for one writer. In this way, we can obtain eight writing samples for one writer. For each query sub-PHI, only the top $S \geqslant 7$ matches are considered since there are seven sub-PHIs of the same writer for each query sub-PHI. The identification percentage is the ratio of the number of correct matches within the top S matches to 7. For example, in the case of $S = 10$, the identification rate is $6/7 \times 100\% = 85.71\%$ if six correct matches are at the top 10 matches. In this experiment, we do not classify the sub-PHIs into training group and query group. All sub-PHIs are used as a query handwriting, and simultaneously other sub-PHIs except the query one play the role as the training handwritings. The identification rates of the wavelet-based GGD method and the Gabor model with different frequency combinations are offered in Table 3 and Fig. 4. Though the identification rate of the wavelet-based GGD method is not very high in this case, it is still satisfied in view of only 16 Chinese characters are used.

Table 2
Average elapsed time 1 for writer identification (second)

Method	Our method	Gabor, $f = 16$	Gabor, $f = 16, 32$	Gabor, $f = 16, 32, 64, 128$
Elapsed time	8.72	53.17	107.03	213.87

Table 3
Writer identification rate 2 (%)

Number of top matches	Our method	Gabor, $f = 16$	Gabor, $f = 16, 32$	Gabor, $f = 16, 32, 64, 128$
7	29.92	10.17	15.32	22.37
10	34.84	16.65	22.48	27.56
20	44.92	25.82	31.63	37.03
30	53.47	35.73	40.07	44.89
50	64.65	44.25	49.11	54.47
70	73.83	52.19	60.38	66.72
100	81.95	60.39	68.65	74.58
150	87.82	68.48	74.61	80.25
200	95.67	73.54	79.17	88.69
300	99.04	80.26	87.53	93.71

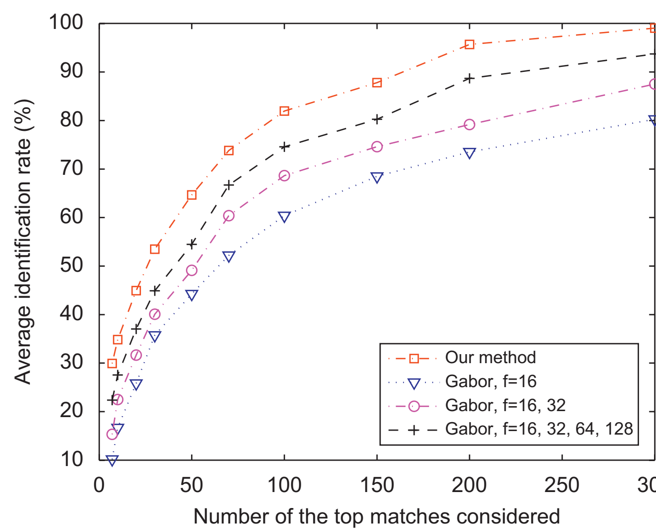

Fig. 4. Identification rate according to the number of top matches considered.

Table 4
Average elapsed time 2 for writer identification (second)

Method	Our method	Gabor, $f = 16$	Gabor, $f = 16, 32$	Gabor, $f = 16, 32, 64, 128$
Elapsed time	0.53	5.01	9.10	17.42

The average elapsed time of our method and 2-D Gabor model in this experiments is offered in Table 4. Combining the results in Tables 3 and 4, our method still outperforms the 2-D Gabor model in this experiment.

4. Conclusions

A novel approach for off-line, text-independent writer identification based on wavelet transform has been presented in this paper. In this approach, a handwriting document image is firstly preprocessed to generate a PHI image, and then the PHI image is decomposed into several sub-images by DWT. Thereafter, the parameters $\{\alpha, \beta\}$ of generalized Gaussian distribution are extracted from the detailed wavelet sub-images. After obtaining the GGD parameters, KLD is adopted to measure the similarity distance between the feature vectors of query PHI and training PHIs. Unlike most existing methods, this approach is based on the global features of the handwriting images. Experiments on our database consisting of thousands of handwriting images show our approach is highly better than the 2-D Gabor model, which is also based on the global features of handwriting images and widely acknowledged as an efficient method for off-line, text-independent writer identification. It must be noted, our approach is text-independent and hence applicable to other language documents, such as English, Korean, Japanese and Latin Language, etc., since text-independent methods do not care about the content of handwriting documents. Recently, we have constructed a novel non-separable filter banks based on centrally symmetric matrices [12], which is much better than traditional wavelets on texture analysis. Therefore, we will use this novel filter banks to replace the db wavelets used in this paper for writer identification in our future work.

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