The Interpersonal and Intrapersonal Variability Influences on Off-Line Signature Verification Using HMM

EDSON J. R. JUSTINO[1] FLÁVIO BORTOLOZZI[1] ROBERT SABOURIN[2]

[1] PUCPR - Pontifícia Universidade Católica do Paraná ,R. Imaculada Conceição, 1155, Curitiba, PR, Brazil - {justino, fborto}@ppgia.pucpr.br
[2] ÉTS - École de Technologie Supérieure, 1100, rue Notre-Dame Ouest, Montréal, Québec, Canada - sabourin@gpa.etsmtl.ca

Abstract

The off-line signature verification rests on the hypothesis that each writer has similarity among signature samples, with small distortion and scale variability. This kind of distortion represents the intrapersonal variability [3]. This paper reports the interpersonal and intrapersonal variability influences in a software approach based on Hidden Markov Model (HMM) classifier [1,5,7]. The experiments have shown the error rates variability considering different forgery types, random, simples and skilled forgeries. The mathematical approach and the resulting software also report considerations in a real application problem.

1. Introduction

The signature verification problem is in theory a pattern recognition task used to discriminate two classes, the original and forgery signatures. Each signature class has a minimization and maximization hypothesis, respectively. The first one is based on the similarity among different signature samples of the same writer, called intarpersonal variability. The second one is based on discordance among different signature samples introduced by other writer, called interpersonal variability [3]. Based on those hypotheses it is possible to define classifier to be able to discriminate the original and forgery signature samples. In many cases this is not totally true, in function of the signature samples instability presented by many writers (see Figure 1a and 1b) and the similarity presented by different writers (see Figure 2a and 2b).

(a)

(b)

Figure 1. The super-imposed examples of the same writer's specimen skeletons, using the gravity center with system axis center: (a) unstable samples; (b) stable samples

(a)

(b)

Figure 2. The super-imposed examples of the same writer's specimen skeletons, using the gravity center with system axis center: (a) writer number 64; (b) writer number 97

The forgery types offer another particular complexity in the intrapersonal variability. The first type, called random forgery, is usually represented by a signature sample that belongs to a different writer of the signature model (see Figure 3b). The second one, called simple forgery, is represented by a signature sample with the same shape of the genuine writer's name (see Figure 3c). The last type is the skilled forgery, represented by a suitable imitation of the genuine signature model (see Figure 3d).

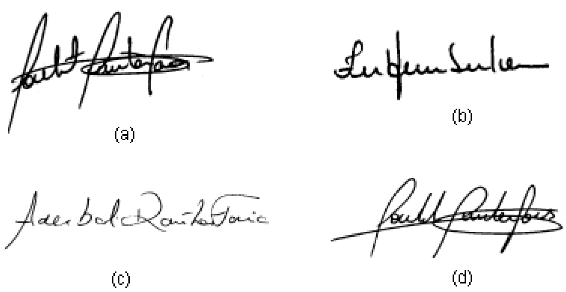


Figure 3. Type of forgeries: (a) genuine signature; (b) random forgery; (c) simulated simple forgery; and (d) simulated skilled forgery

Every type of forgery requests a different recognition approach. Methods based on static approach are usually used to identify random and simple forgeries. The reason is that these methods have shown to be more suitable to describe characteristics related to the signature shape. For this purpose, the graphometry-based approach has many features that can be used, such as calibration, proportion, guideline and base behaviors [7,8]. In addition, other features have been applied in this approach, like pixel density [4] and pixel distributions [6]. However, static features do not describe adequately the handwriting motion. Therefore, it is not enough to detect skilled forgeries.

A skilled forgery has almost the same shape of the genuine signature. In this case, if a writer presents a large variability among genuine signature simples, it is more probably that to have a skilled forgery accepted with genuine. In other words, the intrapersonal variability maximization aids the forgery acceptance. In this case, methods based on pseudodynamic approach have shown to be more robust to identify this forgery type, since they are able to capture handwriting motion details. But, high critical method produces more genuine signature rejection.

2. System Outline

This work demonstrates how a grid approach is adapted to the signature parts, according to their stability [2,7]. In a first level, the objective is to modeling the space around the signature traces, using too static features. In a second level, the proposal is to modeling the signature traces, using a pseudodynamic feature (see Table 1).

Table 1. The feature set table

Feature Name	Feature Type	Analysis
Pixels Density	Static	Graphic Space Occupation
Pixels Distribution	Static	Graphic Space Occupation
Axial Slant	Pseudodynamic	Traces

Each column of cells is converted into a characteristic vector, where each vector element has one or more representative numeric values, depending on the feature used. We used a signature binary image into the grid, to account the number of pixels in each cell (see Figure 4). We used too, the pixel distribution feature. It represents the pixel geometric distribution in a cell. For this purpose, the black pixels are projected in 4 peripheral cell sensors from the central axis of the cell. Each sensor provides a numerical value that corresponds to the total of projected pixels. This numerical values as normalized by the sensor size (see Figure 5). We also have used a signature skeleton image [9], into the grid to determine the predominant stroke slant in each cell (see Figure 6).

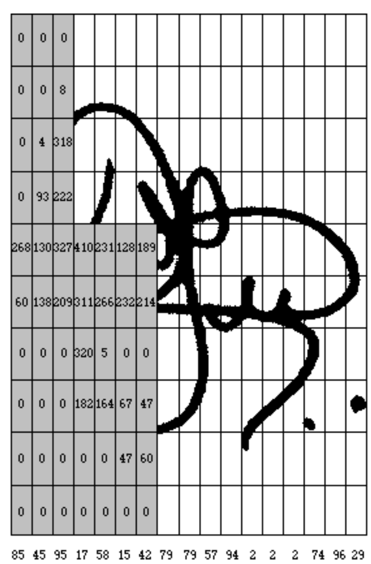


Figure 4. The pixels density example

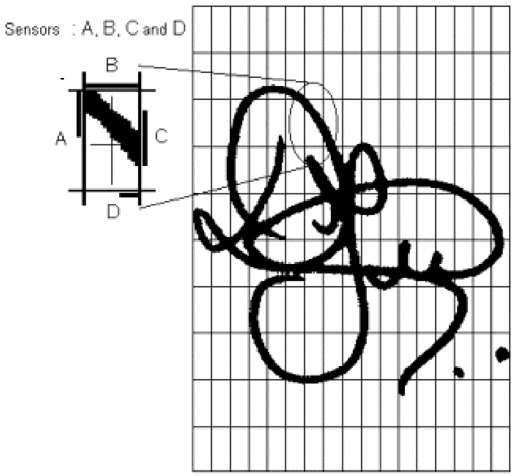


Figure 5. The pixels distribution example

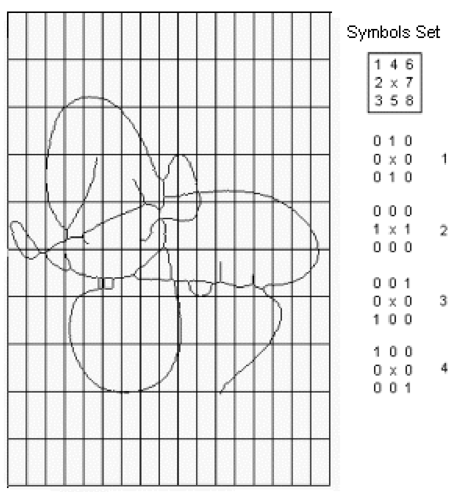


Figure 6. The axial slant example

Afterwards, we have generated a set of codebooks for each feature. To this end, we used a Vector Quantization process [4,5,7], based in the k-means algorithm. In the learning phase, we have generated a HMM $\lambda = \{A, B, \pi\}$ signature model, adapted to each writer. Moreover, the cross-validation procedure was used to dynamically define the optimum number of states for each specific signature model (writer model). The selected topology was a left-right model [1], because it better represents the Latin handwriting characteristics. The best validation probability $p_{cv}(O/\lambda)$ was used to define the most suitable probability model $p_t(O/\lambda)$, for one specific number of states. This model was used to define the threshold parameters. The objective is to determine the acceptation and rejection thresholds taking into account a specific writer (see Figure 7).

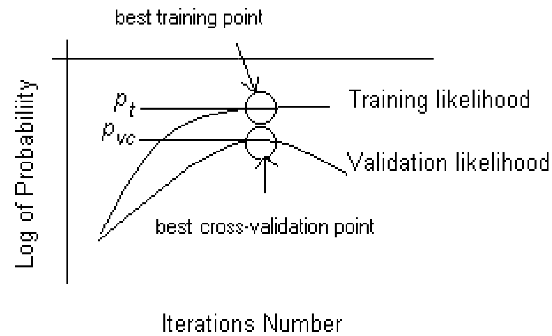


Figure 7. A typical learning and cross-validation curve for a set number of states

The medium threshold in question (1), defined by the p_t, represents the learning probability logarithm, which is normalized by the observation sequence number L.

$$p_{tn}(O/\lambda) = \frac{\log p_t(O/\lambda)}{L} \tag{1}$$

$$p_i = p_{tn} - (p_{tn}.\alpha_1) \tag{2}$$

$$p_s = p_{tn} + (p_{tn}.\alpha_2)\,. \tag{3}$$

In the signature verification procedure, we have used the Forward algorithm [1,7], with the objective to determine the verification probability p_v. The L value also normalizes the probability logarithm p_{vn}. The acceptation and rejection were defined by the equation 5 (see Figure 8).

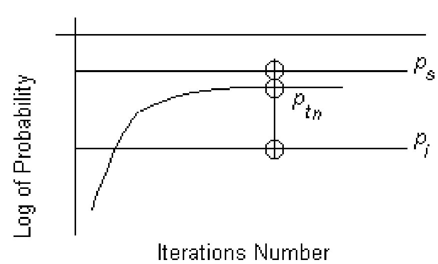


Figure 8. The thresholds used to delimit the acceptation and rejection area in the validation process

$$p_{vn}(O/\lambda) = \frac{\log\ p_v(O/\lambda)}{L} \quad (4)$$

$$p_s \leq p_{vn} \leq p_i\ . \quad (5)$$

3. The Evaluation Protocol

The database was subdivided into two subsets with 40 samples per writer: one subset contains 40 writers (1,600 genuine signature samples); and the other contains 60 writers (2,400 genuine signature samples) [7]. We have added 1,200 forgery specimens in the second subset. These forgery samples were collected using 10 different writers or forgers. Each forger generated a simple and a skilled simulated forgery, only one time and without training.

The first database was used to create the codebooks for each feature. For this purpose, we selected the first 30 samples. Based on that, we converted all databases in an observation symbol sequence. The first database was also used for the learning process. Each writer model was defined using 20 learning samples and 10 cross-validation samples (the same 30 samples used in the VQ). The threshold parameters α_1 and α_2 in equations (2) and (3), were defined using the same 10 cross-validation samples, combined with the sets of 10 cross-validation samples from other 39 writers. This procedure was used for all subsets. The last remaining 10 samples were used to execute the first system experiment. This evaluation was important to define the best number of vertical cells and the codebook size for each feature.

The second subset was used to validate the results obtained in the first experiment. To this end, a set of composed of 10 genuine, 10 simulated simple forgery and 10 simulated skilled forgery samples were used. The best codebook size and number of cells obtained in the first experiment were used in the second experiment. A multiple codebook technique was used to combine pixel density, pixel distribution and axial slant features.

4. Experimental Results

Table 2 shows the signature verification results obtained for each feature. The better number of cells and the codebook size from the first experiment were used in the second experiment. The objective is to produce the best feature combination in the proposed HMM framework. Table 3 shows the signature verification results for individual features using the second subset and taking into account all type of forgeries.

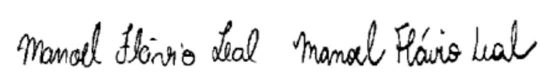
Table 2. Signature verification results for random forgeries using the first subset

Vertical Cells/ Codebook size	Error Type I (%)	Error Type II (%)	Error Type I (%)	Error Type II (%)	Error Type I (%)	Error Type II (%)
10/60	1.50	0.36	2.00	0.42	3.75	0.52
10/70	3.75	0.23	2.25	0.34	5.00	0.40
10/80	1.75	0.24	2.25	0.65	4.50	0.38
10/90	**1.00**	**0.32**	2.00	0.41	3.75	0.43
10/100	1.25	0.29	**1.75**	**0.31**	**3.00**	**0.51**
	Pixels Density		Pixels Distribution		Axial Slant	

Table 3. Signature verification results for individual features using the second subset

Primitives	Cells/ Codebook	Error Type I (%)	Error Type II (%) Random	Error Type II (%) Simple	Error Type II (%) Skilled	Mean Error (%)
Pixels Density	10/90	2.17	1.23	3.17	36.57	7.87
Pixels Distribution	10/100	1.33	1.29	2.83	37.83	7.65
Axial Slant	10/100	4.00	0.72	2.50	32.33	7.92

In the second subset of signatures, 24 writers (40%) used their names in the signature model (see Figure 9a). Thus, we have a high probability to occurs similarity between the genuine signature model and a simple forgery (see Figure 9b). Although, the simple type II error rate has shown almost the same value of random error rate. The same observation is shown in Table 4, when we combine the three types of features in the same HMM [5,9]. However, the same does not occur with the skilled forgery in both experiments. We conclude that the system is not totally prepared to discriminate small differences between the genuine model and a test sample.



(a) (b)

Figure 9. (a) genuine signature and (b) simple forgery signature

Table 4. Signature verification results combining all features in one HMM classifier

Primitives Combined	Cells/ Codebook	Error Type I (%)	Error Type II (%) Random	Error Type II (%) Simple	Error Type II (%) Skilled	Mean Error (%)
Pixels Density/ Pixels Distribution/ Axial Slant	10/90 10/100 10/100	2.83	1.44	2.50	22.67	5.85

The decision threshold is adjusting with the objective to absorb the intrapersonal variability (see Figure 10b). It was possible by the α_1 and α_2 computation in the simulation procedure. One important fact is the mean error stability present between p1 and p3 (see Figure 10a).

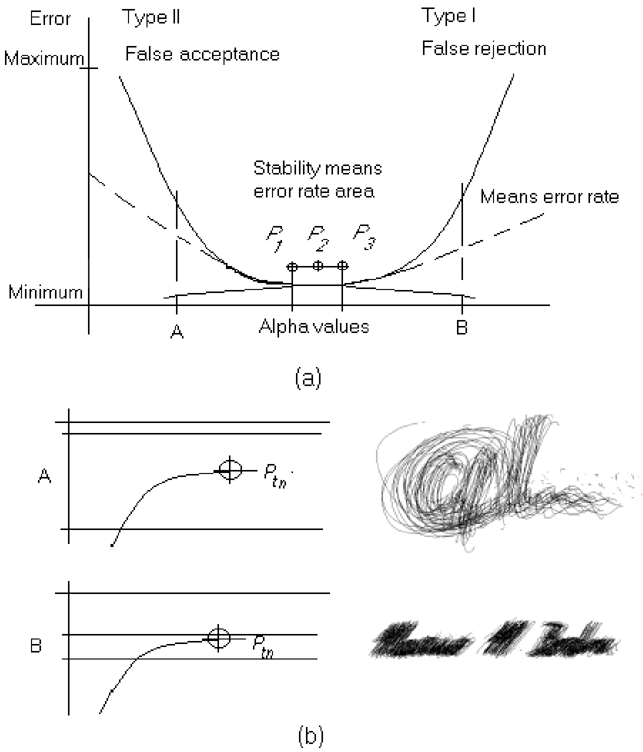


Figure 10. (a) α_1 and α_2 definition curves and (b) threshold definition examples

Table 5 shows a comparative among p1, p2 and p3 alpha values. In p1 the model is more critical for intrapersonal and interpersonal acceptance, and in p3 the model is flexible. In other words, when the model is more critical the acceptance goes down, and the rejections go up for all type of forgery (p_1 case). When the model is flexible the acceptance goes up, and the rejections go down for all type of forgery (p_3 case).

Table 5. Comparative using different alpha values

Primitives Combined	Cells/ Codebook		Error Type I (%)	Error Type II (%) Random	Error Type II (%) Simple	Error Type II (%) Skilled	Mean Error (%)
Pixels Density/	10/90	P_1	4.67	1.38	1.83	13.83	9.25
Pixels Distribution/	10/100	P_2	3.33	1.33	1.83	15.17	5.41
Axial Slant	10/100	P_3	2.83	1.44	2.50	22.67	5.85

5. Conclusion and Future Works

The main objective of this work is to present a study about the interpersonal and intrapersonal variability influences in the signature writer's model definition threshold. For this purpose, we have used simple features, different cell resolutions and multiple codebooks in a HMM framework. The simple and random forgery error rates have shown to be low and stable for all alpha values. This demonstrates the potential of the system in a real application. It is important to observe that there is no simples and skilled forgery sample in the learning database. The reelection between the type I and the type II error rate, in skilled forgery signatures, demonstrates that is necessary to define flexible parameters with the objective to adjust the threshold based on the intrapersonal variability.

6. References

[1] L. Rabiner, B. Juang,, *Fundamentals of Speech Recognition*, Prentice Hall, New Jersey (1993).

[2] Q. Yingyong, B. R. Hunt, "Signature Verification Using Global and Grid Features", *Pattern Recognition* – vol. 22, no. 12, Great Britain (1994), pp.1621--1629.

[3] Drouhard, J.P., R. Sabourin, and M. Godbout, "A neural network approach to off-line signature verification using directional PDF", *Pattern Recognition*, vol. 29, no. 3, (1996), pp. 415--424.

[4] G. Rigoll, A. Kosmala, "A Systematic Comparison Between On-Line and Off-Line Methods for Signature Verification with Hidden Markov Models", 14th International Conference on *Pattern Recognition* - vol. II, Australia (1998), pp. 1755--1757.

[5] A. J. Elms, *The Representation and Recognition of Text Using Hidden Markov Models*, PhD Theses Doctor, University of Surrey, U.K. (1996).

[6] Sabourin, R. and Genest, G., "An Extended -Shadow-Code Based Approach for Off-Line Signature Verification: Part -I – Evaluation of the Bar Mask Definition", 12th IAPR International Conference on Pattern Recognition, Jerusalem,

Israel, October 9-13 - IEEE 1051-4651/94, (1994), pp. 450--455.

[7] Edson J. R. Justino, A. El Yacoubi, F. Bortolozzi and R. Sabourin, “An Off-Line Signature Verification System Using HMM and Graphometric Features”, DAS 2000, 4th IAPR International Workshop on Document Analysis Systems, Rio de Janeiro, Brazil, (2000), pp. 211--222.

[8] Edson J. R. Justino, F. Bortolozzi and R. Sabourin, “Off-Line Signature Verification Using HMM for Random, Simple and Skilled Forgeries”, ICDAR 2001, International Conference on Document Analysis and Recognition, Seattle, USA, v.1, (2001), pp. 105--110.

[9] Ahmed S. Abutaleb, “Automatic Thresholding of ray-Level Pictures Using Two Dimensional Entropy”, *Computers Graphics & Image Processing*, no. 47, (1989), pp. 22--32p.