Off-Line Signature Verification, Without a Priori Knowledge of Class ω_2. A New Approach

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Abstract

This work proposes a ***new approach*** *to signature verification. It is inspired by the* ***human learning*** *and the approach adopted by the* ***expert examiner*** *of signatures, in which an a priori knowledge of the class of forgeries is not required in order to perform the verification task. Based on this approach, we present a Fuzzy ARTMAP based system for the elimination of random forgeries. 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 claimed identity of some writer i by making a one-to-one comparison between the unknown signature S_j^i and a reference set of this writer [6]. This paper is related to **Off-line Handwritten Signature Verification (OHSV)** system in the context of random forgeries. Sabourin et al [7], Mighell et al [4], Cardot et al [1], McCormack et al [3] and others [2], have approached signature verification from pattern recognition perspectives and considered it as being a ***two-class problem***: the class of genuine signatures, ω_1, and the class of forgeries, ω_2, for some writer i. Based on this approach, the OHSV system is trained, for each writer i, with ***genuine signatures of this writer as well as with forgeries***. As a result, the OHSV system acquires a knowledge of the genuine signatures as well as of the forgeries. Acquiring a knowledge of signature forgeries is irrelevant to the objective of the OHSVsystem. We argue that if the verification process is performed by comparing the unknown signature to the reference ones, then the OHSV system should be trained only with genuine signatures, for every writer i.

Plamondon and Lorette [6] have pointed out some of the problems that must be solved before any OHSV system can be put into practice; and have suggested that these problems can be solved by increasing our knowledge of the writing process itself and of the forgery process [6]. These problems are: How to cope with the difficulty of obtaining signature forgeries? What is the best classification protocol for a two-class problem with one class unknown? How to choose the optimum decision threshold to perform the training process? In our opinion, the cause of these problems lies in the approach itself.

A fourth problem intrinsic to this approach, is that system performance with respect to the **False Acceptance Rate (FAR)** error is dependent on the type of forgeries used for training. This is demonstrated by the work of Cardot et al [1]. According to the authors, different types of random forgeries (signatures of other writers in the system)[3] have produced different error rates. One, therefore, is faced with the following question: Which forgeries should be used for training? A fifth problem is that, the FAR error rates are artificially reduced when evaluating the system in the context of random forgeries. As adopted by Sabourin et al [7] and by Mighell et al [4], the experimental data base is divided into two sets: one set for training and another set for evaluation (test)[4]. For each writer i, each set contains genuine signatures of this writer (ω_1) and random forgeries (ω_2) ***taken from all other writers in the system***. With this division criteria, the OHSV system is ***trained and tested with random forgeries that belong to the same writers***. In another words, the random forgeries presented during training are different, but similar, to the corresponding ones presented during test. As a consequence of this division criteria, sys-

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

[3] To cope with the difficulty of obtaining true forgeries, authors have used random forgeries instead.
[4] The data definition criteria, adopted by Cardot et al [1] and by McCormack et [3], is not clearly stated in their papers.

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tem performance, with respect to the FAR errors, is evaluated with respect to the writers enrolled in the system whose signatures the system has a priori knowledge of their characteristics. In our opinion, this is a mistake. In real situations, an unknown signature, if it is a random forgery, it will most probably be produced by a writer that is not enrolled in the system. Therefore, the FAR errors based on the division criteria mentioned above do not reflect the actual performance of the OHSV system. We would like to suggest, in this regard, that a separate set of random forgeries, belonging to writers whose signatures are not learned during training, should be used for evaluation.

1.1 A New Approach To Signature Verification

To eliminate the above mentioned problems, we propose to consider signature verification as a ***one-class problem***: the class of genuine signatures, for some writer *i*, and ***train the OHSV system only with the genuine signatures of this writer***. This is the process adopted by the expert examiner of signatures. According to Mr. Hélio Franco, the chief of the Department of Forensic Sciences in the State of Paraná, the expert examiner performs the verification process by ***comparing*** the questioned signature to the reference ones and then gives his/her decision according to the comparison results. Another motivation for the one-class problem approach, is our ability to recognize the shape of certain class of objects (e.g. apples) without the necessity of learning to recognize the shapes of other objects (e.g. grapes or plums).

Based on the one-class problem approach, we present an OHSV system, based on the Fuzzy ARTMAP neural network, capable of performing the verification task without a priori knowledge of the class of forgeries. The cognitive information learning processing of the Fuzzy ARTMAP makes it ideal for implementing the proposed approach. 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].

2.0 System Description

The overall task of signature verification is divided into four stages: pre-processing, feature extraction and dimensionality reduction, comparison, and decision. A block diagram illustrating these stages is shown in figure 1. 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]

All the signatures in the database 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 designed 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.

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 extracted 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 ARTMAP, or as false otherwise. In mathematical form, this decision rule is written as follow:

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

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 genuines 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**.

3.0 Simulation and Results

The verification capability of the proposed OHSV system, in the context of random forgeries, was evaluated using a data base of 200 signatures taken from 4 writers (40 signatures/writer). 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:

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

and,

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

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 test set T_i, for each writer, is given by:

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

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:

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

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

3.2 Training and Evaluation

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:

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

start;
for $i = 1$ **to** 5; **(For each writer)**
 design the identity grid;
 save the number n and the xy coordinates of the 16-pixel squares and the numbers min_i^p, max_i^p;
end for;
for $J = 1$ **to** 6; **(For each training set)**
  select a training set r_{iJ}^{ref};
  for $i = 1$ **to** 5; **(For each writer)**
   for $K = 1$ **to** $\left|r_{iJ}^{ref}\right|$;
    for $p = 1$ **to** m;
     for M = 1 **to** n;
      train the Fuzzy ARTMAP fa_{Jip};
     end for;
    end for;
   end for;
   for $N = 1$ **to** $\left|T_i\right|$;
    for $p = 1$ **to** m;
     for M = 1 **to** n;
      test the Fuzzy ARTMAP fa_{Jip};
      record the number l;
     end for;
     calculate $D(s_{pj}^i)$;**(according to eq. 1)**
    end for;
   end for;
   calculate $D(S_j^i)$; **(according to eq. 2)**
   if $S_j \in \omega_1^i$ **, AND** $D(S_j^i) = 1$;
    then Good Classification;
   else Type I error;
   if $S_j \in \omega_2^i$ **, AND** $D(S_j^i) = 0$;
    then Good Classification;
   else Type II error;
  end for;
 compute FRR, FAR, and E_t;
end for;
end.

The results of the experiments with respect to 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 (**d**n, **d**n) 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 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 a writer i, and to the sensitivity of neural networks to this 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. The effect of increasing the decision criteria will not have a great effect on increasing the FRR errors as it will have on decreasing the FAR errors. This can be observed from table 3. Another possible way of reducing the FAR error is by evaluating the system performance using an optimum decision pair that will minimize the FAR errors for each writer. Such performance is demonstrated in figure 4. This optimum decision pair was selected directly from the simulations results, with respect to the training set of 3 signatures, as being the decision pair that produced the first lowest FAR value for an individual writer. The performance of the system was then measured for all the other training sets, based on this optimum decision pair. This is one method of selecting an optimum decision pair for each individual writer. Other methods could be investigated.

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 .

4.0 Conclusions

In this paper we have introduce a new approach to signature verification which is based on human learning and on the approach adopted by the expert examiner of signatures. We believe that this approach may provide an efficient solution to unresolved and very difficult problem in the field of signature verification in particular, and in pattern recognition in general. 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 efficiency of the proposed approach on a large database and to overcome the problem of signature variations.

We are also investigating the application of this approach to other similar areas of pattern recognition. One such area currently under investigation in our laboratory, is the classification of cancerous cells.

5.0 References

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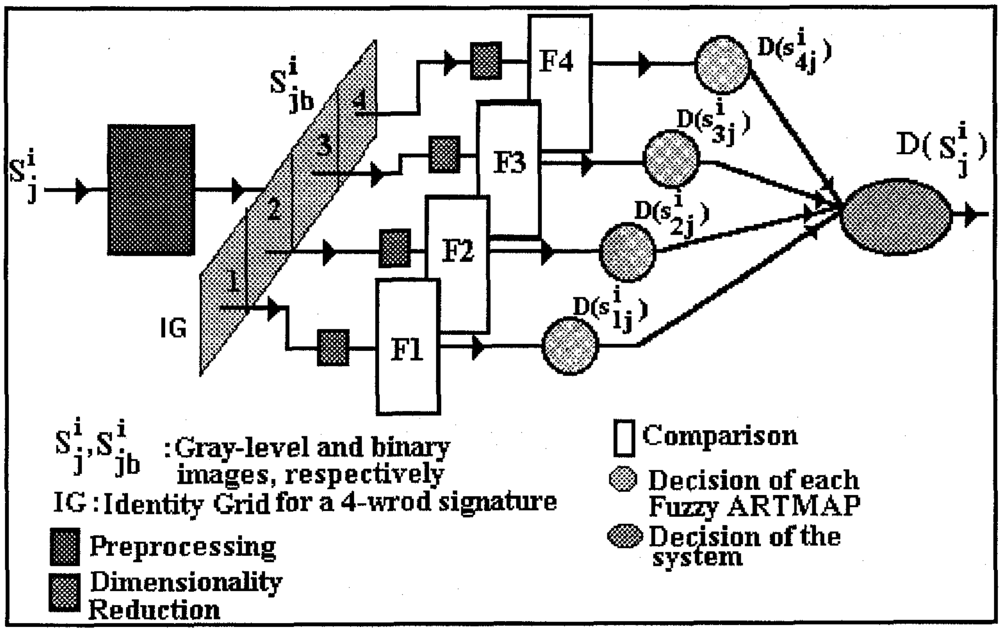

Figure 1.0 Block diagram of the Fuzzy ARTMAP Based OHSV system. An unknown signature is thresholded and then centralized on the image area which becomes also centralized on the identity grid. Thereafter, from each region in the signature, graphical segments are extracted and applied to the BKP network for dimensionality reduction. 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.

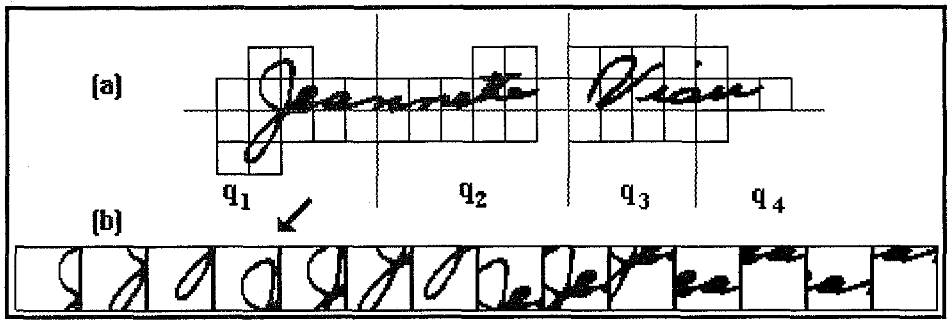

Figure 2. Signature Representation. a) Identity grid of writer b. b) Graphical segments extracted from the first region of the identity grid.

	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.

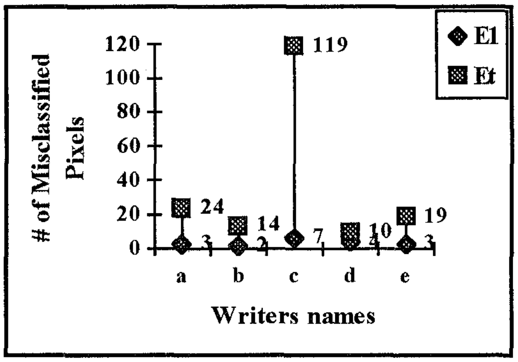

Figure 3. Test results of the BKP network. E1 indicates the highest number of misclassified pixels occurred in reconstructing the signature of an individual writer. Et indicates the total number of misclassified pixels occurred in reconstructing all the signatures of an individual writer.

	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.

Training Set.	% Increase in FRR	% Decrease in FAR
3	4.4	50
6	5.25	10.6
9	3.84	49
12	6.2	6.82
15	4.5	10.12
18	3.88	44

Table 3. Effect of increasing the decision criteria on the FRR and FAR errors.

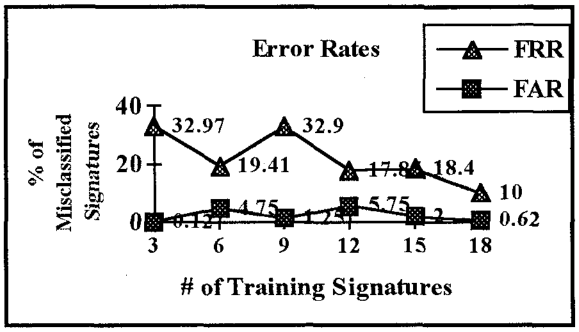

Figure 4. Performance of the system based on the optimum decision criteria.

Authors	FRR	FAR	Et
Mighell et al [4]	1 3	4 14	2.5 8.5
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
The Fuzzy ARTMAP OHSV	7.27	11.00	9.14

Table 4. Comparison between the results obtained with one-class problem approach and those obtained with the two-class problem approach.