# Analysis of Stability in Static Signatures using Cosine Similarity

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***Abstract* — This paper presents a new technique for the analysis of stability in static signature images. The technique uses an equimass segmentation approach to non-uniformly split signatures into a standard number of regions. Successively, a multiple matching technique is adopted to estimate stability of each region, based on cosine similarity. The GPDS database has been considered for the experimental test. The results demonstrate the validity of the novel approach and highlight some directions for further research.**

***Index Terms* — Static Signature, Local Stability, Equimass segmentation, Cosine Similarity.**

## I. INTRODUCTION

Handwritten signatures have long been established as the most widespread means of personal verification. Administrative and financial institutions recognize handwritten signatures as a legal means of verifying an individual's identity. Moreover, people are familiar with the use of signatures in their daily life [1].

Therefore, it is not surprising that automatic signature verification is a research area which has attracted in the recent years many researchers from universities and companies, which are interested in not only the scientific challenges but also the valuable applications this field offers. Comprehensive survey papers reported the progress in the field of automatic signature verification until now [2,3,4,5,6].

Although there is a growing interest toward the field of automatic signature verification, some basic aspects concerning the nature of this very special kind of biometric trait are still open. In fact, it is worth noting that a handwritten signature is the result of a complex generation process. The rapid writing movement underlying signing is determined by a motor program stored into the brain of the signer and realized though the signer's writing system and writing devices (paper and pen type, etc.). Therefore, a signature image strongly depends on the psychophysical state of the signer and the conditions under which the signature apposition process occurs [7,8 ].

In this context, the recognition of stable regions of a signature image is very important, since they are generally very useful both for automatic verification aims and for providing valuable indications for the work of forensic examiners [9, 10]. In literature, the approaches proposed for the analysis of local stability are mainly devoted to dynamic signatures. A local stability function can be obtained by using DTW to match a genuine signature against other authentic specimens. Each matching is used to identify the Direct Matching Points (DMPs), that are unambiguously matched points of the genuine signature. Thus, a DMP can indicate the presence of a small stable region of the signature, since no significant distortion has been locally detected. The local stability of a point of a signature is determined as the average number of time it is a DMP, when the signature is matched against other genuine signatures. Following this procedure low- and high-stability regions are identified [11, 12, 13] in the selection of reference signatures [14, 15] and verification strategies [16, 17]. A client-entropy measure has been also proposed to group and characterize signatures in categories that can be related to signature variability and complexity. The measure, that is based on local density estimation by a HMM, can be used to access whether a signature contains or not enough information to be successfully processed by any verification system [18, 19, 20]. Other types of approaches estimate the stability of a set of common features and the physical characteristics of signatures which they are most related to, in order to obtain global information on signature repeatability which can be used to improve the verification systems [21, 22]. In general, these approaches have shown that there is a set of features that remain stable over long time periods, while there are other features which change significantly in time [23, 24]. Of course, since intersession variability is one of the most important causes of the deterioration of verification performances, specific parameter-updating approaches have been considered [22, 23]. Concerning static signatures, stability analysis has been performed in literature using a multiple pattern-matching strategy [25, 26, 27] and also by the analysis of the optical flow between two genuine signature images [28].

In this paper a new technique is proposed for the analysis of local stability in handwritten signature images. The technique uses a multiple-matching strategies in which feature vectors extracted from corresponding regions of genuine specimens are matched through cosine similarity. The experimental results, carried out on signatures of the

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GPDS database, demonstrate the usefulness of the approach in detecting stability information in static signatures.

The organization of this paper is the following. Section 2 presents the image preprocessing phase. In this section the application of the equimass segmentation algorithm is addressed. Section 3 describes the feature extraction procedure. Cosine similarity and its application to stability analysis is discussed in Section 4. The conclusion of this work is reported in Section 5.

## II. IMAGE PROCESSING

In the preprocessing phase the signature images were binarized and normalized. Successively the Median Noise Removal algorithm was used to clean the images. Figure 1 shows an example of a signature image. The same image after preprocessing is shown in Figure 2.

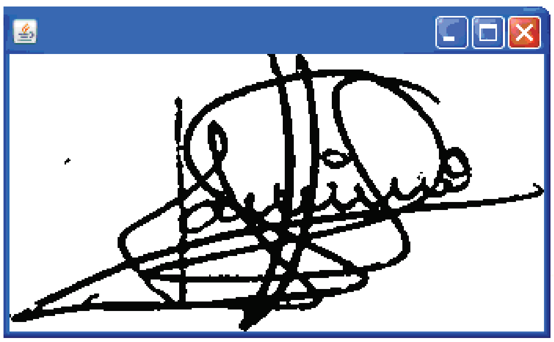


Figure 1. A signature image

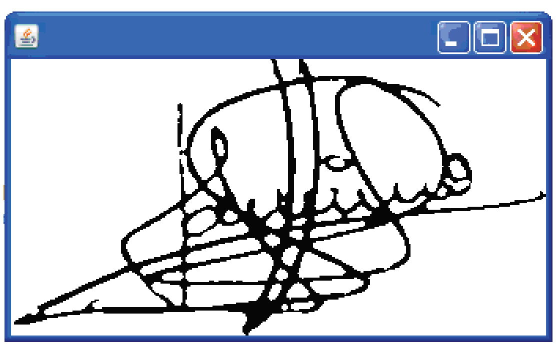
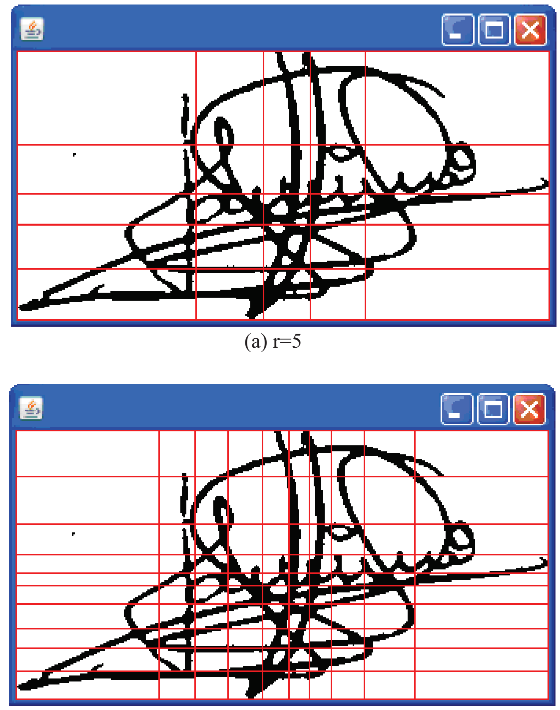


Figure 2. A signature image after preprocessing

Signature regimentation is performed using an adaptive grid approach based on the Equimass approach [29], where the grid lines are found at the equimass divisions of the horizontal and vertical mass histogram of the signature image (the mass being defined as the number of black pixels). More precisely, let I(X,Y) be the signature image where:

- $I(x,y)=0 \rightarrow$ white pixel (1a)
- $I(x,y)=1 \rightarrow$ black pixel; (1b)

If r horizontal (vertical) slices must be defined, the grid is designed so that the mass of each horizontal (vertical) slice is equal to $M_{region}=M/r$, being M the total mass of the signature image. Figures 3a and 3b show the results of the segmentation algorithm for r=5 and r=10, respectively. Of course, when r=5, the number of regions is equal to 25; when r=10, the number of regions is equal to 100.



(a) r=5

(b) r=10

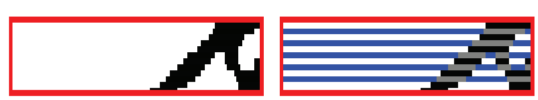
Figure 3. Signature image segmentation

## III. FEATURE EXTRACTION

In the feature extraction, for each (not empty) region of the signature image, five equally-spaced parallel segments are considered for each one of the four main directions (horizontal, vertical, +45°, -45°) and the total number of black pixels intercepted by the segments in each direction are counted. Therefore, from each region $I^s$ of the signature image I(X,Y), a vector of four components (one for each direction) is extracted:

$$F^s = (F^s(1), F^s(2), F^s(3), F^s(4)). \qquad (2)$$

Figure 4a shows a region of the signature image and the five equally-spaced horizontal lined that intercept the pattern.



(a) (b)

Figure 4. Horizontal interceptions

Figures 5 shows the extraction of horizontal and vertical features from all non-empty regions of the signature image.

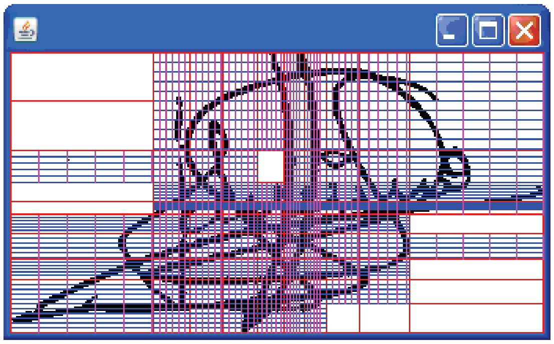


Figure 5. Horizontal and vertical feature extraction

## IV. Stability Analysis

Stability analysis is performed at the level of each image region. In particular, let $I_1(X,Y)$ and $I_2(X,Y)$ be two signature images, and let $I_1^s$ and $I_2^s$ be two corresponding regions of $I_1(X,Y)$ and $I_2(X,Y)$, respectively. The dissimilarity measure (D) between $I_1^s$ and $I_2^s$ is here defined as [30]:

$$D(I_1^s, I_2^s) = 1 - \mathrm{CosSim}(F_1^s, F_2^s) \qquad (3)$$

where the Cosine Similarity (CosSim) between the feature vectors $F_1^s$ and $F_2^s$ is defined as:

$$CosSim(F_1^s, F_2^s) = \frac{F_1^s \bullet F_2^s}{\|F_1^s\| \cdot \|F_2^s\|}. \qquad (4)$$

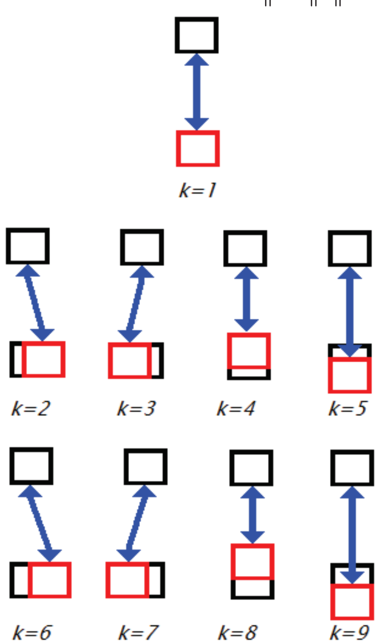



Figure 6. Shifted regions for the matching process

Furthermore, since personal variability in signing can lead to small variations in the alignment of corresponding regions, for the analysis of stability of the region $I_1^s$ of $I_1(X,Y)$, eq. (3) is substituted by

$$D^*(I_1^s, I_2^s) = \mathrm{Max}\{ D^*(I_1^s, I_2^s(k) \mid k=1,2,\dots 9\} \qquad (5)$$

being $I_2^s(1) = I_2^s$ and $I_2^s(2), \dots I_2^s(9)$ eight regions of $I_2(X,Y)$ obtained by shifting the position of $I_2^s$ in the East, West, North, South direction of one (k=2,3,4,5) and two steps (k=6,7,8,9), as Figure 6 shows (step=5 pixels, in our approach).

Now, let $I_i(X,Y)$, i=1,2,…,M, be M genuine signature images of a signer, and $I_i^s$ , i=1,2,…,M, the s-th corresponding regions, the local stability of $I_1^s$ is defined as:

$$Stability(I_1^s) = \frac{1}{M-1}\sum_{i=2}^{M} D^*(I_1^s, I_i^s). \qquad (6)$$

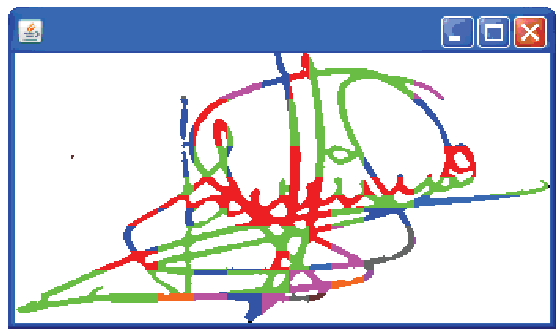


Figure 7. Stability of an Handwritten Signature

Figure 7 shows the stability of an handwritten signature image, as estimated by eq. (6). The colours of each region indicate the degree of stability of that region, according to Table I.

TABLE I. Degrees of Stability

| Degree | Colour | |
|---|---|---|
| $Stability = 0$ | Violet | |
| $0 < Stability \le 0.1$ | Dark green | *Low Stability* |
| $0.1 < Stability \le 0.2$ | Brawn | |
| $0.2 < Stability \le 0.3$ | Lilac | |
| $0.3 < Stability \le 0.4$ | Grey | |
| $0.4 < Stability \le 0.5$ | Light blue | *Medium Stability* |
| $0.5 < Stability \le 0.6$ | Orange | |
| $0.6 < Stability \le 0.7$ | Pink | |
| $0.7 < Stability \le 0.8$ | Blue | |
| $0.8 < Stability \le 0.9$ | Green | *High Stability* |
| $0.9 < Stability \le 1.0$ | Red | |

## V. Experimental Results

The experimental results have been carried out using static signatures of the GPDS database. The database contains 16200 signatures from 300 individuals: 24 genuine signatures and 30 forgeries for each individual [31]. For each signer the stability analysis is performed. Three typical examples of the results of the stability analysis are reported in Figure 8.

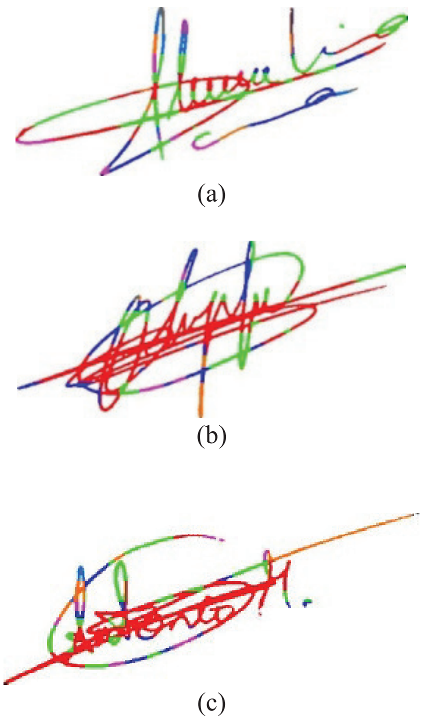



Figure 8. Examples of Stability Analysis

The results of the analysis of stability have also been performed considering three different areas of the signatures: Top Area, Middle Area and Bottom Area. The percentage of the signature image having a specific degree of stability is measured for each area, as Table II reports. The result points out that, in general, the Middle Area of the signature is more stable than Bottom and the Top areas. More precisely, the low stability part of the Middle Area is only the 0.90%, whereas the medium stability and the high stability parts are respectively the 11.50% and 87.60%. The low stability, medium stability and high stability parts of the bottom areas are equal to 4.70%, 25.40% and 69.90%, respectively. For that concerning the Top Area, the low stability, medium stability and high stability parts are equal to 2.20%, 14.70 and 83.10%, respectively. This result is very interesting since it confirms the evidence that signers are generally not very stable in writing complex and pictorial elements, that are mainly located in the Top and Bottom areas of the signatures.

TABLE II. Stability vs Area

| Degree | Top | Middle | Bottom |
|---|---|---|---|
| $Stability = 0$ | 0.90% | 0.40% | 0.70% |
| $0 < Stability \le 0.1$ | 0.40% | 0% | 0.20% |
| $0.1 < Stability \le 0.2$ | 1.50% | 0.10% | 0.50% |
| $0.2 < Stability \le 0.3$ | 1.90% | 0.40% | 0.80% |
| $0.3 < Stability \le 0.4$ | 2.70% | 1.50% | 1.40% |
| $0.4 < Stability \le 0.5$ | 3.70% | 1.60% | 2.90% |
| $0.5 < Stability \le 0.6$ | 6.50% | 3.70% | 4.50% |
| $0.6 < Stability \le 0.7$ | 12.50% | 4.70% | 5.90% |
| $0.7 < Stability \le 0.8$ | 17.20% | 10.30% | 14.70% |
| $0.8 < Stability \le 0.9$ | 30.40% | 30% | 32.40% |
| $0.9 < Stability \le 1.0$ | 22.30% | 47.30% | 36.00% |
| **Total** | **100.00%** | **100.00%** | **100.00%** |

## VI. Conclusion

In this paper presents a new approach for the analysis of local stability in static signature images based on the Cosine Similarity. The experimental results, carried out on static signatures extracted from the GPDS database, demonstrate the new approach is useful to derive information on local stability in static signatures.

Further research is of course necessary to evaluate the is the proposed method can be used to discriminate between short-term and long-term variability, as well as to determine the usefulness of stability information for signature verification aims.

## References

[1] R. Plamondon and G. Lorette, "Automatic Signature Verification and Writer Identification – The State of the Art", Pattern Recognition, Vol. 22, No. 2, Jan. 1989, pp. 107-131.

[2] D. Impedovo, G. Pirlo, "Automatic Signature Verification – The State of the Art", IEEE Transactions on Systems, Man and Cybernetics - Part C: Applications and Review, Vol. 38, No. 5, Sept. 2008, pp. 609 – 635.

[3] S. Impedovo and G. Pirlo, "*Verification of Handwritten Signatures: an Overview*", Proc. 14th International Conference on Image Analysis and Processing - ICIAP 2007, IEEE Computer Society Press, September, 11-13, 2007, Modena, Italy, pp. 191-196.

[4] F. Leclerc and R. Plamondon, "Automatic signature verification: The state of the art—1989–1993," *Int. J. Pattern Recognit. Artif. Intell. (IJPRAI)*, vol. 8, no. 3, pp. 643–660, Jun. 1994 [Series in: MPAI, R. Plamondon, Ed. Singapore: World Scientific, 1994, pp. 3–20].

[5] G. Pirlo, "Algorithms for Signature Verification", in Proc. of NATO-ASI Series *Fundamentals in Handwriting Recognition*, S. Impedovo (Ed.), Springer-Verlag, Berlin, 1994, pp. 433-454.

[6] Y.M. Al-Omari, S.N.H.S. Abdullah, K. Omar, "State of the Art on offline signature verification system", Proc. 2011 Int. Conference on

Pattern Analysis and Intelligent Robotics (ICPAIR), Putrajaya, Kuala Lumpur, Malaysia, June 28-29, 2011, pp. 59-64.

[7] R. Plamondon, “A Kinematic Theory of Rapid Human Movements: Part I: Movement Representation and generation”, *Biological Cybernetics*, Vol. 72, No. 4, 1995, pp. 295-307.

[8] R. Plamondon, M. Djioua, “A Multi-Level Representation Paradigm for Handwriting Stroke Generation”, *Human Movement Science*, Vol 25, No. 4-5, 2006, pp. 586-607.

[9] S.N. Srihari, H.L. Teulings, “A Survey of Computer Methods in Forensic Document Examination”, Proc. of the 11th Conference of the International Graphonomics Society (IGS 2003), 2-5 November 2003, Scottsdale, Arizona, USA, pp. 278-281.

[10] K. Franke and M. Koppen, “A computer-based system to support forensic studies on handwritten documents. International Journal on Document Analysis and Recognition (IJDAR), Vol. 3, n. 4, 2001, pp. 218–231.

[11] G. Congedo, G. Dimauro, S. Impedovo, G. Pirlo, “A new methodology for the measurement of local stability in dynamical signatures”, *4th International Workshop on Frontiers in Handwriting Recognition* (IWFHR-4), Taipei, Taiwan, Dec. 1994, pp. 135-144.

[12] G. Dimauro, S. Impedovo, R. Modugno, G. Pirlo, L. Sarcinella, “Analysis of Stability in Hand-Written Dynamic Signatures”, *8th International Workshop on Frontiers in Handwriting Recognition* (IWFHR-8), Ontario, Niagara-on-the-Lake, Canada, Aug. 2002, pp. 259-263.

[13] K. Huang and H. Yan, “Stability and style-variation modeling for on-line signature verification”, *Pattern Recognition*, Vol. 36, No. 10, Oct. 2003, pp. 2253-2270.

[14] G. Congedo, G. Dimauro, A.M. Forte, S. Impedovo, G. Pirlo, “Selecting Reference Signatures for On-Line Signature Verification”, *8th International Conference on Image Analysis and Processing* (ICIAP-8), Series: Lecture Notes in Computer Science, Vol. 974, Springer-Verlag Berlin, Heidelberg, C. Braccini, L. De Floriani and G. Vernazza (Eds.), San Remo, Italy, Sept. 1995, pp. 521-526.

[15] V. Di Lecce, G. Dimauro, A. Guerriero, S. Impedovo, G. Pirlo, A. Salzo, L. Sarcinella, “Selection of Reference Signatures for Automatic Signature Verification”, *Proc. 5th International Conference on Document Analysis and Recognition (ICDAR-5)*, Bangalore, India, Sept. 20-22, 1999, pp. 597-600.

[16] V. Di Lecce, G. Dimauro, A. Guerriero, S. Impedovo, G. Pirlo, A. Salzo, “A Multi-Expert System for Dynamic Signature Verification”, *1st International Workshop*, *Multiple Classifier Systems (*MCS 2000), Series: Lecture Notes in Computer Science, Springer-Verlag Berlin Heidelberg, J. Kittler and F. Roli (Eds.), Vol. 1857, Cagliari, Italy, June 2000, pp. 320-329.

[17] L. Bovino, S. Impedovo, G. Pirlo, L. Sarcinella, “Multi-Expert Verification of Hand-Written Signatures”, *7th International Conference on Document Analysis and Recognition* (ICDAR-7), IEEE Computer Society, Aug. 2003, Edinburgh, Scotland, pp. 932-936.

[18] N. Houmani, S. Garcia-Salicetti, B. Dorizzi, "A novel personal entropy measure confronted with online signature verification systems' performance", *Proceedings of the 2nd IEEE International Conference on Biometrics: Theory, Applications and Systems (BTAS '08)*, Washington, DC, USA, September 2008

[19] S. Garcia-Salicetti, N. Houmani, B. Dorizzi, "A client-entropy measure for on-line signatures", *Proceedings of the IEEE Biometrics Symposium (BSYM '08)*, pp. 83-88, Tampa, Fla, USA, September 2008.

[20] N. Houmani, S. Garcia-Salicetti, B. Dorizzi, “On assessing the robustness of pen coordinates, pen pressure and pen inclination to time variability with personal entropy”, *Proc. of IEEE 3rd International Conference on Biometrics: Theory, Applications, and Systems, 2009 (BTAS '09)*, Washington, DC, Sept. 28-30, 2009, pp. 1 – 6.

[21] R. Guest, “Age dependency in handwritten dynamic signature verification systems”, *Pattern Recognition Letters*, Vol. 27, N. 10, 15 July 2006, pp. 1098-1104.

[22] R.M. Guest, “The Repeatability of Signatures”, *9th International Workshop on Frontiers in Handwriting Recognition* (IWFHR-9), Kichijoji, Japan, Oct. 2004, pp. 492-497.

[23] H. Lei and V. Govindaraju, “A comparative study on the consistency of features in on-line signature verification”, *Pattern Recognition Letters*, Vol. 26, 2005, pp. 2483-2489.

[24] Y. Kato, D. Muramatsu, T. Matsumoto, “A Sequential Monte Carlo Algorithm for Adaptation to Intersession Variability in On-line Signature Verification”, *Proc. 10th Int. Workshop on Frontiers in Handwriting Recognition* (IWFHR 10), La Baule, France, Oct. 2006.

[25] D. Impedovo, R. Modugno, G. Pirlo, E. Stasolla, “Handwritten Signature Verification by Multiple Reference Sets”, *Proc. of the 11th International Conference on Frontiers in Handwriting Recognition (ICFHR)*, 19-21 Aug. 2008, Concordia University, Montreal, Quebec, Canada, CENPARMI Press, pp. 125-129

[26] D. Impedovo, G. Pirlo, " On the Measurement of Local Stability of Handwriting - An application to Static Signature Verification ", *Proc. of Biometric Measurements and Systems for Security and Medical Applications (BIOMS 2010)*, September, 9, 2010, Taranto, Italy, IEEE Computer Society Press, pp. 41-44.

[27] D. Impedovo, G. Pirlo, E. Stasolla, C.A. Trullo, "Learning Local Correspondences for Static Signature Verification”, *Proc. 11th Int. Conf. of the Italian Association for Artificial Intelligence (AI*IA 2009)*, December 9-12, 2009, Reggio Emilia, Italy, in Lecture Notes in Artificial Intelligence – LNAI, Vol. 5883, 2009, Springer Verlag, Berlin Heidelberg, Germany, pp. 385-394.

[28] D. Impedovo, G. Pirlo, “Static Signature Verification by Optical Flow Analysis”, Proceedings of the 1st International Workshop on Automated Forensic Handwriting Analysis, Beijing, China, September 17-18, 2011, pp. 31-35.

[29] R. Larkins, M. Mayo, “Adaptive Feature Thresholding for off-line signature verification” , Proc. of the 23rd Int. Conference on Image and Vision Computing New Zeland 2008, 26-28 Nov. 2008, Christchurch, New Zeland, pp. 1-6.

[30] P.-N. Tan, M. Steinbach & V. Kumar, "Introduction to Data Mining", Addison-Wesley, 2005.

[31] J.F. Vargas, M.A. Ferrer, C.M. Travieso, J.B. Alonso, “Off-line Handwritten Signature GPDS-960 Corpus”, Proc. 9th ICDAR, Vol. 2, 23-26 Sept. 2007 pp.764-768.