Recent Advancements in Automatic Signature Verification

G. Dimauro, S. Impedovo, M.G.Lucchese, R.Modugno and G. Pirlo
Dipartimento di Informatica, Università degli Studi di Bari,
via Orabona, 4, 70126 Bari, Italy
impedovo@di.uniba.it

Abstract

This paper presents some of the main strategies for dynamic and static verification of handwritten signatures and focuses the most promising directions of scientific research, starting from the analysis of the literature of the last decade.

1. Introduction

Biometry offers potential for automatic personal verification and differently from other means for personal verification, biometric means are not based on the possession of anything (as the case of key, magnetic card or badge) or the knowledge of some information (as the case of password, key-phrase,) [1,2]. Of the various biometrics, signature-based verification has the advantage that signature analysis requires no invasive measurement and is widely accepted since signature has long been established as the most diffuse mean for personal verification in our daily life, including commerce applications, banking transactions, automatic fund transfers, etc. [3,4].

The net result is that signature verification has attracted many researchers from universities and companies, which are interested both to the scientific challenges and to the valuable applications of this field, since no doubts automatic signature verification has a very important role in the set of biometric techniques for personal verification [5]. The enormous work carried out in this field has been comprehensively summarized in the excellent survey paper in ref. [6] , for the years up to 1989, and in ref. [7], from year 1989 to 1993.

This paper presents some recent advancements in the field of automatic signature verification and focuses the most valuable directions of research. Although the complete review of the research activities from 1993 up to now is behind the aim of this paper, specific attention has been devoted to the works carried out in the last decade.

The organization of the paper follows the main phases of the signature verification process: Section 2 presents the basic aspects of data acquisition and preprocessing phase. In Section 3, the feature extraction phase is addressed. The comparison approaches are discussed in Section 4. Section 5 points out some of the most important open questions in signature verification and highlights some of the most profitable directions of research. The conclusion of the paper is reported in Section 6.

2. Data Acquisition and Preprocessing

Handwritten signature verification systems are either on-line (dynamic) or off-line (static), depending on the data acquisition method: On line acquisition devices [8], like graphic tablets, generate electronic signals representative of the signature trace during the writing process. Typical signals generated are: position-,velocity-, acceleration-, pressure- and force-signals. Off line acquisition devices [9], like scanners or cameras, perform data acquisition after the writing process has been completed. In this case the signature is represented as a grey level image. In other words, the on-line case provide a spatio-temporal representation of the input, whereas the off-line case involves analysis of the spatio-luminance of an image.

In both cases, after data acquisition, preprocessing is necessary to enhance the input data. For this purpose, several signal processing algorithms for preprocessing can be used. The preprocessing of a on-line signature generally consists of filtering, in order to remove spurious signals from the signature. Subsequently, a normalization procedure is used to standardize the signatures in time-duration and size domain. Conversely, the preprocessing of an off-line signature must deal with very noisy images since in many practical conditions (bankchecks, etc.) signatures are produced on specific paper forms with complex background patterns. In this case preprocessing is more complex and time consuming than on-line signature. Typical preprocessing steps are signature localization in the image, signature extraction, width/size normalization, skeletonization and smoothing [10].

A very difficult preprocessing task concerns signature segmentation, since different signatures of one writer can differ from each other by local stretching, compression, omission or additional parts. Table 1 reports some of the most relevant signature segmentation techniques. The simplest on-line signature segmentation determines the components of the signature [11,12,13].

Dimauro et al. [14,15] define a components as a piece of the written trace between a pen down and a pen up movement. This approach is based on the consideration that the signature can be regarded as a sequence of writing units delimited by abrupt interruptions. Writing units are the regular parts of the signature, while interruptions are the singularities of the signature [14,15].

Plamondon et al. [16] propose a segmentation approach based on the curvilinear and angular velocity signals of the pen movements during signing. In this approach it is assumed that the basic elements of the handwritten signature are the components and the strings.

Another technique proposed by Brault and Plamondon [17] use perceptual important points for signature segmentation. It is based on a two steps procedure. The first step weights up the perceptual importance of each point of the signature, while the second step identifies the segmentation points as those which are locally more significant from a perceptual point of view.

Dimauro et al. [18] present a segmentation technique based on a dynamic splitting procedure. The basic idea is to perform segmentation of the reference signatures, according to the characteristics of the input (test) specimen. This technique segments the signature to be verified by matching it with the reference signatures by DP. Only the set of segmentation points which correspond unambiguously is derived. This approach allow to segment the test and reference signatures into the same number of perfectly corresponding segments.

Proceedings of the 9th Int'l Workshop on Frontiers in Handwriting Recognition (IWFHR-9 2004)
0-7695-2187-8/04 $20.00 © 2004 **IEEE**

Segmentation by Pen-down/pen-up signals	**On-line**	**Herbst & Liu [11]; M. Castellano et al. [12]; C. Schmidt and K.-F. Kraiss [13]; G. Dimauro et al. [14,15].**
Segmentation by velocity signal analysis	**On-line**	**R. Plamondon et al [16].**
Segmentation by Perceptually relavant points.	**On-line**	**J.J. Brault and R. Plamondon [17].**
Dynamic Segmentation	**On-line**	**G. Dimauro et al . [18].**
Segmentation by Connected Components	**Off-line**	**G. Dimauro et al. [19].**
Segmentation by Tree structure analysis	**Off-line**	**M. Ammar et al [20].**
Segmentation by Statistics of Directional Data	**Off-line**	**R.Sabourin and R.Plamondon [21].**

Table 1. Signature Segmentation Techniques

Concerning off-line signature segmentation, the simplest approach is based on the identification of connected components, by a contour following algorithms [19].

Ammar et al. [20] describe a signature by a tree structure which identifies fundamental segments in the static image. In this approach the signature is segmented horizontally into zones and vertically into elements, by the analysis of projection histograms.

Sabourin and Plamondon [21] present a new version of centroidal linkage region growing with merging algorithm, using the statistics of directional data. The approach permits the extraction of textured regions characterized with local uniformity in the orientation of the gradient.

3. Feature Extraction

Two types of features can be used for signature verification: parameters or functions [6]. When parameters are used as features, the signature is characterized as a vector of elements, each one representative of the value of a feature. When functions are used as features, the signature is characterized in terms of a time-function, whose values constitute the feature set.

In general, function features allow better performance than parameters, but they usually require time-consuming matching procedures. Table 2 presents some of the most diffuse features considered in the literature for signature verification. Velocity is generally considered to be more informative than position and acceleration for dynamic signature verification. Pressure and force functions have been also used frequently and specific devices have been developed to capture them directly during the signing process. In the literature several hundreds parameters have been proposed for signature verification. Table 3 reports some of the most diffuse parameters considered in the literature as features. Some of them are obtained from time-function signals of the signature, and are specifically devoted to on-line signature verification. The average (AVE) , the root mean square (RMS), the maximum (MAX) and minimum (MIN) values are generally derived from the position, displacement, speed and acceleration time-functions representative of a signature [31,32]. Other parameters are determined as coefficients obtained from mathematical transforms. Fourier-, Hadamard- and Wavelet- transforms have been proposed for on-line and off-line signature verification [12,33,23,34,35,36,37]. Other typical parameters for on-line signature verification describe the signature apposition process, as total signature time duration, pen-down time ratio, number of pen-lifts (pen-down, pen-up), etc [31,32].

Concerning off-line signatures, in which dynamic information is not available, many parameters can be extracted from the geometric analysis of signatures. Some of the most diffuse parameters are the signature image area, the signature height and width, the ratio between the signature length and its width, the ratio between middle zone width and signature width, the number of characteristics points (end-points, cross-points, cusps, etc.), number of loops, the presence of the lower zone parts, the number of elements in the signature [20,41,42]. Projections–based features include the number of vertical/horizontal projection peaks, the value of maximum of the vertical/horizontal projections [41]. Also global and local slant-based and orientation-based features have been used [20]. The main contour-based features used concerns the use of parameters extracted from signature envelope and outlines [43,44]. Also grid-based features have been used, in this case the signature image is divided into rectangular regions and ink-distribution in each region is evaluated [40,41]. Finally, texture-based features have been considered, which are based on the co-occurrence matrices of the signature image [41].

Position	**On-line/Off-line**	**Y. Sato and K. Kogure [22]; Q.-Z- Wu et al. [23]; Y. Mizukami et al [24].**
Velocity	**On-line**	**Q.-Z- Wu [23]; G. Lorette and R. Plamondon [25].**
Acceleration	**On-line**	**N.M. Herbst and C.N.Liu [11]; C.N. Liu et al. [26]; J.S.Lew [27].**
Direction of pen movement	**On-line**	**Y. Yoshimura at al. [28,29].**
Pressare	**On-line**	**Y. Sato and K. Kogure [22].**
Forces	**On-line**	**H.D Crane & J.S. Ostrem [30].**

Table 2. Functions

Position, Displacement, Speed, Acceleration AVE/RMS/MAX/MIN of Position, Displacement, Speed, Acceleration	**On-line**	**L.L.Lee et al. [31]; W. Nelson et al. [32].**
Positive/Negative time duration of Position, Displacement, Speed, Acceleration	**On-line**	**L.L.Lee et al. [31]; W. Nelson et al. [32].**
X-Y correlation of Position, Displacement, Speed, Acceleration	**On-line**	**W. Nelson [32].**
Fourier Transform	**On-line/Off-line**	**M. Castellano et al. [12, 33]; Wu et al. [23]; C.F. Lam & D.Kamins [34]; G. Dimauro at al. [35] .**
Hadamard Transform	**Off-line**	**Nemcek and Lin [36.].**
Wavelet Transform	**On-line**	**D. Letjman and S. George [37].**
Total signature time duration	**On-line**	**L.L.Lee et al. [31]; W. Nelson et al. [32].**
Pen-down time ratio	**On-line**	**W. Nelson at al. [32].**
Number of PenUps/Pen Downs	**On-line**	**L.L.Lee et al. [31].**
Direction-based	**On-line/Off-line**	**W. Nelson at al. [32]; Xu-Hong Xiao [38]; K. Huang & Hong Yan [39]; R. Sabourin and Drouhard [40].**
Geometric-based	**Off-line**	**M. Ammar [20]; H. Baltzakis, N. Papamarkos [41]; R. Sabourin [42].**
Projection-based	**Off-line**	**H. Baltzakis, N. Papamarkos [41]**
Slant-based	**Off-Line**	**M. Ammar et al. [20].**
Orientation-based	**Off-Line**	**R. Sabourin [42].**
Contour-based	**Off-line**	**H. Cardot et al. [43]; R. Bajaj and S. Chaudhury [44].**
Grid–based	**Off-line**	**R. Sabourin [40]; H. Baltzakis, N. Papamarkos [41].**
Texture-based	**Off-line**	**H. Baltzakis, N. Papamarkos [41].**

Table 3. Parameters

4. Comparison

In the comparison process the authenticity of the test specimen is evaluated by matching its features against those stored in the knowledge-base. This process produces a single response given in the form of a Boolean value which states the authenticity of the test signature.

Concerning the information in the knowledge base, two different approaches can be considered. The first approach is based on the use of a single template of genuine specimen, for each writer. In this case, the main problem concerns the development of a prototype of genuine signature. Wirts [45] and Schmidt and Kraiss [13] presented new approaches for the development of the optimal average prototype for a signer. The second approach is based on using a set of genuine signatures for reference. In this case the main problem concerns with the choice of an optimal number of reference signatures and the selection of the optimal set of genuine signatures to be used for reference, among those available.

Yoshimura et al. [28] verified that three specimens are sufficient to be representative. They also proposed a system which selects three signatures out of the reference writings. The selection is achieved by clustering the reference signatures into three clusters and selecting one specimen with minimax property from each cluster. Personal threshold is determined by the worst matching result , obtained by comparing the reference signatures with each other, taken two-by-two.

Moreover, in the case in which N_r signature are available for reference, several matching strategies can be adopted to compare the test signature S_t against the reference signatures S_r, $r=1,2,...,N_r$ [2]:

- *wholistic matching*, that consists of matching the test signature S_t against each one of the N_r reference signatures, considered as a whole. In this case the matching between two signatures is performed by considering each signature entirely;
- *regional matching* , that consists of matching the test signature S_t against each one of the N_r reference signatures. In this case the matching between two signature is performed region by region, since each signature is considered by parts;
- *multiple regional matching*, that consists of matching each region of the test signature S_t against each one of the corresponding regions of the N_r reference signatures. In this case the test signature is judged to be a genuine specimen if a suitable number of segments are found to be genuine. This approach allows a regional evaluation of the signature without requiring a large set of reference signatures.

Furthermore, each comparison technique is based on a suitable similarity (or dissimilarity) measure. Some of the most diffuse matching techniques are reported in Table 4. When parameters are used as features, the Euclidean distance is the most diffuse matching strategy [14,15,19,48]. When functions are considered, the matching techniques must take into account the variations of signal duration from one signature to another. Furthermore, random variations due to the writer's pauses or hesitations can create portions of signals, such as deletions, additions and gaps, which complicate the problem of matching. Elastic matching is one of the most common matching methods used for this purpose, since it allows the compression or expansion of the time axis of two signatures in order to match two specimens in such way as to obtain the minimum of a given distance value [14,16,28,29,49,50]. A match among regional correlation, dynamic time warping and skeletal tree matching for signature verification has not shown the superiority

Euclidean Distance	**On-line/Off-line**	**G. Dimauro et al. [14, 15, 19]; R. Sabourin et al [48].**
Elastic matching	**On-line**	**G. Dimauro et al. [14]; R. Plamondon et al [16]; I. Yoshimura [28,29]; B. Wirtz [49]; M. Perizeau and R. Plamondon [50].**
Regional Correlation	**On-line**	**M. Perizeau and R. Plamondon [50].**
Tree Matching	**On-line**	**M. Perizeau and R. Plamondon [50].**
Relaxation Matching	**Off-line**	**K. Huang and H. Yan [39] .**
Split-and-Merge	**On-line**	**Q.Z. Wu et al. [51].**
String Matching	**On-line**	**A. K. Jain et al [52].**
Neural Network	**On-line/Off-line**	**X.-H.Xiao and G. Leedham [38]; R. Sabourin and J.P. Drouhard [40]; H. Cardot et al. [43]; S. Barua [53]; L.Y. Tseng et al. [54]; C. Quek et al. [55].**
HMM	**On-line**	**L. Yang et al. [56, 57]; M. Fuentes et al. [58]; R. Kashi et al [59].**

Table 4. Comparison Techniques

of any of them [50]. Other approaches are based on relaxation matching [39], split-and-merge mechanisms [51] and string-matching [52]. Neural Networks [38,40,43,53,54,55] and Hidden Markov Model [56,57,58,59] have been also widely used for matching. Although neural networks have shown capabilities in generalization, the main drawback of this approach derives from the need of large amounts of genuine and forgery signatures, that are not always available [46]. For this purpose, the use of syntactically generated signatures has also been proposed [47]

5. Handwritten Signature Verification: Open Questions for the Next Future

Notwithstanding the enormous work carried out in the field of signature verification, several questions still remains unresolved. New solutions to these problems will determine the conditions under which the signature verification systems of the next future will be developed.

The selection of the most suitable set of feature for a signer is one of the relevant open questions. Genetic algorithms (GA) have been recently used for this purpose. Xuhua et al. [60] use a genetic algorithm to select the optimal set of the partial curves from a signature and features of each curve. The locations of partial curves and the features contained in the partial curves used for the verification are encoded into the chromosome.

Another promising area of research concerns multi-expert verification. Several approaches have been recently proposed which combine hard [35] or soft [16, 43] decisions. Furthermore, different multi-expert architectures have been proposed based on parallel [16,61], serial [18, 62] or hybrid strategies [63].

Plamondon et al. [16] tries to combine both a parameter and a function approach. They developed a multilevel signature verification system that uses one representation of the signature based on global parameters and two function-based representations.

Cardot et al. [62] proposed a on-line signature verification based on a two-stages serial procedure. The first stage deals with shape-features and it is suitable for fast rejection of poor forgeries. If the signature is not rejected at the first stage, it is fed to the second stage which matches the test and the reference signatures using a dynamic-based distance measure.

Cordella et al. [63] present a hybrid system based on three verification levels. The first and the second level are decision stages, the last level is the decision combination stage. At each decision stage, if the test signature is considered a forgery the verification process stops, otherwise the next stage is activated.

Stroke-based approaches is a specific class of multi-expert systems. Stroke-based verification can lead to lower error rates compared to global approaches, since much personal information is conveyed in specific parts of the signature and cannot be detected when the signature is viewed as a whole [6,12,13,14,15,17,18,19,20,47].

For instance, Dimauro et al. [15] proposed a parallel multi-expert system for signature verification, based on a local verification strategy, which applies spectral analysis on signature components.

Another stroke-oriented verification strategy proposed by Dimauro et al. [18] uses a dynamic segmentation procedure. From the analysis of each reference signature and the test signature, a set of coupled strokes is obtained and, for each of them, a regional threshold is evaluated. The verification process follows a two-level strategy. At the first level, the segmentation results are used to perform a fast rejection of poor forgeries. At the second level, each stroke of the test signature is matched against each corresponding stroke of the reference signatures by an elastic matching procedure and the overall result is used to judge the whole signature.

Di Lecce et al. [64] perform on-line signature verification combining by majority voting the hard decisions provided by three experts. The first expert uses shape-based features and performs signature verification by a wholistic analysis. The second and third experts use speed-based features and perform signature verification by a regional analysis.

Another fundamental problem concerns the analysis of signature stability/variability and of the related aspects, like signature complexity and reproducibility. In fact signature variability is a critical aspect which can significantly affect the performance of a verification system. Two kinds of variability should be considered, in handwritten signatures [65,66,67]:

- Short-time variability depends on the psychological condition of the writer and on the writing conditions;
- Long-time variability depends on modification of the physical writing system of the signer (arm and hand, etc.) as well as on modification of his motor program.

Brault and Plamondon [68] estimate the difficulty in reproducing the signature process. The method derives a model of what a typical imitator must do to copy dynamically any signature. A specific difficulty coefficient is then numerically estimated for a given signature. This coefficient allows an a priori quantitative estimation of the difficulty that could be experience by a typical imitator in reproducing dynamically a particular signature. The basic idea is to divide the task of imitating the signature into several overlapping subtasks. Each subtask concerns the imitation of a singular stroke (angular or curvilinear) of the signature, and consists of three steps performed serially: perception, preparation and execution.

Another work related to variability in dynamic signatures has been proposed by Wu et al. [69]. They present several distortion measurement schemes for dynamic signature verification. The total distortion between two signatures is a combination of both static and dynamic distortions.

Congedo et al. [70] proposed a new approach to measure the stability of signatures by the analysis of local stability in the signing process. A signature stability index is derived from the analysis of deformations among signatures, carried out by multiple comparisons (by elastic matching) between genuine signatures of a writer. Di Lecce et al. [71] use the index of local stability for selecting the best set of genuine signatures, to be considered for reference. From the set of genuine signature available, the subset of signatures which the highest stability correlation is selected. The same approach also allows, for each signer, do define the most profitable function feature in which the signatures are more stable, and consequently more difficult to imitate.

More recently, the degree of stability of a region of the signature has been used to weight the relevance of that region in signature verification. Dimauro et al [72] use the average stability of a stroke to weight the stroke relevance in the process of signature verification. They show that superior results in stroke-oriented verification can be achieved by balancing the decisions obtained at the stroke level according to degree of stability of the strokes.

Finally, performance evaluation of signature verifiers is still an open problem. Although several SVSs have FRR and FAR ranging from 2% to 5% [3], systems developers cannot compare their results due to the lack of a widely accepted protocol for experimental tests, as well as the absence of large, public signature databases [3,4,5].

6. Conclusion

Automatic signature verification is very attractive both from scientific and technological point of view. In this paper the main aspects related to process of signature verification are discussed, with specific attention devoted to the works carried out in the last decade. A useful bibliography is also provided for interested readers.

References

[1] Proc of Workshop on Biometric Authentication - ECCV'02.

[2] G. Pirlo, "Algorithms for Signature Verification", in Fundamentals in Handwriting Recognition, ed. S. Impedovo, Springer Verlag, Berlin, 1994, pp. 433-454.

[3] R. Plamondon, S.N. Srihari, "On-line and off-line handwriting recognition: A Comprehensive Survey", IEEE T-PAMI, , Vol. 22, n. 1, 2000, pp. 63-84.

[4] R. Plamondon (ed.), Progress in Automatic Signature Verification, World Scientific Publ., Singapore, 1994.

[5] B. Wirtz, "Technical Evaluation of Biometric Systems", Proc. of ACCU '98, Hong Kong, 1998.

[6] R.Plamondon and G.Lorette, "Automatic signature verification and writer identification: The state of the art", Pattern Recog. Vol. 22, n . 2 , 1989, pp. 107 131.

[7] F. Leclerc, R.Plamondon, "Automatic signature verification: The state of the art 1989-1993",*IJPRAI*, V.8, n.3, 1994,pp. 643-660.

[8] C.A.Higgins and D.M.Ford, "Stylus driven interfaces-The electronic paper concept", Proc. ICDAR 1991,pp.853-862.

[9] S.Impedovo, L.Ottaviano, S.Occhinegro,"Optical character recognition-A survey",*IJPRAI*,Vol.5,n.1-2,1991, pp. 1-24.

[10] T.Pavlidis, Algorithms for Graphics and Image Processing, Springer Verlag, Berlin, 1982.

[11] N.M.Herbst and C.N.Liu, "Automatic signature verification based on accelerometry", IBM J. Res. and Dev 1977, pp.245-253.

[12] M.Castellano, G.Dimauro, S.Impedovo, G.Pirlo, "On line signature verification system through stroke analysis", in Proc. AFCET, 1990, pp. 47 53.

[13] C. Schmidt, K.-F. Kraiss, "Establishment of personalized templates for automatic signature verification", Proc. ICDAR '97, IEEE Press, pp. 263-267.

[14] G.Dimauro, S.Impedovo, G.Pirlo, "A stroke-oriented approach to signature verification", in From Pixels to Features III - Frontiers in Handwriting Recognition, S. Impedovo and J.C.Simon eds., Elsevier Publ., 1992, pp. 371-384.

[15] G. Dimauro, S. Impedovo, G. Pirlo, "Component-oriented algorithms for signature verification", *IJPRAI*, Vol. 8, n. 3, 1994, pp. 771-794.

[16] R.Plamondon, P.Yergeau and J.J.Brault, "A multi-level signature verification system", in From Pixels to Features III - Frontiers in Handwriting Recognition, S.Impedovo and J.C.Simon eds., Elsevier Publ., pp. 363-370, 1992.

[17] J.J. Brault and R. Plamondon, "Segmenting handwritten signatures at their perceptually important points", IEEE T-PAMI, Vol. 15, n. 9, 1993, pp. 953-957.

[18] G.Dimauro, S.Impedovo and G.Pirlo, "On-line Signature Verification by a Dynamic Segmentation Technique", in Proc. 3th IWFHR, Buffalo, May 1993, pp. 262-271.

[19] G. Dimauro, S. Impedovo, G. Pirlo, "Off-line Signature Verification through Fundamental Strokes Analysis", in Progress in Image Analysis and Processing III, ed. S.Impedovo, World Scientific Publ., 1994, pp.331-337.

[20] M.Ammar, Y.Yoshida and T.Fukumura, "Structural Description and Classification of Signature Images", Pattern Recog., Vol. 23, 7 , 1990, pp. 697-710.

[21] R. Sabourin, R. Plamondon, "Segmentation of Handwritten Signature Images Using the Statistics of Directional Data" , Proc. 9th ICPR, Rome, Italy, Nov. 1988, pp. 282-285.

[22] Y.Sato and K.Kogure, "On-line signature verification based on shape, motion and handwriting pressure", Proc. 6th ICPR, Munich, 1982, vol. 2, pp. 823-826.

[23] Q.-Z.Wu, S.-Y.Lee, I.-C.Jou, "On-line signature verification based on logarithmic spectrum", Pattern Recognition, Vol. 31, No. 12, 1998, pp. 1865-1871.

[24] Y.Mizukami, M.Yoshimura, H.Miike, I.Yoshimura, "An off-line signature verification system using an extracted displacement function", Pattern Recognition Letters,V.23,2002, pp.1569-1577.

[25] G.Lorette and R.Plamondon, "On-line handwritten signature recognition based on data analysis and clustering", Proc. 7th ICPR, Montreal, 1984, vol. 2, pp. 1284-1287.

[26] C.N. Liu, N.M. Herbst and N.J. Anthony, "Automatic Segnature Verification: System Description and Field Test Results", IEEE T-SMC, Vol . 9, 1979, pp. 35-38.

[27] J.S.Lew, "Optimal accelerometer layouts for Data Recovery in Signature Verification", IBM J.Res.Dev., V.24,1980, pp.496-511.

[28] I.Yoshimura and M.Yoshimura, "On-line signature verification incorporating the direction of pen movement-An experimental examination of the effectiveness", in From Pixels to Features III - Frontiers in Handwriting Recognition, S.Impedovo and J.C.Simon eds., Elsevier Publ., pp. 353-362, 1992.

[29] M.Yoshimura, Y.Kato, S.Matsuda and I.Yoshimura, "On-line Signature Verification Incorporating the Direction of Pen Movement", IEICE Transactions, Vol 74,n.7,1991,pp.2083-2092.
[30] H.D.Crane and J.S.Ostrem, "Automatic Signature Verification Using a Three-Axis Force-Sensitive Pen", IEEE T-SMC, Vol. 13, n. 3 , 1983, pp. 329-337.
[31] L.L.Lee, T.Berger, E. Aviczer, "Reliable On-Line Human Signature Verification Systems", IEEE T-PAMI, Vol. 18, n. 6, 1996, pp. 643-647.
[32] W. Nelson, W. Turin and T. Hastie, "Statistical methods for on-line signature verification",*IJPRAI*,v.8,n.3,1994, pp.749-770.
[33] M.Castellano, S.Impedovo, A.Mingolla, G.Pirlo, "A spectral analysis based signature verification system", in Lecture Notes in Computer Science:Recent Issues in Pattern Analysis and Recognition, eds. G. Goos and J.Hartmanis, Springer Verlag, Berlin, 1988, pp. 316 323.
[34] C. F. Lam and D. Kamins, "Signature recognition through spectral analysis", Pattern Recog. 22, 1, 1989, pp. 39-44.
[35] G. Dimauro, S. Impedovo, G. Pirlo, A. Salzo, "A multi-expert signature verification system for bankcheck processing", *IJPRAI*, Vol. 11, n. 5, 1997, pp. 827-844.
[36] W.F.Nemcek and W.C.Lin, "Experimental investigation of automatic signature verification", IEEE T-SMC, Vol. 4, 1974, pp. 121-126.
[37] D. Letjman and S. George , "On-line handwritten signature verification using wavelets and back-propagation neural networks", Proc. of ICDAR '01, Seattle, 2001, pp. 596-598.
[38] X.-H. Xiao, G. Leedham, "Signature Verification by Neural Networks with Selective Attention", Applied Intelligence, Vol .11, 1999, pp. 213-223.
[39] K. Huang, H. Yan, "Off-line signature verification using structural feature correspondence", Pattern Recognition, Vol. 35 , 2002, pp. 2467-2477.
[40] R. Sabourin and J.P. Drouhard, "Off-line signature verification using directional PDF and neural networks", in Proc. of 11th ICPR, 1992, pp.321-325.
[41] H. Baltzakis, N. Papamarkos, "A new signature verification technique based on a two-stage neural network classifier", Engineering Application of AI, Vol. 14 , 2001, pp. 95-103.
[42] R. Sabourin, R. Plamondon, L. Beaumier, "Structural interpretation of handwritten signature images", *IJPRAI*, Vol. 8, 3, 1994, pp.709-748.
[43] H. Cardot, M. Revenu, B. Victorri, M.-J. Revillet, "A Static Signature Verification System based on a cooperative Neural Networks Architecture", *IJPRAI*, Vol. 8, n. 3, 1994, pp. 679-692.
[44] R. Bajaj, S.Chaudhury, "Signature Verification using multiple neural classifiers", Pattern Recogn., Vol.30, No.1, 1997, pp.1-7.
[45] B. Wirtz, "Average Prototypes for Stroke-Based Signature Verification", Proc. ICDAR '97, IEEE Press, pp. 268-272.
[46] J. Kim, J.R. Yu, S.H. Kim, "Learning of prototypes and decision boundaries for a verification problem having only positive samples", Pattern Recognition, Vol.17,1996,pp.691-697.
[47] K. Huang and H. Yan, "Off-line signature verification based on geometric feature extraction and neural network classification", Pattern Recognition,Vol. 30, No.1, 1997, pp.9-17.
[48] R. Sabourin, G. Genesi, F. Preteux, "Off-line Signature Verification by Local Granulometric Size Distributions", IEEE T-PAMI, Vol. 19, n. 9, 1997, pp. 976-988.
[49] Wirtz B., "Stroke-based Time Warping for Signature Verification",Proc.ICDAR 1995,IEEE Press, pp. 179-182.
[50] M. Perizeau and R. Plamondon, "A comparative analysis of regional correlation, dynamic time warping and skeletal tree matching for signature verification", IEEE T-PAMI, Vol. 12, n. 7, 1990, pp. 710-717.
[51] Q.-Z. Wu, S.-Y. Lee, I-C. Jou, "On-line signature verification based on split-and-merge matching mechanism", Pattern Recognition Letters , Vol. 18 , 1997, pp. 665-673.
[52] A.K. Jain, F. D.Griess, S.D. Connell "On-line signature verification", Pattern Recognition, Vol. 35, 2002, pp.2963-2972.
[53] S. Barua, "Neural Networks and their applications to computer security", Proc. SPIE, 1992, pp. 735-742.
[54] L.Y. Tseng and T.H. Huang, "An on-line Chinese signature verification scheme based on the ART1 neural network", Proc. of Int. J. Conf. on NN, Maryland, 1992, pp. 624-630.
[55] C. Quek, R.W. Zhou, "Antiforgery: a novel pseudo-outer product based fuzzy neural network driver signature verification system", Pattern Recognition , Vol. 23 , 2002, pp.1795-1816.
[56] L.Yang, B.K.Widjaja, R.Prasad, "On-line signature verification applying hidden Markov models", in Proc. of 8th Scandinavian Conf. Image Analysis, Tromso, 1993, pp. 1311-1316.
[57] L. Yang, B. K. Widjaja, R. Prasad, "Application of hidden Markov models for signature verification", Pattern Recognition, Vol.28, No. 2, pp.161-170, 1995.
[58] M. Fuentes, S. Garci-Salicetti, B. Dorizzi, "On line Segnature Verification: Fusion of a Hidden Markov Model and a Neural Network via a Support Machine", Proc. of IWFHR-8, Canada, 2002, pp.253-258.
[59] R. Kashi, J. Hu, W.L. Nelson, W. Turin, "A Hidden Markov Model approach to on-line handwritten segnature verification", IJDAR, Vol. 1, 1998, pp. 102-109.
[60] Y.Xuhua, T. Furuhashi, K.Obata, Y. Uchikawa, "Selection of features for signature verification using the genetic algorithm", Computers ind. Eng. , Vol. 30, No. 4, 1996, pp. 1037-1045.
[61] Y. Qi, B.R. Hunt, "A multiresolution approach to computer verification of handwritten signatures", IEEE Trans. Image Processing, Vol. 4, n. 6, 1995, pp. 870-874.
[62] H. Cardot, M. Revenu, B. Victorri, M.J. Revillet, "Cooperation de réseaux neuronaux pour l'autentification de signatures manuscrites", Proc.of Int. Conf. Neuro-Nimes, 1991.
[63] L.P. Cordella, P. Foggia, C. Sansone, F. Tortorella , M. Vento, "A Cascaded Multiple Expert System for Verification", in Multiple Classifier Systems, ed. J.Kittler and F.Roli, LNCS, Springer 2000, pp. 330-339.
[64] V. Di Lecce, G. Dimauro, A. Guerriero, S. Impedovo, G. Pirlo, A. Salzo, "A Multi-Expert System for Dynamic Signature Verification", in Multiple Classifier Systems, eds.J.Kittler and F.Roli, LNCS, Springer 2000, pp.320-329.
[65] R. Plamondon, "A Kinematic Theory of Rapid Human Movements: Part I: Movement Representation and generation", Biological Cybernetics, vol. 72, 4, 1995, pp. 295-307.
[66] R. Plamondon, "A Kinematic Theory of Rapid Human Movements: Part II: Movement Time and Control", Biological Cybernetics, vol. 72, 4, 1995, pp. 309-320.
[67] R. Plamondon, "A Kinematic Theory of Rapid Human Movements: Part III: Kinetic Outcomes", Biological Cybernetics, Jan. 1997.
[68] J.-J. Brault, R. Plamondon, "A complexity Measure of Handwritten Curves: Modeling of Dynamic Signature Forgery",IEEE T-SMC, Vol. 23, no. 2, 1993, pp. 400-413.
[69] Q.-Z. Wu, I-C. Jou, B.-S. Jeng, N.-J. Cheng, S.-S. Huang, P.-Y. Ting, D.-M. Shieh, C.-J. Wen, "On the Distorsion Measurement of On-Line Signature verification", Proc. of IWFHR IV, Taipei, Taiwan, Dec. 7-9, 1994, pp. 347-353.
[70] G. Congedo, G. Dimauro, S. Impedovo, G. Pirlo, "A new methodology for the measurement of local stability in dynamic signatures", Proc. IWFHR IV, Taiwan, 1994, pp. 135- 144.
[71] V.DiLecce,G.Dimauro,A.Guerriero,S.Impedovo,G.Pirlo, A.Salzo, L.Sarcinella,"Selection of Reference Signatures for Automatic Signature Verification",Proc.ICDAR'99,India, 1999, pp. 597-600.
[72] G. Dimauro, S. Impedovo, R. Modugno, G. Pirlo, L. Sarcinella, "Analysis of Stability in Hand-Written Dynamic Signatures", Proc. IWFHR-8, Canada, 2002, pp. 259-263.