

## Short Contribution

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# Writer identification using fractal dimension of wavelet subbands in gabor domain

Zhenyu He<sup>a,c</sup>, Xinge You<sup>b,c,\*</sup>, Long Zhou<sup>b</sup>, Yiuming Cheung<sup>d</sup> and Jianwei Du<sup>e</sup>

<sup>a</sup>*Harbin Institute of Technology Shenzhen Graduate School, Harbin, China*

<sup>b</sup>*Department of Electrical and Information Engineering, Wuhan Polytechnic University, Wuhan, China*

<sup>c</sup>*Department of Electronics and Information Engineering, Huazhong University of Science and Technology, Wuhan, China*

<sup>d</sup>*Department of Computer Science, Hong Kong Baptist University, Hong Kong, China*

<sup>e</sup>*Department of Mathematics and Physics, Beijing Institute of Petrochemical Technology, Beijing, China*

**Abstract.** Writer identification is an important and active branch of biometrics, which means the methods for uniquely recognizing humans based upon their intrinsic physical or behavioral traits. In this paper, we propose one new method for off-line, text-independent writer identification by using the fractal dimension of wavelet subbands in Gabor domain of the handwriting images. In this method, the handwriting images are firstly decomposed into a series of Gabor subbands at different orientations and frequencies. Every Gabor subband is extended into one data sequence. Then, every sequence is decomposed into a series of wavelet subpatterns by wavelet transform. Afterwards, the mesh fractal dimensions of every wavelet subpattern are extracted as the feature for writer identification. Compared to the traditional Gabor method for off-line, text-independent writer identification, our method can extract more effective features to distinguish the handwritings, and hence achieve much better identification results.

**Keywords:** Writer identification, gabor, wavelet, fractal dimension

## 1. Introduction

Biometrics, which means automatic recognition of humans based on their individual biometrical features, is proposed as an effective solution of human identification. Biometric authentication is gaining popularity as a more reliable alternative to password-based security systems because it satisfies three basic requirements on ways of personal identification: uniqueness, security and consistence. For example, it is almost impossible to steal, copy, or guess biometric properties. Furthermore, one can forget his password, whereas forgetting is even not an issue for biometric properties [1]. Nowadays, various types of biometric systems are being used

for real-time identification, and the most popular ones are based on face, iris and fingerprint matching. For instance, in Hong Kong, the new Residence ID card contains the people's fingerprint information. Of course, there also exist many biometric systems that utilize other biometrical information, such as retinal scan, speech, signature and hand geometry.

For many applications, the personal identification technique must be accessible, cheap, reliable and acceptable. Handwriting-based identification meets these criteria well. So, in spite of the existence and development of the biometric person identification systems based on face [5,27,34], hand [15], retina [7,30], iris [14,20], gait [8,16], fingerprint [2,24], etc., it appears that the identification of a person on the basis of a handwritten sample still remains as an attractive application because it is better accepted by the general public. Currently, handwriting-based writer identi-

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\*Corresponding author: Dr. Xinge You, Department of Electrical and Information Engineering, Wuhan Polytechnic University, Wuhan, China. E-mail: youxg@mail.hust.edu.cn.

fication enjoys a huge interest from both industry and academy [12,18,24,28,35].

A survey summarized the early work of the handwriting-based writer identification into two general approaches. One is transform technique, and the other is histogram description [22]. Lately, in view of the handwriting of different people usually is visually different, and at the same time inspired by the idea of multichannel spatial filtering technique, Said et al. proposed a texture analysis approach [12]. 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 features of such textures. Besides the global features, some researchers found valuable features from single word or text line. For example, Leedham et al. presented eleven innovative binarised features, which could be extracted from handwritten digits [10]. Bulacu et al. used the edge-based directional probability distributions as features for writer identification [19]. Hertel et al. designed a system for writer identification based on the text line features [6]. Schlapbach et al. proposed the hidden Markov model (HMM) based recognizer which also extracted the text line features [3]. Zois et al. morphologically processed horizontal projection profiles of single words. To increase the identification efficiency, the projections were derived and processed in segments. Bayesian classifier or neural network was used for classification [9]. All these features were binarized to form a binary feature vectors of constant lengths. Then the formed binary feature vectors were measured by Hamming distance for writer discrimination [10]. Li and Ding proposed a histogram-based feature for Chinese writer identification. This feature was extracted from the edge image of the handwriting image [31]. Helli et al. presented a method based on feature relation graph for Persian writer identification. In this method, pattern based features are extracted by using Gabor and XGabor filter and the extracted features are represented for each person by using feature relation graph [4].

In this paper, we propose a novel method for off-line, text-independent writer identification. The basic idea of this method is to combine the Gabor filters, wavelet decomposition and fractal dimension to more effectively extract the direction and frequency information of the handwriting images. As proved in the experiments, this method can achieve higher identification accuracies than the existing Gabor-based method [12] does.

The rest of the paper is organized as follows. In Section 2, we discuss the used methodologies: Gabor filters and fractal dimension. In Section 3, the proce-

dures of our algorithm is proposed. The experiments using our algorithm are offered in Section 4. Finally, the conclusion is made in Section 5.

## 2. Methodology

### 2.1. Gabor feature representation

Gabor function is widely used in image processing [8,29,34] because Gabor function is of similar shape as the receptive fields of simple cells in the primary visual cortex, and is localized in both space and frequency domains and has the shape of plane waves restricted by a Gaussian function. Generally, the Gabor function is a representative of time-frequency analysis and multichannel filtering technology, and is used in a wide range of image processing applications.

The multichannel 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 [11].

We use pairs of isotropic Gabor filters with quadrature phase relationship. The spatial frequency responses of the Gabor functions are [25,26]

$$H_e(u, v) = \frac{[H_1(u, v) + H_2(u, v)]}{2} \quad (1)$$

$$H_o(u, v) = \frac{[H_1(u, v) - H_2(u, v)]}{2j} \quad (2)$$

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

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

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

Here,  $f$ ,  $\theta$  and  $\sigma$  are the spatial frequency, orientation and space constant of the Gabor envelope, separately.

Frequency responses of an even-symmetric Gabor filter are shown in Fig. 1. The frequency parameter  $f$  corresponds to the distance from the origin to the center of the Gaussians. The orientation parameter  $\theta$  corresponds to the angle from the  $u$ -axis to the center of the Gaussians.

For a given input image  $I$ ,  $H_e$  and  $H_o$  will combine to provide different channel outputs of the input image with different  $f$ ,  $\theta$  and  $\sigma$ ,

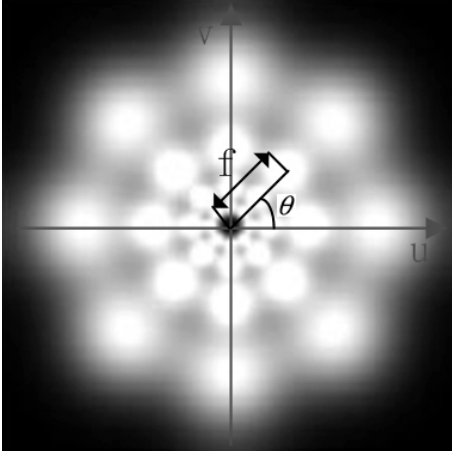


Fig. 1. Frequency responses of an even-symmetric Gabor filter.

$$\begin{cases} Q_e^{f,\theta} = H_e^{f,\theta} * FFT(I), \\ Q_o^{f,\theta} = H_o^{f,\theta} * FFT(I), \end{cases} \quad (3)$$

where,  $Q_e^{f,\theta}$  and  $Q_o^{f,\theta}$  are even and odd Gabor-filtered output matrix, respectively, at orientation  $\theta$  and frequency  $f$ , and  $FFT$  means the fast Fourier transform.

Then the Gabor-filtered output matrix is obtained in the following way:

$$Q^{f,\theta} = \sqrt{[IFFT(Q_e^{f,\theta})]^2 + [IFFT(Q_o^{f,\theta})]^2}. \quad (4)$$

Here,  $IFFT$  stands for the inverse fast Fourier transform. Thereafter, the set  $q = \{q^{f,\theta} : f \in \{f_0, f_1 = f_0 * 2^1, \dots, f_{M-1} = f_0 * 2^{M-1}\}, \theta \in \{\theta_0 = 0, \theta_1 = \theta_0 + \frac{\pi}{N}, \dots, \theta_{N-1} = \theta_0 + (N-1)\frac{\pi}{N}\}\}$  forms the Gabor representation of the handwriting image.  $M$  is the frequency level,  $f_0$  is the minimum frequency. Tan pointed out that for any image of size  $N \times N$ , the important frequency components can be found within  $f \leq \frac{N}{4}$  degree [26]. In other words, the frequency components with  $f > \frac{N}{4}$  are less valuable for texture identification. According to Tan's conclusion and experiments, we choose  $M = 4$  and  $f_0 = 4$  because the handwriting images used in our research are of size  $256 \times 256$ . That is, the frequency  $f \in \{8, 16, 32, 64\}$ . As for the orientation number  $N$ , since the Gabor filter is symmetric, we only need to consider the orientation space within  $[0, \pi]$  rather than  $[0, 2\pi]$ . Usually, we choose  $N = 4$ . That is,  $\theta \in \{0, 45^\circ, 90^\circ, 135^\circ\}$ .

In the existing Gabor-based method [12], the mean ( $m$ ) and standard deviation ( $\sigma$ ) of the outputs  $Q$  are selected as features to represent writer global features for writer identification. After extracting the writing features, weighted Euclidean distance (WED) is applied for feature matching,

$$WED(k) = \sum_{i=1}^{Num} \frac{(m_i - m_i^k)^2}{\sigma_i^k}, \quad (5)$$

where,  $m_i$  denotes the  $i$ th mean value of the query handwriting,  $m_i^k$  and  $\sigma_i^k$  denote the  $i$ th mean and standard deviation of the training handwriting of writer  $K$ , respectively, and  $Num$  denotes the total number of mean values. For simplicity, we denote this Gabor-based method as *Gabor&WED* in this paper. In our method, we use the fractal dimensions to represent the features of  $Q$ . Similarly, we denote our method as *Gabor&Fractal* in this paper.

## 2.2. Fractal dimension

So far, there is not a strict definition yet in fractal geometry as to what is fractal. The famous geometry expert K. Falconer listed only five items of characteristics of fractal set  $F$  described in uncertain language in his monograph instead of giving an exact definition of fractal. The five characteristics of fractal set are:

- Elaborate structure.
- Being too irregular.
- Some self-similarity.
- Its “fractal dimension” being often bigger than its topology dimension.
- Being recursion in most cases.

Fractal dimensions are important numeric characteristics of fractal, containing geometrical structure information of curve or image, being the measurement of fractal information characteristics [17].

By dividing a  $n$ -dimension space  $R^n$  into  $\Delta$ -mesh as small as possible, usually square and rectangle meshes are both ok, the fractal set  $F$  is changed into a digital discrete point set. In this way,  $N_\Delta$  is equal to the point counting number of the set in the discrete space where distance from one point to another point is  $\Delta$ . Then, we enlarge  $\Delta$  mesh into  $k\Delta$  mesh. Naturally,  $N_{k\Delta}$  represents the point counting number of the set in the discrete space where distance from a point to another point is  $k\Delta$ . So that there are  $k$  kinds of point counting number on different mesh width  $N_{k\Delta}$ ,  $k = 1, 2, \dots, K$  or ( $k = 1, 2, \dots, 2^{K-1}$ ).

Let

$$\begin{cases} x_k = \log k \\ y_k = \log N_{k\Delta} \end{cases} \quad (6)$$

There are three methods as follows to approximately calculate mesh fractal dimensions [21]:

- (1) Average Method:

$$d_N(X) = \frac{1}{C} \sum_{k,k'} \frac{\log(N_{k\Delta}/N_{k'\Delta})}{\log(k'/k)}, \quad (7)$$

$$1 \leq k < k' \leq K,$$

where,  $C$  is the number of summation formula  $\sum$  and  $X$  stands for a 2-D curve from which the fractal dimension is computed.

(2) Minimal Residual Algorithm:

Consider  $y_k = -dx_k + b$ ,  $k = 1, 2, \dots, K$ , the minimal residual algorithm may be used to calculate  $d$  and  $b$  as follows:

Let

$$f(d, b) = \sum_{k=1}^K (y_k + dx_k - b)^2, \quad (8)$$

calculate the deflection derivative, then let

$$\begin{cases} \frac{\partial f}{\partial d} = 2 \sum_{k=1}^K (y_k + dx_k) = 0 \\ \frac{\partial f}{\partial b} = 2 \sum_{k=1}^K (y_k + dx_k - 1) = 0 \end{cases}. \quad (9)$$

Thus, we get

$$d_N = \frac{K \sum x_k y_k - \sum x_k \sum y_k}{K \sum x_k^2 - (\sum x_k)^2} = \frac{K \sum \log k \log N_{k\Delta} - \sum \log k \sum \log N_{k\Delta}}{K \sum \log^2 k - (\sum \log k)^2} \quad (10)$$

(3) Simplifying Estimation:

For digital images, in the case of knowing the resolution ratio  $\Delta$  (that is distance from a point to another point),  $\log N_{\Delta}$  is a function of  $\log k$ , which is not only a monotone decreasing function, but also a convex function. Then, the result of minimal residual algorithm is easily obtained as,

$$d_N F \approx \frac{\log N_{\Delta}}{\log K}, \quad (11)$$

where,  $K = \max\{k : N_{k\Delta}\}$ ,  $k\Delta$  is the mesh width of covering set  $F$ ,  $N_{\Delta}$  is discrete image point counting number when the resolution ratio is  $\Delta$ .

### 3. Implementation issues

As we have mentioned above, writer identification is a typical problem of pattern recognition. It contains two key steps: feature extraction and similarity measurement. Feature extraction means extracting features to fully represent the given handwriting image. Similarity measurement means using a certain measurement function to calculate the similarity between extracted features of the query handwriting image and the training handwriting images. The whole procedure of feature extraction is described in Fig. 2. And the key steps of the procedure are explained in the following.

#### 3.1. Feature extraction

**Step 1.** Decomposing the input handwriting image  $I(x, y)$  by the 2-D Gabor filters. In the Subsection 2.1, we have described in detail how to use the Gabor filters to convolute the input handwriting images to generate a series of Gabor subbands at different orientations and at varied frequencies. That is,

$$I \Rightarrow S = \{S_1, \dots, S_{16}\}, \quad (12)$$

where,  $S$  represents the set of Gabor subbands, and the symbol " $\Rightarrow$ " means "after this step". In other words, after this step, we can get the right side  $S$  from the left side  $I$ .

**Step 2.** Extending the Gabor subbands  $S_i$  into a data sequence  $C_i^0$ ,

$$S_i \Rightarrow C_i^0 : C_i^0(y \times width + x) = S_i(x, y). \quad (13)$$

Obviously, the data sequence  $C_i^0$  can be regarded as a curve line and therefore its fractal dimension is able to be calculated. Here,  $width$  is the width of the Gabor subbands  $S_i$ .

**Step 3.** Decomposing the curve  $C_i^0$  using the wavelet filters. Wavelets are mathematical functions that cut up data into different frequency components, and then study each component with a resolution matched to its scale [13]. Compared to the traditional Fourier methods, wavelets are better to analyze such physical situations where the signals (1-D) and images (2-D). Currently, wavelets have been widely used in different applications, such as damage detection of highrise buildings [33], traffic flow forecasting [32], analysis of earthquake energy [36], freeway incident detection [23]. To well extract the features of the curve  $C_i$ , we decompose  $C_i^0$  into a series of wavelet subpatterns at different resolutions. Here, the wavelet filters used are Daubechies wavelets [13]. The value of the wavelet decomposition level  $j$  is 6 in our experiments.

$$C_i^j(k) = \sum_n h_{n-2k}^* C_i^{j-1}(n), \quad \text{and} \quad (14)$$

$$D_i^j(k) = \sum_n g_{n-2k}^* C_i^{j-1}(n)$$

Therefore, we obtain the curve  $C_i^0$  and its  $6 \times 2 = 12$  wavelet subpatterns  $\{C_i^1, C_i^2, C_i^3, C_i^4, C_i^5, C_i^6\}$  and  $\{D_i^1, D_i^2, D_i^3, D_i^4, D_i^5, D_i^6\}$  from each Gabor subband  $S_i$ .

**Step 4.** Computing the mesh fractal dimension of each curve. As we mentioned above, there are 3 methods to compute the mesh fractal for the curve, namely, (1) average method, (2) minimal residual algorithm,

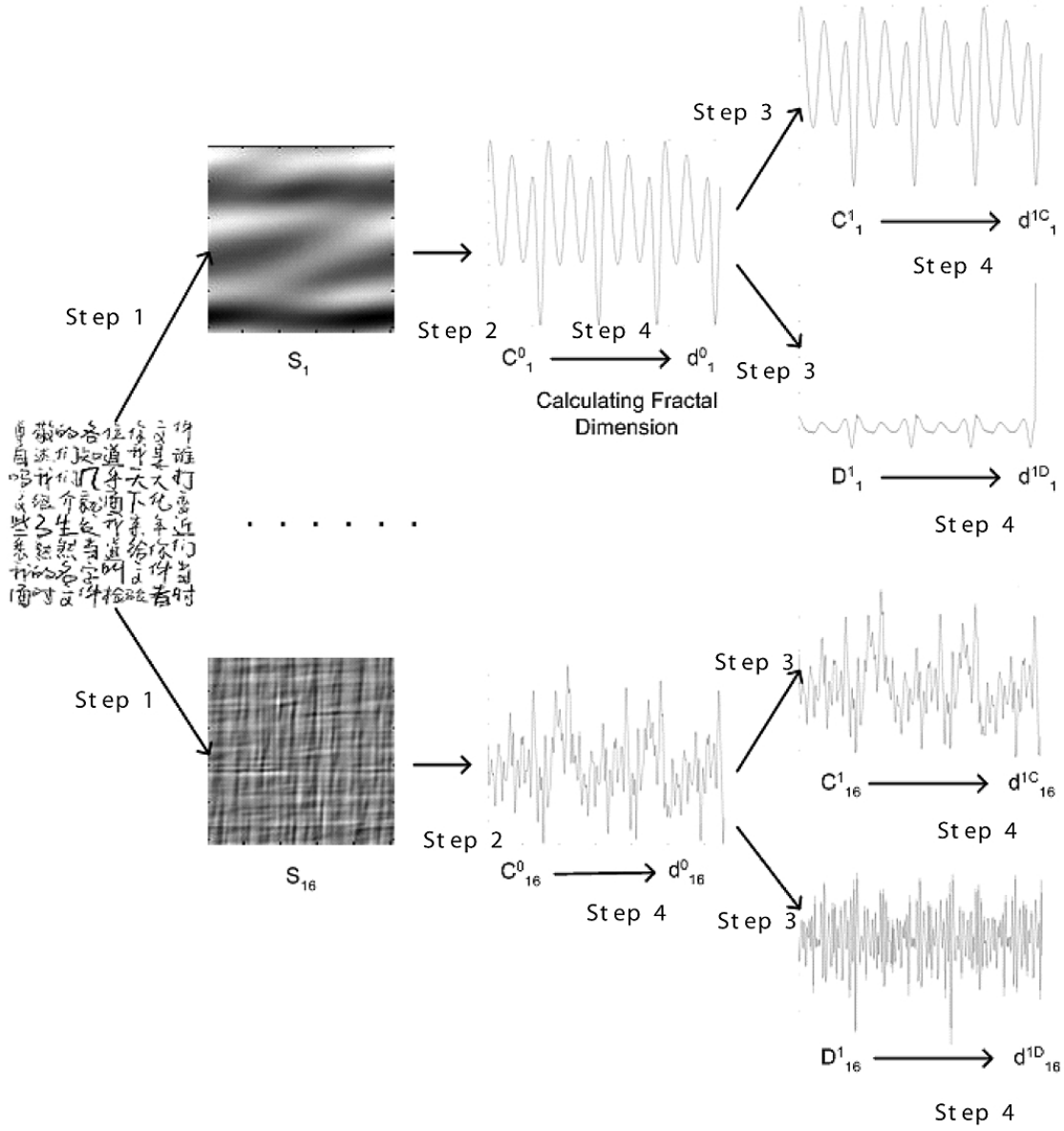


Fig. 2. Diagram of the procedure of feature extraction.

(3) simplifying estimation. Since we have known the resolution ratio, we adopt the simplifying estimation. We can get one mesh fractal dimension  $d_i^{jC}$  ( $d_i^{jD}$ ) from each curve  $C_i^j$  ( $D_i^j$ ),

$$C_i^0 \Rightarrow d_i^0, C_i^j \Rightarrow d_i^{jC}, D_i^j \Rightarrow d_i^{jD}, \quad (15)$$

$$i = 1, \dots, 16, j = 1, \dots, 6$$

Consequently, a handwriting image can be fully represented by this Gabor-fractal feature vector  $F = \{F_1 = (d_1^0, d_1^{1C}, \dots, d_1^{6C}, d_1^{1D}, \dots, d_1^{6D}), F_2, \dots, F_{16}\}$ .

### 3.2. Similarity measurement

From the procedures of our algorithm, we know 16 Gabor subbands are obtained from one handwriting image and 13 fractal dimensions are obtained from each subband. So, the similarity distance of each Gabor subbands should be firstly computed and then the summary of similarity distances of 16 Gabor subbands is computed as the similarity distance of two handwriting images. Normalized Euclidean distance (NED) is adopted for similarity measurement.

Table 1  
Identification Result of Gabor & Fractal and Gabor & WED

Handwriting Name	G-Fractal	G-WED	Handwriting Name	G-Fractal	G-WED
0102	4	6	2602	1	1
0202	2	2	2702	1	2
0302	1	1	2802	2	2
0402	4	5	2902	8	13
0502	1	1	3002	1	1
0602	1	1	3102	7	8
0702	1	1	3202	1	1
0802	2	2	3302	2	2
0902	2	2	3402	1	2
1002	1	1	3502	1	1
1102	2	2	3602	1	1
1202	2	2	3702	11	20
1302	1	1	3802	1	1
1402	2	2	3902	1	1
1502	2	12	4002	1	1
1602	1	1	4102	1	1
1702	1	2	4202	1	2
1802	7	11	4302	5	10
1902	2	4	4402	1	2
2002	3	3	4502	2	2
2102	3	3	4602	1	1
2202	1	1	4702	5	6
2302	1	2	4802	1	2
2402	1	1	4902	2	8
2502	1	1	5002	1	2

$$NED(K_i) = \left[ \sum_{j=1}^{13} (F_i(j) - F_i^K(j))^2 \right]^{1/2}, \quad (16)$$

$$NED(K) = \sum_{j=1}^{16} NED(K_i), \quad (17)$$

where,  $F_i(j)$  denotes the  $j$ th element of  $F_i$  of the query handwriting,  $F_i^K(j)$  denotes the  $j$ th element of  $F_i^K$  of the training handwriting of writer  $K$ .  $NED(K)$  represents the NED between the training handwriting image and the query handwriting image.

#### 4. Experiments

This section assesses the performance of our Gabor-fractal method for writer identification. 100 Chinese handwritings written by 50 persons have been carried out in our experiments, with one training handwriting and one query handwriting for each person. All handwritings are scanned into computer with a resolution of 300 dpi in a binary image format. We produce one normalized handwriting image from each original handwriting, and totally 100 normalized handwriting im-

ages are obtained. The training and query normalized handwriting images both consist of 64 Chinese characters with size  $32 \times 32$  pixels, arranged in an  $8 \times 8$  array, shown in Fig. 3.

We only consider the k-nearest neighbor classifier. We measure the distance between the query handwriting and each class in the training set. Smaller distance means larger similarity. The distance measure used here is NED described in Eqs (16) and (17). Identification result is to find the top  $N$  handwriting classes which are most similar to the query handwriting image. Table 1 shows the matching results of all query handwritings considered in our experiment. In this table, “Handwriting Name” refers to the name of query handwriting. “Gabor&Fractal” refers to the matching result of the Gabor&Fractal method. “Gabor&Wed” refers to the matching result of the Gabor&Wed method. For example, in the left part of the first row, “0102, 4, 6” means that the training handwriting belonging to the same writer (indexed as 0101) is the top 4th match and the top 6th match in Gabor&Fractal method and Gabor&Wed method, respectively.

One evaluation criteria of identification is defined as follows: for each query handwriting, if the training handwriting belonging to the same writer is ranked at



Fig. 3. A part of normalized binary handwritings (10 persons) carried out in our experiment.

the top  $S$  matches, we say this is a correct identification, otherwise the identification fails. The identification rate is the percentage of the correct identification. The identification results are recorded in the Table 2.

Next, we change the evaluation criteria. We regard

the true writer is ranked at the top  $S$  matches as the case that the true writer is accepted otherwise the true writer is rejected. Obviously, in our system, the FRR always equals to FAR because in our system, falsely rejecting the true writer is identical to falsely accepting the false

Table 2  
Writer Identification Rate of Gabor & Fractal and Gabor & WED(%)

Number of Top Matches	Gabor & Fractal	Gabor & WED
1	56	42
2	80	74
3	84	78
4	88	80
5	92	82
6	92	86
7	96	86
8	98	90
9	98	90
10	98	92
11	100	94

writer. Therefore, in our system,  $FRR = FAR = EER$ .  $S$  can be viewed as the threshold. The identification results are recorded in the Table 3.

## 5. Conclusions

In this paper, we present a new method for off-line, text-independent writer identification by combining Gabor filters, wavelet decomposition and fractal dimension. In this method, the handwriting images are firstly convoluted with well-designed Gabor filters to generate multiple Gabor subbands. These Gabor subbands are extended into data sequences, which are decomposed into a series of wavelet subpatterns by wavelet transform. Thereafter, the generated wavelet subpatterns are characterized by the mesh fractal dimensions. Finally, the normalized Euclidean distance is adopted to measure the similarity of the mesh fractal dimensions, and the measured similarity is regarded as the similarity of different handwritings. Compared to the traditional Gabor-based method, our method can more accurately characterize the features of handwriting images. Therefore, the identification performance of our method is obviously higher than that of the traditional Gabor-based method, as proved in our experiments.

Though the proposed method outperforms the existing Gabor-based method, its identification result still can not make us very satisfied. Hence, in the future, we would like to find new features which can better characterize the features of different handwritings. Another way to improve the identification accuracy is to design a hybrid identification system using multiple features. But there arises new problems, that is, which multiple features should be combined and how to reasonably distribute the weighting factors for various features. So, finding the solutions to solve these problems is also our work in the future research.

Table 3  
Equal Error Rate of Gabor & Fractal and Gabor & WED(%)

Number of Top Matches	Gabor & Fractal	Gabor & WED
1	44	58
2	20	26
3	16	22
4	12	20
5	8	16
6	8	14
7	4	14
8	2	10
9	2	10
10	2	8
11	0	6

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