A New Approach For Off-Line Signature Verification Using Fuzzy ARTMAP

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ABSTRACT

This paper deals with the detection of freehand forgeries of signatures based on the averaged directional amplitudes of gradient vector which are related to the overall shape of the handwritten signature and fuzzy ARTMAP neural network classifier. In the first step, signature images are extracted from the background by a process involving noise reduction and automatic thresholding. Next, twelve directional amplitudes of gradient vector for each pixel on the signature line are measured and averaged through the entire signature image. With these twelve averaged directional gradient amplitudes, the fuzzy ARTMAP neural network is trained and tested for the detection of freehand forgeries of signatures. The experimental results show that the fuzzy ARTMAP neural network can classify a signature whether genuine or forged with greater than 95% overall accuracy.

Ⅰ. INTRODUCTION

Automatic handwritten signature verification would be of great interest in numerous application domains(e.g. for banks and crime investigations). There have been over a dozen prior research efforts involving the computer analysis of handwriting. The summaries of these efforts are shown in [1]. However, most of the prior works on handwriting have used real-time input. Only a few papers dealt with "off-line" signature verification i.e. when prewritten signatures on paper or bank checks are considered. The problem of off-line signature verification can be stated simply as the following: given a signature and knowing the identity of the person whose signature is presented(i.e., by credit card number), verify that the signature belongs to that person or declare it to be a forgery. This task is quite harder because the kinematic information of handwriting is lost. Nemcek and Lin proposed a method with the features extracted from an image after Hadamard transformation [2], and Nagel and Rosenfeld described a system for automatically detecting freehand forgeries based on characterizing handwriting strokes in terms of a set of kinematic parameters [3]. And, for the signature where the true and the forged samples are almost alike, Ammar *et* al. introduced an effective approach based on pressure features on the signature image [4]. In the recent year, a classical back-propagation neural network classifier with the directional probability of gradient on the signature image as a feature set was introduced for the detection of random forgeries [5].

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Handwritten signature are subject to several different types of forgeries: simple, random, freehand and traced [1][6]. Freehand forgeries are written in a forger's own handwriting without knowledge of the appearance of the genuine signature, where random forgeries uses his/her own signature instead of the genuine signature to be tested. In this paper, an artificial neural network(ANN) based classifier, so called fuzzy ARTMAP with the averaged directional gradient amplitudes as a feature set, has been investigated to detect freehand forgeries. The approach to be taken for the detection of freehand forgeries in this context contains the following steps. The first step involves scanning the actual signatures. Signatures that are written in a specified area of 0.5″ by 2″ are scanned and digitized with 256 dots per inch, and memorized in 128 by 512 pixel matrix, according to its grey level representation, quantified into 256 levels. The second step is to extract the signature image from the background after noise reduction. The third step involves to measure twelve directional amplitudes of gradient vector for each pixel on the signature line and average them through the entire signature image. Finally, those features after normalization are used as the input of fuzzy ARTMAP neural network classifier for the detection of freehand forgeries.

II. SIGNATURE EXTRACTION AND FEATURE MEASUREMENT

Signature Extraction: In this study, I used a four step preprocessing operation proposed by Ammar *et* al. to extract the signature image from the noisy background [4]. The first work in this method is to equalize and reduce the background by equation (1) and (2),

$$p'(i,j) = p(i,j) - \frac{1}{m}\sum_{l=1}^{m} p(l,j) \qquad (1 \le i \le m,\ 1 \le j \le n) \tag{1}$$

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

where p(i, j): the original image, p′(i, j): the equalized image, p″(i, j): the equalized image after clipping and m by n is size of the image(128 by 512). Then, the noise reduction is taken through the image by averaging shown in equation(3),

$$\bar{p}(i,j) = \frac{1}{9}\sum_{l=i-1}^{i+1}\sum_{k=j-1}^{j+1} p''(l,k) \tag{3}$$

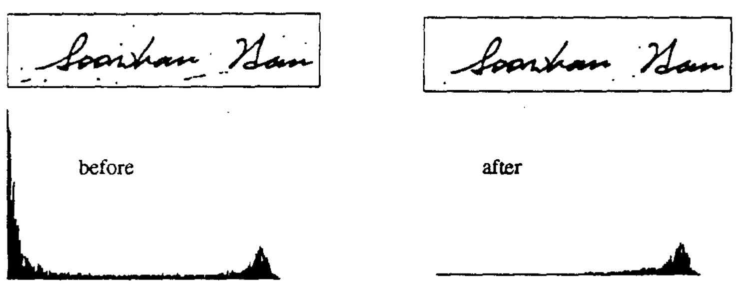

Figure 1. A sample signature image and it's histogram before and after the preprocessing stage.

where $\bar{p}(i, j)$ is the averaged image. After this phase, the signature becomes separable from background by thresholding. The threshold value, THD, is selected automatically based on entropy method proposed by Kapur *et al* [7]. Next, the orignal density information is restored in the image by using equation (4).

$$\hat{p}(i, j) = p(i, j) \ \text{ if } \ \bar{p}(i, j) > THD, \ \ otherwise \ \hat{p}(i, j) = 0 \tag{4}$$

where $\hat{p}(i, j)$ is the extracted image. A sample signature before and after preprocessing stage is shown in Fig. 1.

Feature Measurement: The one used as the input of fuzzy ARTMAP neural network classifier is the averaged directional amplitudes of gradient vector over the entire signature image. They depend on the overall shape of the signature image and so are assumed to have enough information for the detection of freehand forgeries in this study. Sobel 3 by 3 mask[8] shown in Fig. 2 is applied to each pixel on the signature image and the amplitude and orientation of gradient vector are computed by equation (5) and (6).

$$Row\ gradient\ Gr \Rightarrow \frac{1}{4}\begin{vmatrix} 1 & 0 & -1 \\ 2 & 0 & -2 \\ 1 & 0 & -1 \end{vmatrix} \qquad Column\ gradient\ Gc \Rightarrow \frac{1}{4}\begin{vmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{vmatrix}$$

Figure 2. Sobel 3 by 3 edge detector

$$G(i, j) = \{[Gr(i, j)]^2 + [Gc(i, j)]^2\}^{1/2} \tag{5}$$

$$\theta(i, j) = \tan^{-1}\left[\frac{Gc}{Gr}\right] + \frac{\pi}{2} \quad where \ \ 0 \le \theta(i, j) < \pi, \ \bmod \pi \tag{6}$$

For the reduction of dimensionality for the input of fuzzy ARTMAP, only twelve directional gradient amplitudes with 15 degree increment are utilized. Therefore, the directional gradient amplitudes for each pixel are derived by

$$Gd(i, j, \theta_k) = |\cos(\theta - \theta_k) \times G(i, j)| \tag{7}$$

where θ: angular orientation by Sobel operator, θ_k: $15 \times k$, (k = 0, 1, 2, 3, ..., 11). Finally, the twelve averaged directional amplitudes of gradient vector for each pixel on the signature image, $A(\theta_k)$, are found by equation (8),

$$A(\theta_k) = \sum_{i=1}^{128}\sum_{j=1}^{512} \frac{Gd(i, j, \theta_k)}{NP} \tag{8}$$

where NP is the total number of pixel on the signature line. The equation (7) and (8) show the feature vector, $A(\theta_k)$, is weighted more significantly for the pixels located on the well defined gray-level edge of signature image to preserve the overall shape information. It also has a property to be invariant in size and shift, but sensitive in rotation. These feature vectors are used to train and test for the evaluations of fuzzy ARTMAP neural network classifier after linearly scaling to lie between 0.0 and 1.0.

Ⅲ. FUZZY ARTMAP ARCHITECTURE

The fuzzy ARTMAP incorporates two fuzzy ART modules, ART_a and ART_b, that are linked together via an inter-ART module, F^{ab}, called a map field. The map field is used to form predictive associations between categories and to realize the match tracking rule, whereby the vigilance parameter of ART_a, ρ_a, increase in response to a predictive mismatch at ART_b. Match tracking reorganizes the category structure so that the predictive error is not repeated on subsequent presentations of the input. The basic architecture of fuzzy ARTMAP is shown in Fig. 3. During the training period, the ART_a module receives a data stream {a} of input patterns and ART_b receives a data stream {b} of target patterns, where b is a corresponding target to a. If a vector a is associated with a vector b, then any other input that activates the a's category node will predict the category of target pattern b. However, when a mismatch at the map field between the ART_a category activated by an input b and the ART_b category activated by the input b occurs, the net increases the ART_a vigilance parameter, ρ_a, by the minimum amount needed to search for and, if necessary, create a new cluster(category). The new cluster is created to learn a new ART_a category whose prediction matches the ART_b category. After the training is completed, which means the net predicts a correct corresponding target pattern for each of the training input patterns, the test input patterns are presented at ART_a without the use of ART_b. Because of the combinations of match tracking and fast learning, the fuzzy ARTMAP neural network can learn a different prediction for a rare event than for a cloud of similar frequent events in which it is embedded. In other words, the fuzzy ARTMAP establishes different categories for very similar ART_a inputs that make different prediction, while also

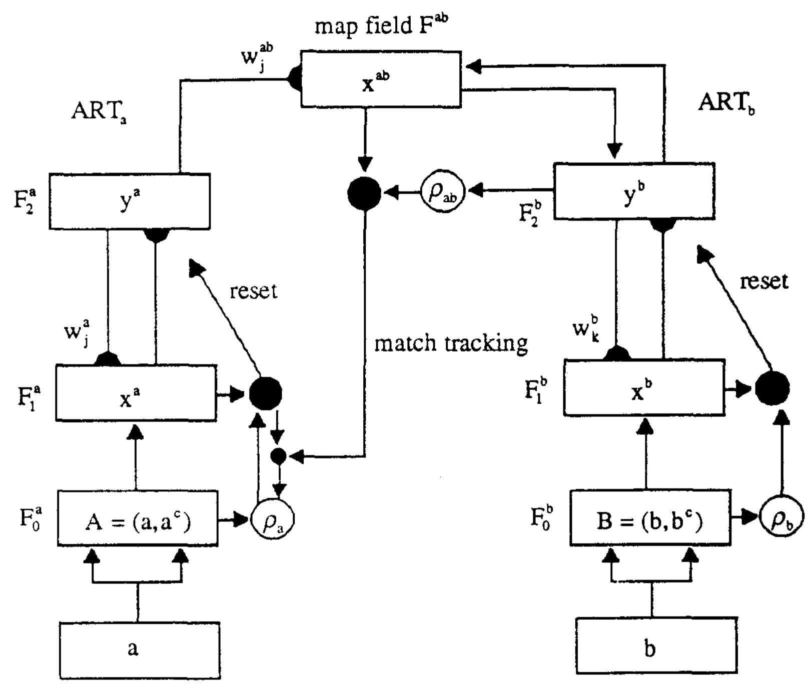

Figure 3. Fuzzy ARTMAP structure block diagram.

allowing very different ART_a inputs to form categories that make the same prediction. More details about the learning algorithms of fuzzy ART and fuzzy ARTMAP can be found in [9]-[11] and its applications on pattern recognition in [12]-[13]. For the experimental results shown in the next section, a fast learning algorithm with a *five*-voting strategy and the following parameters were utilized: learning rate = 1, choice parameter = 0.005, vigilance parameter for $ART_a = 0.95$, vigilance parameter for $ART_b = 0.5$, and the map field parameter = 0.5. And complement coding is applied to the inputs of the fuzzy ARTMAP for the normalization of the input vectors because proliferation of categories is avoided in the fuzzy ARTMAP by normalization of the input patterns [11]. Therefore, the dimensionality of inputs of the neural network classifier becomes twenty-four.

Ⅳ. PERFORMANCE ASSESSMENT AND EXPERIMENTAL RESULTS

The data used in the verification experiments consisted of two data set. Each of them contains 80 signatures taken from four different writers. One of four different writers was chosen as a target and asked to write his own name twenty times on the white sheet of paper using similar black ink ballpoint pens, with no constraint on the handwriting process, except for the 0.5″ by 2″ box where the signatures have to be written. Three of the remaining writers were assigned to be forgers. Each of the forgers was asked to write the targeted name twenty times in his/her own handwriting. The forgers were not allowed to study samples of the original signature. Thus 20 genuine signatures and 60 freehand forgeries were collected for each data set. The target for the data set 1 is "Soowhan Han", and the other is "Dohong Jeon". Some samples of genuine and forged signatures are shown Fig.4 and 5.

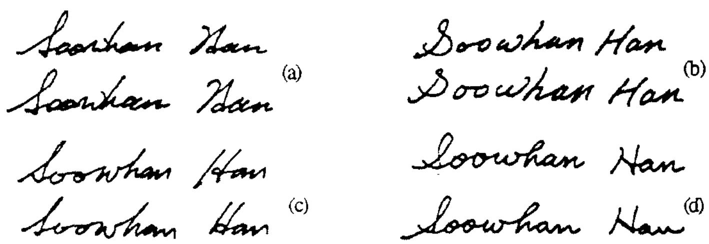

Figure 4. Samples of signature taken in data set 1.
((a):genuine, (b)-(d):freehand forgeries from three other writers.)

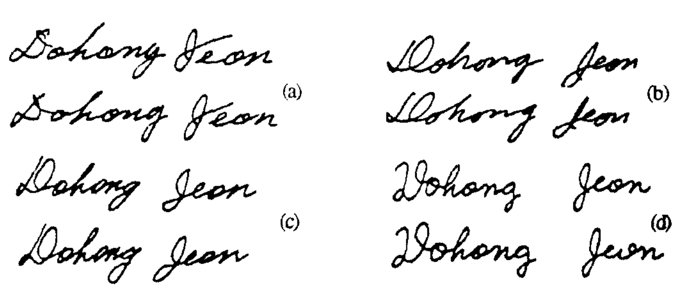

Figure 5. Samples of signatures taken in data set 2.
((a):genuine, (b)-(d):freehand forgeries from three other writers.)

In this study, three different scenarios of classification experiments were performed. The first one treated the four groups of signatures from four writers as four classes and the fuzzy ARTMAP, when presented with an unknown signature, assigned it to one of the classes. This is called writer indentification. For this scenario, the fuzzy ARTMAP was trained with 40 signatures(10 signatures taken randomly for each writer) and the remaining 40 signatures(10 signatures for each writer) were tested. A *five*-voting strategy in fuzzy ARTMAP [11] was used to improve the performance of the network, thus the fuzzy ARTMAP was trained five times on a given training set with five different orderings, the prediction of test patterns for each ordering was recorded. The final prediction for a given test set was the one made by the largest number of simulations. Twenty independent simulations were performed with different choice of training signatures, and the averaged correct classification ratio of fuzzy ARTMAP neural network classifier was 89.4% for data set 1 and 91.1% for data set 2. In these results, no response of the fuzzy ARTMAP was also counted as an error. The correct classification ratio shows that fuzzy ARTMAP trained with the twelve averaged directional gradient amplitudes performs relatively well to identify the writers even though the only small size of letters is available as signatures on the credit card.

The second scenario was the signature verification test. In this test, a labeled signature was presented to the fuzzy ARTMAP which decided whether the signature was that of the person indicated by the label or was forgery. Each of data set was subdivided into two groups: one contained twenty genuine signatures and the other did sixty freehand forgeries. 10 genuine signatures and 30 forgeries were randomly taken from each of two groups in a data set to train the fuzzy ARTMAP. Thus the choice of forgeries did not have the equal probability for each of three different forgers in this experiments. It was considered that, in practical situations involving forgery detection, the number of available sample for each forger is not the same. A *five*-voting strategy was also applied to increase the correct classification ratios and twenty independent simulations were performed with different choice of training signatures. Performance results were calculated by using the expressions shown in Eqs. (9)-(11) and averaged. They are summarized in Table 1. In this scenario, no response of the fuzzy ARTMAP which means the network cannot make sure whether a test input is a genuine or a forgery was counted as a forgery because there might exist an unknown forger whose samples were chosen a very little or never chosen for training the fuzzy ARTMAP.

$$\text{Correctly Classified Genuine (C.C.G.)} = \frac{\text{no. of correctly classified genuines}}{\text{total no. of tested genuines}} \times 100 \tag{9}$$

$$\text{Correctly Classified Forgery (C.C.F.)} = \frac{\text{no. of correctly classified forgeries}}{\text{total no. of tested forgeries}} \times 100 \tag{10}$$

Total Correct Classification Ratio by fuzzy ARTMAP (T.C.C) =

$$\frac{\text{no. of correctly classified genuines} + \text{no. of correctly classified forgeries}}{\text{total no. of tested signatures}} \times 100 \tag{11}$$

Table 1. Averaged verification results(%)for data set 1 and 2 under the scenario 2.

	Data Set 1(Soowhan Han)	Data Set 2(Dohong Jeon)
C.C.G.	96	98.5
C.C.F.	93.33	97.17
T.C.C.	94	97.5

In the first and second scenarios, it took the only one or two epochs to learn completely all of the training input patterns because of the fast learning algorithm and a small choice parameter in the fuzzy ARTMAP. Thus in the third scenario, the classification performance was evaluated during the only one presentation of all 80 signatures to the fuzzy ARTMAP for each data set. Under this simulation environment, the fuzzy ARTMAP verified a presented signature at first whether it was genuine or forgery based on the information about past inputs, then it learned a presented signature pattern only once with the correct answer. Thus the verification system, so called fuzz ARTMAP neural network classifier, was updated continuously with all of the tested signatures. Simulations of this on-line process by the fuzzy ARTMAP used each incomming data as both a test item and a training item. It imitates the conditions of a human operating in a natural environment, and could be an advantage for practical use over the conventional neural network classifier off-line trained with a fixed size of signature patterns. All of the 80 signatures were randomly presented to the fuzzy ARTMAP at once and the classification results were checked during this on-line process. The verification results were accumulated after the first two signatures were presented, and they are shown in Table 2. The results in Table 2 were also obtained by averaging the classification ratios of twenty independent simulations. In this testing mode, the performance of the fuzzy ARTMAP improved gradually with increments of presented signature patterns because the learning occured once with every incoming signature patterns after each verification. This is shown in Table 3.

Table 2. Averaged verification results(%)for data set 1 and 2 under the scenario 3.

		Data Set 1(Soowhan Han)	Data Set 2(Dohong Jeon)
C.C.G.		97.37	99.74
C.C.F.		94.83	97.03
T.C.C.		95.45	97.69

Table 3. Averaged total correct classification ratios with increments of input patterns for the data set 1 and 2 under the scenario 3.(Results in section 1 were obtained from the 3^{rd} presented input to the 10^{th}. By the same way, results in section 2 were obtained from the 11^{th} to the 25^{th}, results in section 3 from the 26^{th} to the 40^{th}, results in section 4 from the 41^{st} to the 60^{th}, and results in section 5 from the 61^{st} to the 80^{tt}.)

		section 1	section 2	section 3	section 4	section 5
Data Set1		81.25	94.67	97.00	97.75	98.25
Data Set2		89.38	97.00	99.33	98.25	99.75

V. CONCLUSIONS

The results from this study show that fuzzy ARTMAP neural network classifier, trained with the twelve averaged directional amplitudes of gradient vector on the signature image, performs well to detect the freehand forgeries and even for writer identification problems with small size of letters available. In the simulation procedure, the fuzzy ARTMAP was easy to train; only one to two training epochs were needed in the off-line process for the network to predict the correct target patterns by using the fast-learning algorithm and a small choice parameter. Moreover, conventional problems in other neural network classifiers such as learning rate limitation for maintaining the stability of the network, difficulty in selection the optimal number of hidden units for the specified tasks, and limitation of memory capacity were mitigated by using this network. And, we can increase the classification rates with the voting strategy when the availability of training input patterns is not plentiful like the data set in this study. Possible interesting areas for further research could be to investigate feature extractions on the signature image which is insensitive in rotation and contains more detail shape information to characterize each writer while keeping the small dimensionality for the input of the fuzzy ARTMAP. And also, a large data set with more variety of the writers should be evaluated for the real world environment.

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