Off-Line Signature Verification Using Fuzzy ARTMAP Neural Network

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Abstract

This work presents a Fuzzy ARTMAP Based Off-line Signature Verification System. Compared to the conventional systems proposed thus far, the presented system is trained with genuine signatures only. Six experiments have been performed on a data base of 200 signatures taken from five writers (40 signatures/writer). Evaluation of the system was measured using different numbers of training signatures (3, 6, 9, 12, 15 and 18).

1. Introduction

In the field of signature verification, be it on-line or off-line, the objective is to decide upon the authenticity of an unknown signature S_j^i, with respect to a set of genuine signatures R_i of some writer i, by making a one-to-one comparison between the features in this signature and those in the reference set. In on-line signature verification, a set of dynamic features (velocity, relative pressure, etc.) are used for the comparison process. Whereas in off-line signature verification, a set of spatial and geometrical features are used. This paper is related to **off-line Signature Verification Systems (OHSV)** in the context of random forgeries. In the last two decades several systems have been proposed for off-line verification. The comparison stage in those systems is either based on classical pattern recognition classifiers (Sabourin et al [7]) or on neural networks (Mighell et al [4], Cardot et al [1], McCormack et al [3] and others)[2]. A common feature among those systems is that the comparison stage is trained with genuine signatures as well as with forgeries, with respect to every writer i. In practice it is not always possible to obtain signature forgeries, and if it is it becomes impractical when dealing with real system for banking applications. To cope with the difficulty of obtaining signature forgeries, researchers have used the signatures of other writers in the system as being the signature forgeries. By definition, this type forgeries is called random forgeries. Another common feature is that system performance with respect to the **False Acceptance Rate**[3] **(FAR)** is artificially reduced, in the context of random forgeries. For example, if an OHSV is trained with genuine signatures of writer 'a' and with random forgeries taken from writers 'b', 'c' and 'd', then the system will acquire a knowledge of the features contained in the signatures of those writers. During the evaluation phase when the system is presented with signatures from writers 'b', 'c' and 'd', as being random forgeries, it will use its knowledge, acquired during the training, and will most probably classify those signatures as random forgeries. The actual performance may not be the same if the system is presented with signatures of other writers that it did not learn about during the training phase.

In this work, we propose to use Fuzzy ARTMAP neural network, at the comparison stage, for off-line signature verification and to train the system with genuine signatures only. The use of the Fuzzy ARTMAP is motivated by its abilities to form categorical classes in response to binary and analog input patterns and to perform a comparison process between an input paterrn and the category exemplar before learning takes place. These two features make it possible to train the OHSV with genuine signatures only. During the training stage, the system would learn the features constituting the genuine signatures of some writer i by forming as much categorical classes as there are distinct features. When training have been completed, the system would have had a knowledge of the genuine signatures of this writer only. With this approach to system training, the above two mentioned problems are eliminated.

In section 2.0, a complete description of the Fuzzy ARTMAP based OHSV system is introduced. Section 3.0 presents the numerical experiments and the obtained results. Description of the Fuzzy ARTMAP neural networks can be found in Carpenter et al [2].

2. System Description

The overall task of signature verification is divided into four stages: pre-processing, feature extraction and

[1] Author to whom corresponcence should be sent.
[2] A complete bibliography can be found in [6].

[3] The percentage of false signatures accepted as being genuine.

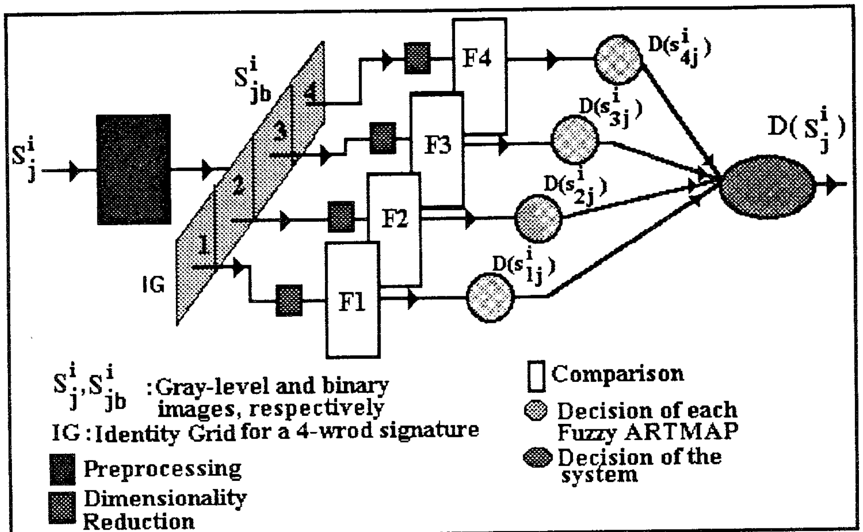

Figure 1.0 Block diagram of the Fuzzy ARTMAP Based OHSV system. An unknown signature is thresholded and then centralized on the image area which becomes also centralized on the identity grid. Thereafter, from each region in the signature, graphical segments are extracted and applied to the BKP network for dimensionality reduc-tion. The reduced segments are then applied to the respective Fuzzy ARTMAP for comparison. The whole process is repeated for all the regions in the signature. The final decision of the system, with respect to the authenticity of the unknown signature, is given according to equations 1 and 2.

dimensionality reduction, comparison, and decision. A block diagram illustrating these stages is shown in figure1. All stages are used during learning and evaluation, except the decision stage which is used during evaluation only.

At the first stage, the signature is segmented from the background, using Ostu's algorithm [5], and then centralized onto the image area (512x128) such that it becomes **divided into *m*** regions, through the use of an **identity grid**. The centralization is performed by translating the center of gravity of the binary image to the center of the image area. Thereafter, graphical segments of size 16x16 pixels with 50% overlapping in the x and y directions are extracted from each region in the binary signature and applied to a Back-propagation network (BKP) which reduces the size of these segments by 1/3. The reduced graphical segments are then applied to the comparison stage for learning/verification. This stage is composed of *m* Fuzzy ARTMAP networks, each of which is responsible for one region in the signature. This structure can be viewed as having **different experts examining different regions of the signature**. Finally, the decision stage analyzes the results produced by each Fuzzy ARTMAP and gives the decision of the system with respect to authenticity of the unknown signature.

2.1 Database Description [7]

The database is composed of 200 genuine signatures taken from 5 writers (40 signatures/writer). The signatures are digitized with vidicon camera and a standard frame grabber. Each signature is written on a white paper (3x12 cm), with a Pilot Fineliner pen with flexible felt tip and black ink. The output of the frame grabber is a 256 gray level image of size 512x128 pixels.

2.2 Definition of The Identity Grid

In order to divide the input signature (during training/evaluation) into regions, an identity grid was design-ed for each writer such that its shape reflects the average overall shape of the reference signatures of this writer, and its surface was divided into *m* regions, where *m* equals twice the number of words composing the reference signature. Furthermore, each region was divided into 16-pixel squares. The geometrical structure of the identity grid was defined with respect to the center of the image area such that, when a given signature is centralized on the image area, it becomes also centralized on the identity grid and, consequently, becomes divided into *m* regions. An example of an identity grid for a writer whose signature is composed of two words is shown in figure 2a.

2.3 Signature Representation

Each input signature is divided into a set of graphical segments of size 16x16 pixels with 50% overlapping in the x and y directions. An example a graphical segments extracted from one region of a signature is shown in figure 2.

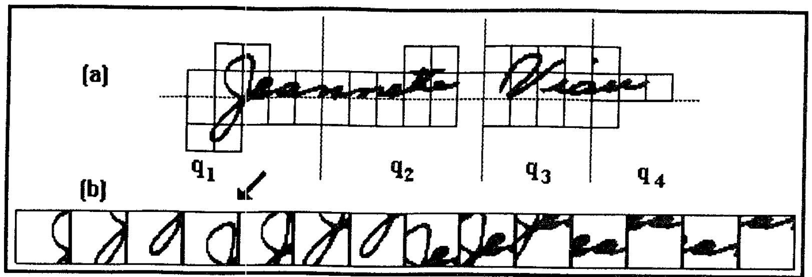

Figure 2. Signature Representation. a) entity grid of writer b. b) Graphical segments extracted from the first region of the identity grid.

2.4 Dimensionality Reduction

A Backpropagation network of size 4_3_4 was used for the purpose of dimensionality reduction. The network was trained in its autoassociative mode to reconstruct the same input pattern at the output layer. To obtain good generalization for all signatures in the database, i.e., good image reconstruction quality for all signatures, the training patterns consisted of all the possible binary patterns, namely the binary equivalence of the decimal numbers (0, 1, 2, ..., 15). The network was trained using the Quickpro learning rule. Training was terminated when the network error reached 0.01. After training, the network was then tested to reconstruct each one of the 200 binary signatures in the database. The results of the reconstruction are shown in figure 3. During system training/evaluation, each extract-ed graphical segment is scanned by a 2x2 window and then applied to the BKP network. The output of the middle layer is then formed into a vector of size 768. This vector forms the input to the Fuzzy ARTMAP network.

2.5 The Decision Stage

Based on the definition of the identity grid and on the structure of the comparison stage given above, the decision of the system with respect to the authenticity of an unknown signature is made according to the following two ***majority decision rules***:

1. Consider one of the m regions of the signature, situated in one of the m regions in the identity grid of writer i as genuine, if the number of graphical segments l extracted form this region, is within the expected range $[min_i^p, max_i^p]$, that may exist in that region and, if **half or more than half** of these segments are classified correctly by the respective Fuzzy ART-MAP, or as false otherwise. In mathematical form, this decision rule is written as follow:

$$D(s_{pj}^i) = \begin{cases} 1, & min_i^p \le l \le max_i^p \text{ and } \left(\sum_{q=1}^{n} dfa_{ip}(seg_{qj}) \right) \ge \frac{l}{2} \\ 0, & \text{otherwise} \end{cases} \qquad (1.0)$$

where $p = 1, 2, ..., m$.

2. Consider the signature S_j as genuine with respect to the writer i reference signatures, if **half or more than half** of the m regions of this signatures are considered genuine by the first rule, or as false otherwise. In mathematical form, the second rule is represented as follow:

$$D(S_j^i) = \begin{cases} 1, & \text{if } \left(\sum_{p=1}^{m} D(s_{pj}^i) \right) \ge \frac{m}{2} \\ 0, & \text{otherwise} \end{cases} \qquad (2.0)$$

where '1' and '0' indicate, respectively, genuine and forgery and $dfa_{ip}(seg_{oj}^p)$ is the decision of one of the m Fuzzy ARTMAPs. $D(s_{pj}^i)$ and $D(S_j^i)$ represent, respectively, the decision of the system with respect to the authenticity of one of the m regions and the decision of the system with respect to the authenticity of test signature S_j^i. For later discussion, the decision criteria **half or more than half** will be symbolized by the letter **d**.

3. Simulation and Results

The verification capability of the proposed OHSV system, was evaluated in the context of random forgeries. Six experiments were performed using different numbers of training signatures. All the experiments were performed with the Neural Works simulator and an IBM Compatible PC DX2/66MHZ.

3.1 Definition of the Experimental Data

The total genuine signatures $|R_i^T| = 40$, for each writer i, was divided into two sets: a reference set

R_i^{ref} and a test set R_i^{tes}. Both sets are defined as follow:

$$\left|R_i^{ref}\right| = 18 \qquad (3.0)$$

and,

$$\left|R_i^{tes}\right| = 22 \qquad (4.0)$$

the reference set was further divided into six different subsets as follow:

$$R_i^{ref} = \{r_{i1}^{ref}, r_{i2}^{ref}, r_{i3}^{ref}, r_{i4}^{ref}, r_{i5}^{ref}, r_{i6}^{ref}\} \qquad (5.0)$$

where each Jth reference subset $\{J = 1,2, ..., 6\}$consisted of a number of signatures equal to $3J$. These reference subsets were used for training. The reasons for such division is that banks uses a set of three signatures as the reference set for each writer. The test set T_i, for each writer, is given by:

$$\left|T_i\right| = \left|R\right| - \left|R_i^{ref}\right| \qquad (6.0)$$

where R is the total number of signatures in the database.

For a writer i, the training set consisted of genuine signatures of this writer ***only*** and the test set consisted of a set of genuine signatures ω_1^i and a set of random forgeries ω_2^i as defined bellow:

$$\left|\omega_1^i\right| = \left|R_i^T\right| - \left|R_i^{ref}\right| \qquad (7.0)$$

$$\left|\omega_2^i\right| = \left|R\right| - \left|R_i^T\right| \qquad (8.0)$$

3.2 Training and

The training and evaluation procedures are summarized in the following experimental protocol. The constants l and n indicate, respectively, the number of graphical segments extracted from each region in the test signature and the number of the 16-pixel squares composing each region of the identity grid of writer i. The parameters of each Fuzzy ARTMAP network were:

$$\rho = 0.75,\ \alpha = 0.001,\ \beta = 1.0$$

1. **start**;
2. **for** i = 1 **to** 5; **(For each writer)**
3. design the identity grid;
4. save the number n and the xy coordinates of the 16-pixel squares and the numbers min_i^p, max_i^p;
5. **end for**;
6. **for** J = 1 **to** 6; **(For each training set)**
7. select a training set r_{iJ}^{ref};
8. **for** i = 1 **to** 5; **(For each writer)**
9. **for** K = 1 **to** $\left|r_{iJ}^{ref}\right|$;
10. **for** p = 1 **to** m;
11. **for** M = 1 **to** n;
12. train the Fuzzy ARTMAP fa_{Jip};
13. **end for**;
14. **end for**;
15. **end for**;
16. **for** N = 1 **to** $\left|T_i\right|$;
17. **for** p = 1 **to** m;
18. **for** M = 1 **to** n;
    test the Fuzzy ARTMAP fa_{Jip};
19. record the number l;
20. **end for**;
21. calculate $D(s_{pj}^i)$;**(according to eq. 1)**
22. **end for**;
23. **end for**;
24. calculate $D(S_j^i)$; **(according to eq.2)**
25. **if** $S_j \in \omega_1^i$ **, AND** $D(S_j^i) = 1$;
    then Good Classification;
26. **else** Type I error;
27. **if** $S_j \in \omega_2^i$ **, AND** $D(S_j^i) = 0$;
    then Good Classification;
28. **else** Type II error;
29. **end for**;
30. compute FRR, FAR, and E_t;
31. **end for**;
32. **end**.

he results of the experiments with respect to the **False Rejection Rate**[4] **(FRR)**, **FAR** errors, and total error E_t, are shown in tables 1 and 2, respectively, for various combinations of the decision pairs. Each combination of a decision criteria is denoted in the table by the decision pair (dn, dn) where n = 1 or 2. The first decision applies to equation 1, whereas the second decision applies to equation 2. The digits 1 and 2 indicates, respectively, **half or more than half** and **more than half**. For example, the decision pair (d2,d1) indicates a decision criteria of more than half in equation 1 and a decision criteria of half or more than half in equation 2. The total error E_t is calculated according to the following formula:

$$E_t = (FRR + FAR) / 2 \qquad (9.0)$$

3.3 Comments on the results

As it can be observed from the table 1, the error rates are acceptably good, though are not as good as it should be. It can also be observed from table 2 that, the best performance is obtained with the training set of 18

[4] The percentage of genuine signatures rejected as being foregeries

signatures. The rather high rate of false rejection FRR , was mainly due to the natural local and global variations characterizing the handwritten signature images of an individual writer, and to the sensitivity of neural networks to these variations. The cause of the FAR error rates could be related to the recoding characteristic and to the matching criteria of the Fuzzy ARTMAP. It was not possible to verify this hypotheses, since the simulator is not provided with a visualizing module that would allow the user to study the internal representation of the network.

The FRR and FAR errors can be reduced, respectively, by rendering the Fuzzy ARTMAP insensitive to variations in scale, rotation and translation and by increasing the decision criteria, as demonstrated in table 1.

As it can be seen from the table 4, our results compare favorably to those of the other authors based on the two-class problem. A major difference, however, is that the FAR errors based on the one-class problem reflect the real performance of the system. Whereas those obtained based on the two-class problem do not, for the reasons mentioned previously. In general, it is difficult to judge which system performs best. This is due to the fact that the experimental database, the division criteria and the experimental protocol are different from one system to another .

4. Conclusions

In this paper we have proposed the use of Fuzzy ARTMAP neural network for off-line signature verification and train the system with genuine signatures only. It was demonstrated that system training could be performed using genuine signatures only. We believe that this approach may provide an efficient solution to unresolved and very difficult problem in the field of signature verification Our initial results are very promising. However, we are very well aware that we have evaluated the efficiency of this approach with a small database. Our next step is to evaluate the robustness of the system using a large database and to overcome the problem of signature variations.

5. References

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	Decision Pares							
	(d1,d1)		(d2,d1)		(d1,d2)		(d2,d2)	
# Sig.	FRR	FAR	FRR	FAR	FRR	FAR	FRR	FAR
3	17.27	6.25	23.64	4.63	54.55	0.125	62.73	0.13
6	7.27	22.63	8.18	16.38	30.91	3.75	38.18	2.13
9	11.82	6.13	16.36	4.0	38.18	0.5	45.45	0.13
12	4.54	14.5	6.36	12.13	21.82	3.25	28.18	2.13
15	9.09	11.38	11.82	8.3	31.82	1.75	40.91	1.13
18	7.27	11.00	9.09	7.63	23.64	0.38	28.18	0.25

Table 1. Performance of the system in terms of FRR and FAR errors. All values are in percentage.

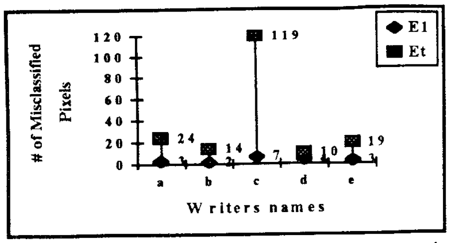

Figure 3. Test results of the BKP network. E1 indicates the highest number of misclassified pixels occurred in reconstructing the signature of an individual writer. Et indicates the total number of misclassified pixels occurred in reconstructing all the signatures of an individual writer.

	Decision Pairs			
	(d1,d1)	(d2,d1)	(d1,d2)	(d2,d2)
# Sig.	Et	Et	Et	Et
3	11.23	14.13	25.46	30.06
6	14.55	12.89	17.17	18.72
9	9.19	10.06	18.64	24.56
12	9.09	9.63	14.13	16.77
15	10.09	9.25	16.48	19.36
18	9.14	8.36	12.0	14.22

Table 2. Performance of the system in terms of the total error. All values are in percentage

Authors	FRR	FAR	Et
Mighell et al [4]	1	4	2.5
Cardot et al [1]	5	2	3.5
McCormack et al [3]	13.8	10.6	12.2
Sabourin et al [7]	0.2	(mean)	0.2
Fuzzy ARTMAP OHSV	7.27	11.00	9.14

Table 3. Comparison of the results obtained in this work to those obtained by other authors using genuine signatures for training as well as forgeries.