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Detection of Forged Signatures Using Directional Gradient Spectrum of Image Outline and Weighted Fuzzy Classifier

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ABSTRACT

In this paper, a method for detection of forged signatures based on spectral analysis of directional gradient density function and a weighted fuzzy classifier is proposed. The well defined outline of an incoming signature image is extracted in a preprocessing stage which includes noise reduction, automatic thresholding, image restoration and erosion process. The directional gradient density function derived from extracted signature outline is highly related to the overall shape of signature image, and thus its frequency spectrum is used as a feature set. With this spectral feature set, having a property to be invariant in size, shift, and rotation, a weighted fuzzy classifier is evaluated for the verification of freehand and random forgeries. Experiments show that less than 5% averaged error rate can be achieved on a database of 500 signature samples.

Keywords: Gradient orientation, directional density function, weighted fuzzy mean classifier

1. INTRODUCTION

Handwritten signature verification problem is concerned with determining whether a particular signature truly belongs to a person, so that forgeries can be deleted. Most of us are familiar with the process of verifying a signature for identification, especially in legal, banking, and other high security environments. It can be either on-line or off-line, which is differentiated by the data acquisition method[1-3]. In an on-line system, signature traces are acquired in real time with digitizing tablets, instrumented pens, or other specialized hardwares during the signing process. In an off-line system, signature images are acquired with scanners or cameras after the complete signatures have been written. There have been over a dozen prior research efforts and the summaries of these efforts are shown in[1,3].

However, most of the prior works on handwriting have used real-time input, which means they dealt with on-line system[4-6]. Relatively only a few methods focused on off-line signature verification. In off-line system, image of a signature written on a paper is obtained either through a camera or a scanner and obviously dynamic information is not available. Since the volume of information available is less, signature analysis using off-line techniques is relatively more difficult. To solve this off-line signature verification problems, elastic image matching techniques[7,8], extended shadow-coding method[9], and 2-D FFT (Fast Fourier Transform) spectral method[10] were presented in the past. And Nemcek *et al.* proposed a method with the features extracted from an image after Hadamard transformation[11]. Nagel *et al.* described a system for automatic detection of freehand forgeries based on characterizing hand-

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writing strokes in terms of a set of kinematic parameters[12]. For the case when the actual (or true) signature and the forgery are very similar, Ammar *et al.* introduced an effective approach based on pressure features of the signature image[13]. More recent efforts tend to utilize a neural network classifier or a fuzzy classifier with the directional probability of the gradient on the signature image[14-17] and with geometric features[18,19] for the detection of random and freehand forgeries. And for the detection of skilled forgeries, Hidden Markov Model (HMM) is successively applied[20,21].

On reviewing the literature it was realized that a direct comparison of results from different researchers is often impossible. This is due to factors such as different data set used, field conditions, training and test data size, and the way in which the issue of forgery was handled[1,3,5]. Therefore, the main focus of this paper is to introduce a new technique for carrying out off-line signature verification and it is compared with our previous work[16] only. In this study, the global features based on FFT spectrum of directional gradient density function, which can abstract the overall shape information of signature image, and a weighted fuzzy classifier are proposed. The feature set extracted from directional gradient density function was developed earlier and widely used in off-line signature verification systems[14-17]. It is easy to extract and relatively well contains the overall shape information of signature image. However, the directional density function in[14-17] was derived from the entire signature image and easily affected by the rotation of image. Thus in this paper, the directional density function is extracted from only the outline of signature image not the entire signature image because the overall shape information is more densely located at the outline of image, and the FFT spectrum of that is utilized as a feature vector for invariance of image rotation and data reduction. In the experiments, data set including the signature images written by the simple Korean letters is tested as well.

The summary of our verification process is as follows. The first step involves scanning actual signature images. A signature written in a specified rectangular area is scanned and digitized with 300 dots per inch, and stored in a 200 by 925 pixel matrix, according to its gray level representation (quantified into 256 levels). The second step includes lowpass filtering, adaptive thresholding, image restoration and erosion process to extract the outline of signature image from the noisy background. The third step is to derive the directional gradient density function from the pixels only on the extracted outline of signature image by using Sobel gradient mask[22]. After the normalization, the FFT spectrum[23] is extracted from this directional density function which preserves the overall shape information of signature image, and is used as a feature set. This feature vector is invariant to translation, rotation and scaling of the signature image, and fed into the weighted fuzzy classifier to verify a signature whether it belongs to a genuine or forgery. The overall processing steps are shown in Fig. 1.

The design of a complete AHSVS (Automatic Handwritten Signature Verification System) which is able to cope with all classes of forgeries (random, freehand, and traced[1]) is a very difficult task because of computational resources and algorithmic complexity[24]. A better solution might be to subdivide the decision process in a way to eliminate rapidly gross forgeries like random or freehand forgeries. In this study, we focus on the construction of a first stage of verification system in a complete AHSVS. Thus, only the freehand forgeries, which are written in forgers' own handwriting style without knowledge of the appearance of genuine signature, or the random forgeries, which use his/her own signatures instead of genuine signatures, are considered.

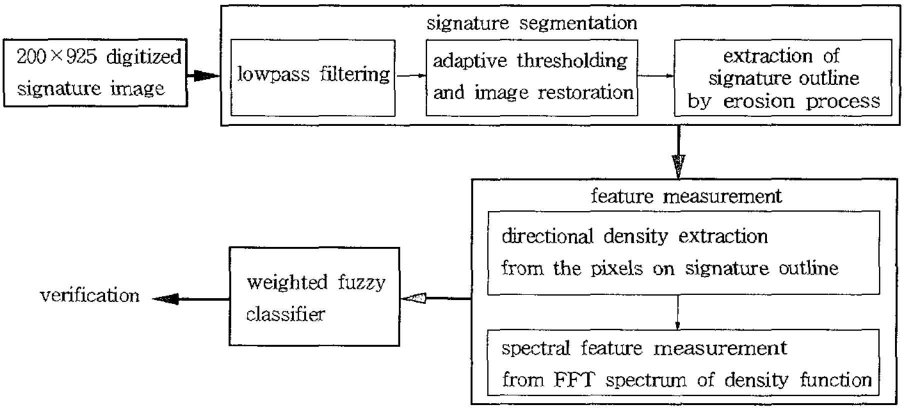


Fig.1. Overall processing steps for the proposed freehand or random forgery detection system.

2. SIGNATURE IMAGE SEGMENTATION AND FEATURE MEASUREMENT

Signature image segmentation: In this paper, the extraction of a signature image from the noisy background is done as follows. The first work is to apply a lowpass filter, shown in equation (1), to a scanned image for the noise reduction.

$$p'(i,j) = \frac{1}{9}\sum_{l=i-1}^{i+1}\sum_{k=j-1}^{j+1} p(l,k) \quad (1)$$

$$(1 \le i \le m,\ 1 \le j \le n)$$

where $p(l,k)$: the original image, $p'(i,j)$: the averaged image and m by n is the size of image (200 by 925). In a next, the threshold value, THD, is automatically selected from the averaged image, based on a simple iterative algorithm proposed by *Ridler et al*[25], and the fine signature image is restored as shown in equation (2).

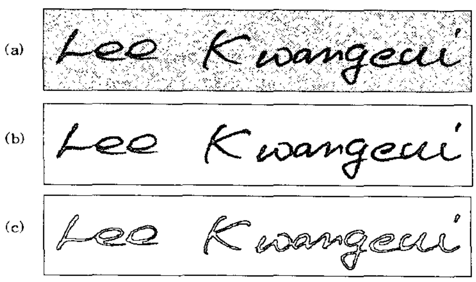
$$p''(i,j) = p(i,j) \text{ if } p'(i,j) > THD, \quad (2)$$
$$\textit{otherwise } p''(i,j) = 0$$

where $p''(i,j)$: the restored image. In a third, the outline of signature is extracted from the restored image $p''(i,j)$ by using the erosion process. If $p''(i,j) > 0$ and its 8-neighbor count is below 8, $p''(i,j)$ must be on the outline of signature image, which is shown in equation (3).

$$\hat{p}(i,j) = p''(i,j) \text{ if } p''(i,j) > 0 \text{ and } Np < 8$$
$$\textit{otherwise } \hat{p}(i,j) = 0 \quad (3)$$

where Np is a count of 8-neighbor pixels which are greater than zero. A sample signature image restored from noisy background and its outline is shown in Fig. 2.

Feature Measurement: The one utilized as the input of a weighted fuzzy mean classifier for the verification process is the FFT spectral feature vector of directional gradient density function extracted from only the outline of signature image. It depends on the overall shape of the signature image, and so is assumed to have enough information for the detection of freehand or random forgeries. In the gradient computation process, Sobel 3 by 3 mask shown in Fig. 3 is convolved with each pixel on the restored image if and only if it is on the outline of signature image, and the



(a) : an original image (b) : a restored image (c) : its outline

Fig. 2. A sample signature restored from noisy background and its outline.

row gradient *column gradient*

$$S_r = \frac{1}{4}\begin{bmatrix} 1 & 0 & -1 \\ 2 & 0 & -2 \\ 1 & 0 & -1 \end{bmatrix} \quad S_c = \frac{1}{4}\begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix}$$

Fig. 3. Sobel 3 by 3 gradient mask.

amplitude and angular orientation of gradient vector are computed by equation (4) and (5).

if and *only* if $\hat{p}(i,j) > 0$,

$G_r(i,j) = S_r(i,j) \otimes p''(i,j)$

$G_c(i,j) = S_c(i,j) \otimes p''(i,j)$ and,

$$G(i,j) = \sqrt{G_r(i,j)^2 + G_c(i,j)^2} \tag{4}$$

$$\theta(i,j) = [\tan^{-1}(\frac{G_c}{G_r}) + \frac{\pi}{2}] * \frac{128}{\pi} \tag{5}$$

where $\hat{p}(i,j)$: a pixel on the outline of signature image and $p''(i,j)$: a pixel on the restored image. The multiplication term, $\frac{128}{\pi}$ in equation (5), allows the angular orientation $\theta(i,j)$ to have a range from 0 to 127 for FFT. In a next, the directional gradient density function for the pixels on the outline of signature image, $DF(\theta_k)$, is derived by equation (6) and its normalized term, $NF(\theta_k)$, by equation (7).

$$DF(\theta_k) = \sum_{i=1}^{200} \sum_{j=1}^{925} X(\theta_k, i, j) \tag{6}$$

where $X(\theta_k, i, j) = G(i,j)$, $\theta(i,j) = \theta_k$ derived by equations (4),(5), and k=0,1,2,...127.

$$NF(\theta_k) = \frac{DF(\theta_k)}{\sum_{\theta_k=0}^{127} DF(\theta_k)} \tag{7}$$

The normalized directional gradient density, $NF(\theta_k)$, extracted from a sample signature image in Fig. 2 is shown in Fig. 4.

Finally, as a means of data reduction and feature selection, the 128 point FFT is taken into the normalized directional gradient density, which is shown in equation (8).

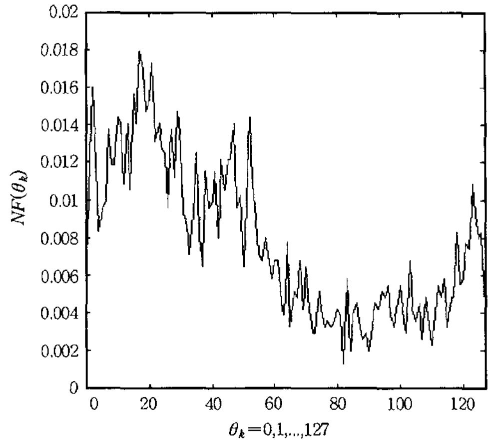


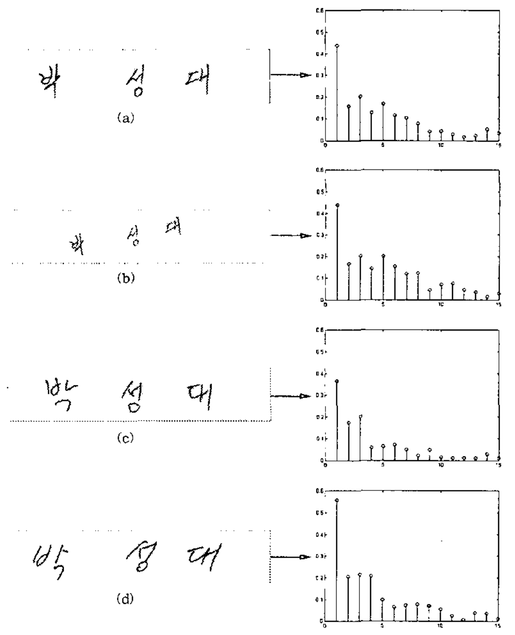
Fig. 4. The normalized directional gradient density extracted from a sample signature shown in Fig.2.

$$F(m) = abs(\sum_{\theta_k=0}^{127} NF(\theta_k)\exp(-2\pi j\theta_k m/128)) \tag{8}$$

where m=0,1,2,....,127. A D.C. component, F(0), is always zero because the mean value of $NF(\theta_k)$ is removed before FFT. Thus, in this study, the first 15 spectral components except F(0) are utilized as a feature vector to be an input of the weighted fuzzy classifier for verification. The feature vector formed with F(1),F(2),....,F(15) has a property to be invariant in size, shift, and rotation. Fig. 5 shows some samples of genuine and forged signatures and their feature vectors. The FFT spectral feature vectors extracted from two genuine signatures, even one of them is scaled and rotated, are very similar together, but different with feature vectors extracted from two kinds of freehand forgeries written by two different person.

3. A WEIGHTED FUZZY CLASSIFIER

The construction of a fuzzy classifier depends on the type of a fuzzy membership function and the calculation method of a fuzzy mean value [26-28]. The triangular type of membership function has a simple configuration and is easy to apply where the only one reference feature set for one target pattern is used as in our experiments. Thus



(a)(b) genuine samples
(c)(d) forgeries by two different person

Fig. 5. Samples of genuine and forged signatures and their FFT spectral feature vectors.

the one used in this paper as a classifier is combined a triangular fuzzy membership function with a weighted fuzzy mean method which utilizes the variances of each dimensional feature value in a reference feature set as the weights, w_i. This is shown in equation (9).

$$h_w(\mu_1(x_1), \mu_2(x_2), \cdots, \mu_n(x_n); w_1, w_2, \cdots, w_n) = \sum_{i=1}^{n} \mu_i(x_i) \cdot w_i, \quad (\sum_{i=1}^{n} w_i = 1) \tag{9}$$

where h_w: a weighted fuzzy mean value, μ_i: a membership grade extracted from a triangular membership function, w_i: a weight for an i^{th} feature value, x_i , and n is the dimension of incoming feature vector (15 in this paper).

This type of classifier does not require a training stage while the classifier based on neural network algorithms does. And the performance of a neural classifier highly depend on its architecture and learning algorithm[29]. In this fuzzy classifier, the triangular fuzzy membership functions of each of fifteen-dimensional feature values and their variances used as weights are simply constructed and computed by using the reference feature set, and utilized for the verification of a signature image without any further process. Thus the evaluation process is much simpler and easier than that of the conventional neural network classifier. For an incoming test signature, the fifteen membership grades are computed by pre-established triangular membership function, and its weighted fuzzy mean value is derived by equation (9). If it is greater than a threshold value, this signature is verified as a genuine signature, and if not, it is discarded as a forgery. More details about this fuzzy classifier based on triangular membership function and weighted fuzzy mean value can be founded in our previous work[16].

4. EXPERIMENTS AND PERFORMANCE ASSESSMENT

In our experimental process, a total of 500 signature images were corrected and verified by both of the proposed method and our previous algorithm where the twelve-dimensional directional density extracted from an entire signature image by using 5 by 5 Nevatia-Babu gradient mask had been utilized as a feature vector[16]. Test images belong to five sets of different signatures. Signature data collection for each set was done by as follows. One of five different writers was chosen as a target and asked to write his own name twenty times on an A4 page, and four of the remaining writers were assigned to be forgers. Each of the forgers was asked to write the targeted name twenty times in his own handwriting on an A4 page. The forgers were not allowed to study the samples of the original signature because this study focused on only freehand or random forgery detection not skilled forgery detection. Each set comprises one A4 page of genuine and four A4 pages of freehand forgery signatures. They were scanned, one page at a time, at resolution of 300 dpi, 8-bit gray-scale, and each signature was stored in a 200 by 925 pixel matrix. Thus each set contains 20 genuine signatures and 80 freehand forgeries. By use of each of five writers' own signature as a target, five sets of different signature classes were made. Some samples of data set 1 to 5 are shown in Fig. 6.

Signature verification with a neural classifier needs the variety of forged signatures to train the classifier for the high performance[15,30,31]. However, under the real world environment, only a few forged signature samples are available. In this study, a fuzzy mean classifier without any knowledge of forged signatures is presented to decide an incoming signature whether it belongs to a genuine or forged signature. The construction of a fuzzy classifier and the verification process were done by as follows.

(a):dataset 1 (b):dataset 2 (c):dataset 3 (d):dataset 4 (e):dataset 5

Fig. 6. Sample signatures in data set 1 to 5.

In a first, the reference feature set is constructed only with the randomly selected genuine signature samples shown in equation (10), and the weights for each of fifteen-dimensional feature values are derived by equation (11).

$$rf(x_i) = \frac{1}{nm}\sum_{j=1}^{nm} f_j(x_i)\ ;\ i=1,2,\ldots,15 \qquad (10)$$

where nm: the number of selected genuine signature samples, $f_j(x_i)$ is an i^{th} feature value of a selected signature sample, f_j, and $rf(x_i)$ is an i^{th} feature value of reference feature set. For the weights, the normalized variances for each of fifteen-dimensional feature values, $vr_1, vr_2, \ldots, vr_{15}$, are drived as in our previous work[16]. And if a normalized variance for the i^{th} feature values extracted from the selected signature samples, vr_i, is a p^{th} larger value among $[vr_1, vr_2, \ldots, vr_{15}]$, then a weight for the i^{th} feature value is defined as $w_i = \text{a } (16-p)^{th}$ larger value in $[vr_1, vr_2, \ldots, vr_{15}]$. (11)

By the equation (11), the i^{th} feature which has a smaller variance has a larger weight, and it means the i^{th} feature whose values are not significantly changed between genuine signature samples is more weighted in verification process. After this stage, the verifier performance is evaluated. For an incoming signature image, the membership grades of its feature values are derived by equations (12)-(14).

$$\mu_i(x_i) = \frac{(x_i - rf(x_i))}{rf(x_i)} + 1 \quad \text{if} \quad x_i < rf(x_i) \qquad (12)$$

$$\mu_i(x_i) = -\frac{(x_i - rf(x_i))}{rf(x_i)} + 1 \quad \text{if} \quad x_i \geq rf(x_i) \qquad (13)$$

$$\mu_i(x_i) = \begin{cases} \mu_i(x_i) & \text{if} \quad \mu_i(x_i) \geq 0 \\ 0 & \text{if} \quad \mu_i(x_i) < 0 \end{cases} \qquad (14)$$

where x_i is an i^{th} feature value of input signature image, $rf(x_i)$ is an i^{th} feature value of reference feature set, and $\mu_i(x_i)$ is a membership grade for x_i. All of membership functions are configured as a triangular type shown in Fig. 7.

In a next, the weighted fuzzy mean value is derived by equation (15) and the signature is verified by equation (16).

$$h(\mu_1(x_1), \mu_2(x_2), \cdots, \mu_{15}(x_{15}); w_1, w_2, \cdots, w_{15}) = \sum_{i=1}^{15} \mu_i(x_i) \cdot w_i \quad (15)$$

where h is the weighted fuzzy mean value of an incoming signature image, μ_i is a membership grade of the i^{th} feature value, and w_i is a weight shown in equation (11).

$$\begin{aligned} h &\geq Th \text{ accepted as a genuine signature} \\ h &< Th \text{ rejected as a forged signature} \end{aligned} \quad (16)$$

where Th is a threshold value. The particular value of Th will determine the probabilities of false rejection(FRR: Type I error) and false acceptance (FRA: Type II error). The choice of Th should therefore be based on the cost of these two types of errors. In our experiments, Th is expressed by equation (17), and selected to minimized the verification error, ERR, defined by equation (18).

$$Th = mh - nh\left(1 - \frac{K}{sh}\right) \quad (17)$$

where mh, nh and sh are mean, minimum and standard deviation of the weighted fuzzy mean values in equation (15), respectively, which are derived by the selected genuine signature samples, that were used for the construction of reference feature set, utilized as the input of fuzzy classifier, and K is a constant.

$$ERR(\%) = \frac{FRR + FRA}{2} \quad (18)$$

ERR is computed with the changes of constant K, and Th that corresponds to K's value which gives the minimum ERR is chosen as the pre-established Th. Fig. 8 shows the relation between FRR, FRA, and ERR with the different values of K, which determines Th. ERR is usually smallest around the crossing point of FRR and FRA curves, which means Th is selected where type I and type II error rates do not have a significant difference. And it is also shown in fig. 8 that selecting Th is not critical because ERR is less than 10% for a wide range of K.

In the experiments, the performance of weighted fuzzy classifier was evaluated for both random and freehand forgeries. Additionally, it was checked with the twelve-dimensional directional feature set from[16] as well for the comparison purpose. For each case, five independent simulations with a different choice of five randomly selected genuine signature samples for the construction of reference feature set were performed, and the verification results were averaged. Under random forgery test, all data sets except the one with identification number the same as the classifier were applied. The average ERR for all of signature class is just below 4.1% by the proposed method and 5.7% by

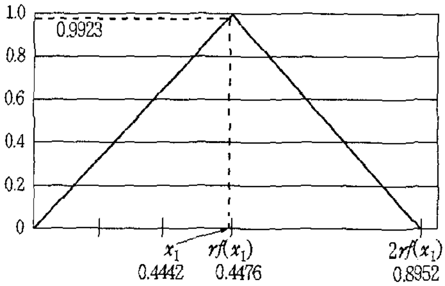


Fig. 7. A fuzzy membership grade, $\mu_1(x_1)$, for a signature sample shown in Fig.5-(a)

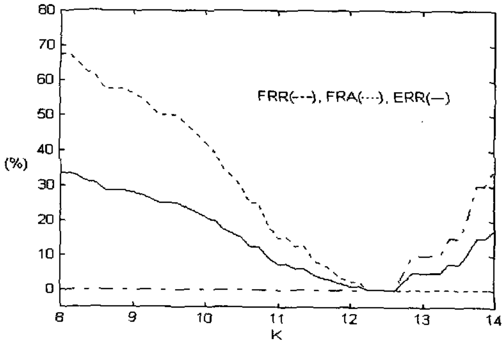


Fig. 8. The relation between FRR, FRA and ERR with different values of K.

the algorithm in [16], for a test set size of 420 signature samples (20 genuine signatures and 400 random forgeries for each signature class). They are summarized in Table 1 for each signature class. Under freehand forgery test, the test size for each signature class is 20 genuine samples and 80 freehand forgery samples written by four different forgers, and the average *ERR* with the proposed feature set and with the directional feature from [16] were about 5.3% and 9.6% respectively. They are summarized in Table 2 for each signature class and in Table 3 for all of signature data sets. From Table 1 and 2, it is obvious that the performances by both algorithms with random forgery are better than with freehand forgery because the feature vectors used in both of two approaches are based on the overall shape of signature images. In random forgery test, the difference of *ERR* by two algorithms is not significant even though the *ERR* by the proposed method is always lower for each signature class. However, the proposed method shows much better results in freehand forgery test, which means the directional feature set extracted from the outline of signature image has more accurate shape informations than the feature set from the entire signature image does. The verification process between similar signature images, such as freehand forgery test, always requires more precise shape information. Additionally, the feature set from [16] is variant to the image rotation. It might be possibly one of the reasons why the overall results by the proposed method are superior for both random and freehand forgery test, even the rotation of our test data set is not severe. And it is shown that, in both of random and freehand forgery test, the verification results with signature classes "Han(data set 1)" and "박(data set 5)" are relatively high. It is caused by that the

Table 1. Average verification results for random forgery test after five independent simulations

Result / dataset	$FRR = \frac{\text{\# of false rejected signatrue}}{20} \times 100$		$FRA = \frac{\text{\# of false accepted signatrue}}{400} \times 100$		$ERR = \frac{FRR + FRA}{2}$	
	proposed method	algorithm in [16]	proposed method	algorithm in [16]	proposed method	algorithm in [16]
"Han"(dataset 1)	2%	4%	1.8%	3%	1.9%	3.5%
"장"(dataset 2)	5%	5%	10%	12%	7.5%	8.5%
"Lee"(dataset 3)	1%	2%	10.25%	13%	5.63%	7.5%
"Jin"(dataset 4)	2%	4.7%	7.9%	9.5%	4.95%	7.1%
"박"(dataset 5)	0%	1%	0.5%	2%	0.25%	1.5%
Average	2%	3.34%	6.09%	7.9%	4.05%	5.62%

Table 2. Average verification results for freehand forgery test after five independent simulations

Result / dataset	$FRR = \frac{\text{\# of false rejected signatrue}}{20} \times 100$		$FRA = \frac{\text{\# of false accepted signatrue}}{80} \times 100$		$ERR = \frac{FRR + FRA}{2}$	
	proposed method	algorithm in [16]	proposed method	algorithm in [16]	proposed method	algorithm in [16]
"Han"(dataset 1)	2%	5.6%	0.75%	4%	1.38%	4.8%
"장"(dataset 2)	7%	10%	13.75%	19%	10.38%	14.5%
"Lee"(dataset 3)	5%	9.2%	7.5%	11.5%	6.25%	10.35%
"Jin"(dataset 4)	4%	10%	9%	17.6%	6.5%	13.8%
"박"(dataset 5)	3%	5%	1.25%	4%	2.13%	4.5%
Average	4.2%	7.96%	6.45%	11.22%	5.33%	9.59%

Table 3. Average number of errors in all of signature data sets under freehand forgery test

# of total false rejected signature		# of total genuine signature	# of total false accepted signature		# of total forgery
proposed method	algorithm in [16]		proposed method	algorithm in [16]	
4.27개	7.96개	100개	25.87개	44.88개	400개
FRR=4.2%	FRR=7.96%		FRA=6.45%	FRA=11.22%	

shapes of these two signature classes are more unique than others' as shown in Fig. 6.

The overall experimental results in this study show that the weighted fuzzy classifier with the feature vector extracted from FFT spectrum of directional gradient density function of signature outline is relatively effective in both of random and freehand forgery detection, even the signature image is written by Korean letters. This proposed method has rotation invariant characteristic and preserves more accurate shape information from the outline of signature images. Thus it can be possibly applied as a first stage verifier in off-line signature verification system.

5. CONCLUSIONS

An off-line signature verification method based on spectral feature extraction of signature outline and weighted fuzzy classifier is described and its effectiveness is evaluated with 500 signature samples. In our experiments, only the genuine signature samples are utilized for the construction of reference feature because a few forged signature samples are available under the real world environment, and the training period is not required in this type of classifier. And from the high performance results, it is known that the proposed system detects relatively well the random or freehand forgeries. Thus this kind of verifier utilized as a first stage verifier can help to improve both the speed and accuracy of the complete off-line signature verification system.

The further research should involve the evaluation with a larger data set written by more varied writers for the real world applications and the investigation of skilled forgeries detection system for the complete off-line signature verification system.

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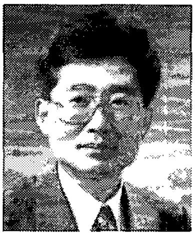

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