Multi Levels Wavelet Decompositions for Off-line Signatures Verification

Rabeb Ben Abdelbaki[#1], Hamid Amiri[#2]

[#] *Signal, Image and Information Technologies*
National Engineering School of Tunis
Tunis, Tunis-Belvedere, Tunisia
[1]rabeb.benabdelbaki@gmail.com
[2]hamid.amiri@enit.rnu.tn

Abstract— **The recognition of persons based on biometric measurements has become a very active area of research especially in the financial sector. In this paper, we focus on the problem of off-line signature verification and skilled forgeries detection. We propose a novel approach based on two levels wavelet decomposition for characterizing signatures. We have preceded to different multi levels wavelet decomposition combinations to determine the best decomposition levels and the adequate mother wavelet in order to enhance signatures characterization. The performance of the proposed approach has been proved using SigWiComp2013 database and Artificial Neural Networks (ANN) classifier.**

Keywords— Off-line; signature verification; skilled forgeries; Discrete Wavelet Transform; ANN.

I. INTRODUCTION

Biometry is a well developed technique allowing human recognition basically on what they own. In fact, biometry represents a novel aspect of traditional identification methods such as logins, passwords, and access cards which could be forgotten or stolen. Biometry offers novel strategies for human recognition based on unchangeable personal features. Biometric measures can be classified to two categories: physiological, e.g. palm print, finger print, iris pattern, etc. and behavioural, e.g. speech and handwriting.

Handwritten signatures verification is a behavioural biometric verification and one of the most widely accepted personal attributes for identity verification. As a symbol of consent and authorization, especially in the prevalence of credit cards and bank checks, handwritten signatures are commonly used to approbate the contents of a document or to authenticate a financial transaction. Therefore, handwritten signature has long been the target of fraudulence.

In reality, signature verification process is usually done by visual inspection. A person compares the appearance of two signatures and accepts the given signature if it is sufficiently similar to the stored signature, for example, on a credit card. In the majority of situations where a signature is required, no verification takes place at all due to the amount of time and effort that would be required to manually verify signatures. Automating the signature verification process will improve the current situation and eliminate fraud. Therefore, with the growing demand for processing of individual identification faster and more accurately, the design of an automatic signature verification system faces a real challenge.

Handwritten signatures are of different shapes and sizes and the variations in them are so immense that it is difficult for a human being to distinguish a genuine signature from a forged one by having a glance at the signature. In fact, many factors influence handwritten signatures such as stress, behaviour, writing position, age, and cause different natures of variations; inter-personal and intra-personal variations as well as time dependency variation. Due to huge variability of signing, forgeries can be classified to three types: random forgery, simple forgery and skilled forgery [1], [2], [3].

The main objective of a signature verification system is to exploit the singular and personal character of writing in order to extract a set of least variable features able to distinguish genuine signatures from forgeries [15], [28]. This kind of system should verify that what has been signed corresponds to the unique characteristics of an individual.

The signature verification problem can be categorized into on-line and off-line. In general, online systems achieve better performance since they can count on dynamic features such as, time, pressure, and speed, which can be easily obtained from an electronic tablet. In offline systems, image of a signature written on a paper is obtained through a scanner so dynamic information are not available. The signature verification system has to rely only on features that can be extracted from the trace of the static signature image describing only signatures geometry making the verification task more complicated.

In the following, we are interested to offline handwritten signatures which still represent an active research axis, motivating several researchers to invest in it in order to minimize the error rates which remain relatively high compared to the importance of the issue in question [4], [5], [6].

In this paper, we present our contribution to handwritten signatures verification based on the principle of signatures characterization using the multi wavelet decompositions. We propose also a verification approach based on the classic wavelet decomposition. The second approach is used as a validation approach for our handwritten signatures contribution. Several experiments have been tested in order to determine the best combination of levels decomposition and mother wavelet enhancing signatures characterization and

given the best signatures verification rate. ANN was used to perform both validation and proposed approaches. The recorded results show the efficiency of taking into account the local information offered by the multi wavelet decompositions.

The remaining of the paper is organized as follows: Section 2 proposes an overview of the handwritten signatures verification previous works. Section 3 presents our proposed approach for modelling signatures. Section 4 reports experiment results obtained using SigWiComp2013 database. Finally, conclusions and future work are presented in section 5.

II. RELATED WORKS

An easy way to comply with the conference paper formatting requirements is to use this document as a template and simply type your text into it.

For many decades, a lot of researches have been conducted on off-line signature verification and many approaches have been proposed in order to solve this problem. Nevertheless, off-line signature verification stills an actual problem aiming to provide an automatic biometric behavioural secure authentication system.

In the recent literature, signature verification approaches can be classified in two categories: writer-dependent and writer-independent. When writer-dependent approaches are used, a specialized classifier is trained for each writer. The writer-independent approach uses a single classifier for all writers, which is trained using genuine and forged specimens of the entire population of individuals considered for training. In this paper, we focused on writer- dependant approach.

Diverse researches are based on global features extraction to characterize signatures in a global way [7], [8], [9], [10], [11], [12], [13]. A large set of global features are calculated from the whole signatures images such as area, perimeter, height, width, aspect ratio, circularity, convex surface, etc.

Some others researches have focused on the analysis of signatures at the local level in order to extract local features able to characterize signatures details. Those parameters describes local and topological features of signatures strokes which can lead to lower error rate compared to global strategies, since they focused on the extraction of personal information located in specific parts of the signatures (component level or pixel level). Derived from pixels distribution, researchers proposed diverse component-oriented features such as stroke distribution, stoke orientation, slant orientation, relative positions of stokes, etc. We can find also pixel-oriented features such as grid-based information, pixel density, gray-level intensity, etc.) [12], [14], [15], [16], [17], [18].

In other cases, to solve signatures verification problem, researchers have used structural descriptors such as graph-based methods, tree-based methods as well as directional coding methods [15] [19] [20] [21]. However, signatures characterization using structural descriptors have not been very successful compared to statistical descriptors which have been widely used in the literature for the signatures' modelling thanks to their power to represent shapes such as moment descriptors [17], [22], fractal dimension [23], [24] or

transformation-based methods which offers a new shape's representation in the frequency domain. Among these descriptors, we find, in literature, Fourier, Wavelet and Contourlet Transforms used to characterize offline signatures [8], [25], [26], [27], [28], [29].

Another classification of the literature survey can be done based on signatures classification methods which differ from an approach to another. Indeed, the performance of offline signatures verification systems depends on measures used to characterize signatures. However, to propose an efficient verification system, we had to implement a reliable and performing classification module. Basically, researchers used Dynamic Time Warping (DTW) [30], [31], Hidden Markov Models (HMM) [32], [33], Support Vector Machine (SVM) [7], [14], [32] and ANN [7], [12], [13], [34], [35], [36].

III. PROPOSED APPROACH

Based on the literature overview, we note that the use of wavelets as a shape descriptor is very efficient compared to other signatures verification methods. Although, we find that wavelet descriptor is not sufficiently exploited, wavelet properties can provide a considerable boost for a discriminating representation in favour of signatures verification.

In fact, signatures are considered as a spontaneous and complicated writing, so it is interesting to use Discrete Wavelet Transform (DWT) to represent them at different resolutions, in order to characterize signatures by decomposing them into several information elements often simpler to interpret in order to analyze signatures details. However, wavelet decomposition is considered as a global descriptor, presenting only the global aspect of signatures without detecting local information which highlights signatures particularities.

Based on this statement, rests the principle of our approach which relies on multi discrete wavelet decompositions of offline handwritten signatures. Thus, we purpose a textural characterization at two different stages of decomposition. Our idea is to apply a first wavelet decomposition at the most general level; it is the level "1" which offers a global view of the considered shape, followed by second wavelet decomposition at an "n" level to be determined. In fact, we aim to increase the pertinence of the first wavelet decomposition primitive's vector using the second primitive vector issued from the second wavelet decomposition at level "n".

The benefit of the second wavelet decomposition is to provide a more detailed view allowing access to increasingly accurate representations of a given signature. In fact, at this level, we can extract signatures singularities present in the different sub-bands of wavelet decomposition in order to enhance signatures modelling process.

To ensure optimal verification of offline handwritten signatures, we had to determine the appropriate mother wavelet as well as the apt level of decomposition of the second wavelet Transform. The choice of adequate

combination is performed on the basis of several experiments, varying mother wavelets and decompositions' levels.

A. Pre-processing

Input signatures images are pre-processed in three consecutive stages. Each signature image is converted from RGB colour into gray level image. A size normalization step is then proceeded in order to fix the images sizes. As well as, a noise reduction process is applied using the median filter.

B. Features Extraction

The choice of discriminative features set is a crucial step for signature verification system. Due to its powerful and ability to describe signals, DWT and a reduction method are applied in this step as a shape descriptor to extract the features needed for the verification step.

Orthogonal wavelets transform have recently become a popular representation for multi-scale signal and image analysis. It enables us to have an invariant interpretation of a signature image at different resolutions, and presents a multi-resolution analysis in the form of coefficient matrix. Since the detail of a signature image at different resolutions generally characterizes different physical structures of the signature, coefficients obtained from a wavelet transform can be very useful in verification. However, in spite of their effectiveness, the 8 sub bands signatures representation drawback, based on multi levels wavelet decomposition, is their lack of statistical information.

Literature offers several statistical features used in features reduction (mean, entropy, standard deviation, mean error, energy, etc.). Although, to reduce the number of wavelet parameters, we have only retained mean and standard deviation of the approximation coefficients as well as mean and standard deviation of the other three matrixes of details coefficients for each wavelet level decomposition.

Based on this approach, the characteristic vector relative to a tested signature is composed of:

$V=(moyAPP_1,\ moyDH_1,\ moyDV_1,\ moyDD_1,\ moyAPP_n,\ moyDH_n,\ moyDV_n,\ moyDD_n,\ ectAPP_1,\ ectDH_1,\ ectDV_1,\ ectDD_1,\ ectAPP_n,\ ectDH_n,\ ectDV_n,\ ectDD_n).$

With:

- $moyAPP_1$: mean of the approximation sub-band relative to decomposition at level 1.
- $moyDH_1$: mean of the horizontal detail sub-band relative to decomposition at level 1.
- $moyDV_1$: mean of the vertical detail sub-band relative to decomposition at level 1.
- $moyDD_1$: mean of the diagonal detail sub-band relative to decomposition at level 1.
- $moyAPP_n$: mean of the approximation sub-band relative to decomposition at level n.
- $moyDH_n$: mean of the horizontal detail sub-band relative to decomposition at level n.
- $moyDV_n$: mean of the vertical detail sub-band relative to decomposition at level n.
- $moyDD_n$: mean of the diagonal detail sub-band relative to decomposition at level n.

- $ectAPP_1$: standard deviation of the approximation sub-band relative to decomposition at level 1.
- $ectDH_1$: standard deviation of the horizontal detail sub-band relative to decomposition at level 1.
- $ectDV_1$: standard deviation of the vertical detail sub-band relative to decomposition at level 1.
- $ectDD_1$: standard deviation of the diagonal detail sub-band relative to decomposition at level 1.
- $ectAPP_n$: standard deviation of the approximation sub-band relative to decomposition at level n.
- $ectDH_n$: standard deviation of the horizontal detail sub-band relative to decomposition at level n.
- $ectDV_n$: standard deviation of the vertical detail sub-band relative to decomposition at level n.
- $ectDD_n$: standard deviation of the diagonal detail sub-band relative to decomposition at level n.

C. Classification

To evaluate the verification system, we opted to adopt ANN classifier due to its ability to imitate human perception and generate a system similar to human brain, able to detect singularities and discriminate authentic signatures from forgeries. ANN is distinguished from the other classifiers especially by their power of learning and generalization.

Based on the writer-dependant approach, we assign an ANN classifier for each database's writer. The verification process was performed in two phases. The training phase trains the ANN model with a signature training set, containing 70% of the writer's sample (109 signature images). The test phase validates the constructed ANN model with a signature test set containing 30% of the presumed writer's sample (46 signature images).

D. Database

The signature database used comes from Signature Verification and Writer Identification Competitions for On and Off-line Skilled Forgeries (SigWiComp2013)", in *Proc. of the 12th International Conference on Document Analysis and Recognition (ICDAR) 2013*. The dataset includes both online and offline signatures of which we only use the offline signatures for Dutch signers. The dataset is split into a training set and testing set of no overlapping IDs. The Dutch training set contains data from the SigComp2009 and the SigComp2011Competitions. In this work, we treated only signatures from SigComp2009 Dutch data which includes a total of 1860 images for 12 signers (IDs), with about 5 genuine signatures and 150 forged signatures for each ID [37].

We decided to classify the Dutch signatures dataset used to perform the proposed system into 3 categories: cursive signatures, semi-cursive signatures and graffiti signatures.

IV. EXPERIMENTAL RESULTS

To proof the efficiency of using wavelet transform at two different levels and doping wavelet decomposition primitives vector by the second wavelet decomposition at an "n" level, we choose to verify offline handwritten signatures firstly using the classic wavelet transform to make sure that our idea

based on two levels decomposition is better than application of basic wavelet transform. Same process is applied to the validation and proposed approach.

To determine adequate discrete mother wavelet, belonging to Daubechies, and appropriate levels of wavelet decomposition, we have implemented all possible combinations (mother wavelet, decomposition levels) able to characterize signatures and enhance correct verification rate.

For verification, a verification model is implemented for each database signer, based on writer-dependent approach's principle. ANN was used to classify authentic signatures from skilled forgeries. The performance of the verification systems is evaluated by the Confusion Matrix (CM) and the Correct Verification Rate (CVR).

Authentic Signatures classified as Authentic (AS_A)	Authentic Signatures classified as Forged (AS_F)
Forged Signatures classified as Authentic (FS_A)	Forged Signatures classified as Forged (FS_F)

Fig. 1 Confusion matrix

We have chosen a writer for each type of signatures present in the SigWiComp2013 database to test the verification performance of our proposed approach in order to determine the appropriate mother wavelet as well as the best decomposition levels leading to an optimal good verification rate. The first signer represents a sample of cursive signatures; the second writer shows a sample of semi-cursive signatures and the third scripter belongs to the graffiti signatures.

TABLE I
CORRECT VERIFICATION RATE DEPENDING ON WAVELET DECOMPOSITION'S NATURE RELATED TO MOTHERS WAVELET "DB1", "DB2", "DB3"

Filter	Signer 1					
	i=1 (Db1)		i=2 (Db2)		i=3 (Db3)	
	CM	CVR (%)	CM	CVR (%)	CM	CVR (%)
Dbi(1)	1 0 / 2 43	95,65	1 0 / 3 42	93.47	1 0 / 1 44	97.82
Dbi(2)	1 0 / 1 44	97,82	1 0 / 1 44	97,82	1 0 / 1 44	97,82
Dbi(3)	0 1 / 0 45	97,82	0 1 / 1 44	95,65	0 1 / 1 44	95,65
Dbi(4)	1 0 / 1 45	97,82	0 1 / 0 45	97,82	0 1 / 0 45	97,82
Dbi(5)	0 1 / 0 45	97,82	0 1 / 3 42	91,30	1 0 / 3 42	93,47
Dbi(6)	1 0 / 4 41	91.30	0 1 / 1 44	95,65	1 0 / 3 42	93,47
Dbi(1,2)	1 0 / 1 45	97,82	1 0 / 1 44	97,82	1 0 / 1 44	97,82
Dbi(1,3)	1 0 / 0 45	100	1 0 / 0 45	100	1 0 / 1 44	97,82
Dbi(1,4)	1 0 / 1 44	97,82	1 0 / 0 45	100	1 0 / 1 44	97.82
Dbi(1,5)	1 0 / 1 44	97,82	1 0 / 0 45	100	1 0 / 0 45	100
Dbi(1,6)	1 0 / 3 42	93,47	1 0 / 1 44	97,82	1 0 / 1 44	97,82

Table I presents correct verification rates' distributions depending on wavelet decomposition's nature, mother wavelet and decompositions' levels of the two presented approaches. Indeed, we have chosen to vary the types of mother wavelets as well as the decompositions levels in order to study the impact of these two factors on signatures verification and to determine the best combination given the optimal correct verification rate. We notice efficiency and performance of our proposed approach based on doping multi levels wavelet decompositions compared to the validation approach based on the classic wavelet decomposition. The correct verification rates reached by our proposed approach are better than the validation approach and reaches 100% for some combinations of mother wavelets and decomposition levels : *Db1(1,3), Db2(1,3), Db2(1,4), Db2(1,5), Db3(1,5)*.

By analyzing results obtained by the proposed approach, we find that the verification system succeeds in differentiating authentic signatures from forgeries. Indeed, it recognizes authentic signatures in all multi wavelet decompositions combinations which proof the discriminatory power of the proposed approach. So, we have decided to perform signatures verification for the different database's writers based on the Multi wavelet decomposition approach.

TABLE II
CORRECT VERIFICATION RATE DEPENDING ON MOTHER WAVELET NATURE AND LEVELS OF DECOMPOSITIONS RELATED TO SIGNER 2 AND SIGNER 3

Filter	Signer 2		Signer 3	
	CM	CVR (%)	CM	CVR (%)
Db1(1,2)	0 1 / 0 45	97,82	0 1 / 0 44	97,82
Db1(1,3)	0 1 / 0 45	97,82	0 1 / 2 43	93,47
Db1(1,4)	0 1 / 0 45	97,82	0 1 / 1 44	95,65
Db1(1,5)	0 1 / 1 44	95,65	0 1 / 0 45	97,82
Db1(1,6)	0 1 / 0 45	97,82	0 1 / 0 45	97,82
Db2(1,2)	0 1 / 0 45	97,82	0 1 / 1 44	95,65
Db2(1,3)	0 1 / 0 45	97 ,82	0 1 / 0 45	97,82
Db2(1,4)	0 1 / 0 45	97,82	0 1 / 0 45	97,82
Db2(1,5)	0 1 / 0 45	97,82	1 0 / 0 45	100
Db2(1,6)	1 0 / 0 45	100	1 0 / 0 45	100
Db3(1,2)	0 1 / 1 44	95,65	0 1 / 0 45	97,82
Db3(1,3)	0 1 / 0 45	97,82	0 1 / 2 43	93,47
Db3(1,4)	0 1 / 0 45	97,82	0 1 / 1 44	95,65
Db3(1,5)	0 1 / 0 45	97,82	0 1 / 0 45	97,82
Db3(1,6)	1 0 / 0 45	100	1 0 / 0 45	100

Table II represents the distribution of correct verification's rates according to the Daubechies mother wavelet's type and the levels of decomposition related to the second and third scripter.
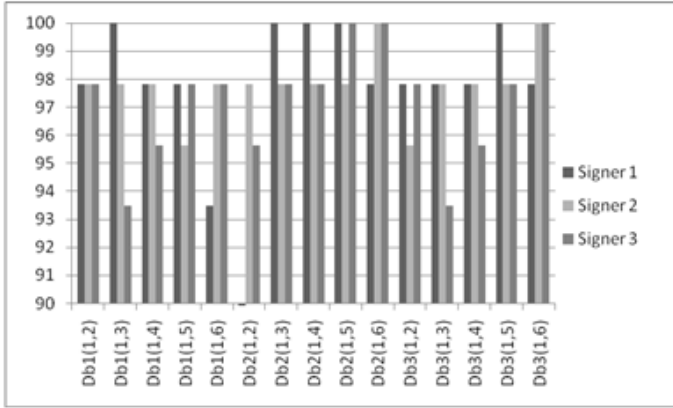

Fig. 2 Correct verification rate depending on mother wavelets used and multi decompositions' levels applied for the second and third database's signer

We note that the proposed system achieves 100% of correct verification rate using *Db2(1,6)*, *Db3(1,6)* for both the second and third writer, which incites us to keep this two combinations of multi levels wavelet decompositions. We notice also that the system achieves 100% using *Db2(1,5)* for both the first and third database's writer, so we keep also this decomposition combination.

TABLE III
CORRECT VERIFICATION RATE DEPENDING ON THE SELECTED COMBINATIONS OF MOTHER WAVELETS AND DECOMPOSITION LEVELS RELATED TO THE REMAINING DATABASE'S SIGNERS

Signers	Db2(1,5)		Db2(1,6)		Db3(1,6)	
	CM	CVR (%)	CM	CVR (%)	CM	CVR (%)
Signer 4	1 0 0 45	100	1 0 3 42	93.47	1 0 1 44	97.82
Signer 5	1 0 1 44	97,82	1 0 1 44	97,82	1 0 1 44	97,82
Signer 6	0 1 0 45	97,82	0 1 1 44	95,65	0 1 1 44	95,65
Signer 7	1 0 2 43	95,65	0 1 1 44	95,65	0 1 1 44	95,65
Signer 8	0 1 0 45	97,82	0 1 2 43	93,47	1 0 3 42	93,47
Signer 9	1 0 4 41	91.30	0 1 1 44	95,65	1 0 3 42	93,47
Signer 10	1 0 0 45	100	1 0 1 44	97,82	1 0 1 44	97,82
Signer 11	1 0 0 45	100	1 0 0 45	100	1 0 2 43	95,65
Signer 12	1 0 1 44	97,82	1 0 0 45	100	1 0 0 45	100

Table III represents the distribution of correct verification's rates according to the selected decompositions combinations related to the remaining database's scripter. In fact, the behaviour of the verification system differs from a signer to another among to signatures types and the applied decomposition combination.

TABLE IV
CORRECT VERIFICATION RATE OF THE PROPOSED APPROACH USING THE SELECTED MULTI DECOMPOSITION COMBINATIONS

Multi Wavelet decomposition using	Db2(1,5)	Db2(1,6)	Db3(1,6)
Correct Verification Rate CVR (%)	98,004	97,27	97,09

Table IV shows the mean correct verification rates reached by the proposed system using the selected multi decomposition combinations for all database's signers.

V. CONCLUSION

A novel offline signatures verification approach has been proposed in this paper. A multi decompositions wavelet-based method has been applied and the doping of multi levels extracted primitives in order to enhance signatures characterization.

The best correct verification rate achieved using *Db2(1,5)* multi levels decomposition is 98,004%. This rate is better than results performed in [38], [39], [40] which achieved respectively 95,95%, 91,12% and 92,96%.

REFERENCES

[1] M. El Yassa, D. Mammass, A. Chalifour and F. Nouboud, " Etat de l'art sur la vérification Off-line de signatures manuscrites," in *Conf. Inter. : Sciences, Electroniques, Technologie de l'Information et des Télécommunications*, Sousse, Tunisie, Mar. 17-21 2003.
[2] J.Fierrez-Aguilar, J.Ortega-Garcia and J.Gonzalez Rodriguez, "Target Dependent Score Normalisation Techniques and their Applications to Signature Verification, " *ICBA 2004*, LNCS 3072, pp.498-504, Berlin Heidelberg 2004.
[3] M. Arathi, A. Govardhan, " An Efficient offline Signature Verification System, " *International Journal of Machine Learning and Computing*, Vol. 4, No. 6, Dec. 2014.
[4] M. C. Fairhurst, "Signature verification revisited: Promoting practical exploitation of biometric technology," *Inst. Elect. Eng. Electron. Commun. Eng. J. (ECEJ)*, vol. 9, no. 6, pp. 273–280, Dec. 1997.
[5] M. C. Fairhurst and E. Kaplani, "Perceptual analysis of handwritten signatures for biometric authentication," *Inst. Elect. Eng. Proc. Vis., Image Signal Process.*, vol. 150, no. 6, pp. 389–394, Dec. 2003.
[6] 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.
[7] E. Özgündüz, T. Şentürk and M. E. Karslıgil, "Offline signature verification and recognition by Support Vector Machine," in *Eusipco-2005*, 4-8 Sep. 2005, Antalya, Turkey, pp. 113-116.
[8] S. Biswas, T. Kim and D. Bhattacharyya, "Features extraction and verification of signature image using clustering technique," in *International Journal of Smart Home*, Vol.4, No.3, Jul. 2010
[9] H. Baltzakis and N. Papamarkos, "A new signature verification technique based on a two-staged neural network classifier," in *Engineering Applications of Artificial Intelligence*, 2001, pp 95-103.
[10] Y. Qi and B. R. Hunt, "Signature verification using global and grid features," in *Pattern Recognition 1994*, 27(12), 1621-1629.
[11] B. Kovari, B. Toth, H. Charaf, "Classification approaches in off-line handwritten signature verification," *WSEAS TRANSACTIONS on MATHEMATICS*, Issue 9, Volume 8, Sep. 2009.
[12] K. Huang and H. Yan, "Off-line signature verification based on geometric feature extraction and neural network classification," *Pattern Recognition*, Vol. 30, No.1, pp. 9-17, 1997.

[13] R. Bajaj and S. Chaudhury, "Signature Verification using multiple neural classifiers," *Pattern Recognition*, Vol. 30, no. l, 1997.

[14] J. F. Vargas, M. A. Ferrer, C. M. Travieso and J. B. Alonso, "Offline signature verification based on pseudo-cepstral coefficients," in *Proc. of the 10th Int. Conference on Document Analysis and Recognition ICDAR '09*, Barcelona, Spain, 26-29 Jul. 2009, pp. 126 – 130.

[15] I.A. Ibrahim, "Offline signature verification using graph matching," *Turk. J. Elec. Engin. TÜBITAK*, 15 (1), pp. 89–104, 2007.

[16] S. Wilkinson and W. Goodman, "Slope Histogram Detection of forged handwritten signatures," in *High-Speed Inspection Architectures, Barcoding, and Character Recognition*, 1990.

[17] H. Lv, W. Wang, C. Wang and Q. Zhuo, "Off-line chinese signature verification based on support vector machines," *Pattern Recognition Lett.*, vol. 26, pp. 2390–2399, 2005.

[18] B. Kovari and H. Charaf, "A study on the consistency and significance of local features in off-line signature verification," *Pattern Recognition Lett.*, vol. 34, pp. 247–255, 2013.

[19] H. Lv, X. Bai, W. Yin and J. Dong, "Offline signature verification using graphical model," in *Proc. ICPR*, Istanbul, Turkey, pp. 3784-3788, 2010.

[20] G. Dimauro, S. Impedovo and G. Pirlo, "Component oriented algorithms for signature verification," in *Int. J. Pattern Recognit. Artif. Intell. IJPRAI*, vol. 8, no. 3, pp. 771–794, 1994.

[21] H. Zhang, H. Shu, P. Haigron, L. Luo and B. Li, " Construction of a complete set of orthogonal Fourier-Mellin moment invariants for pattern recognition applications," *Image and Vision Computing*, vol. 28, iss. 1, Jan. 2010.

[22] K. R. Radhika, M. K. Venkatesha and G. N. Sekhar, "Off-line signature authentication based on moment invariants using support vector machine", *Journal of Computer Science*, vol. 6, no. 3, pp. 305-311, 2010.

[23] M. Radmehr, S. M. Anisheh, M. Nikpour and A. Yaseri, "Designing an offline method for signature recognition," *World Applied Sciences Journal*, vol. 13 (3), pp. 438-443, ISSN 1818-4952, 2011.

[24] A. Foroozandeh, Y. Akbari, M. J. Jalili and J. Sadri, "Persian signature verification based on fractal dimension using testing hypothesis," in *International Conference on Frontiers in Handwriting Recognition*, 2012.

[25] G. Congedo, G. Dimauro, S. Impedovo and G. Pirlo, "Offline signature verification by fundamental components analysis," in *Proc. 7th Int. Conf. Image Anal. Process. (ICIAP-7), Progr. Image Anal. Process. III*, S. Impedovo, Ed. Monopoli, Italy: World Scientific, Sep. 1993, pp. 331–337.

[26] G. Dimauro, S. Impedovo, G. Pirlo and A. Salzo, "A multi-expert signature verification system for bank check processing," in *Int. J. Pattern Recognit. Artif. Intell. IJPRAI*, vol. 11, no. 5, pp. 827–844, 1997.

[27] V. E. Ramesh and M. N. Murty, "*Offline signature verification using genetically optimized weighted features*," Pattern Recognition, vol. 32, no. 2, pp. 217–233, Feb. 1999.

[28] D. K. McCormack, B. M. Brown and J. F. Pedersen, "Neural network signature verification using haar wavelet and Fourier transforms," in *Proc. SPIE*, vol. 2064, pp. 14–25, Aug. 1993.

[29] M. Yang, Z. Yin, Z. Zhong, S. Wang, P. Chen and Y. Xu, "A contourlet-based method for handwritten signature Verification," in *International Conference on Automation and Logistics*, Jinan, pp. 1561–1566, August 2007.

[30] Y. Chen and X. Ding, "Sequence-matching-based feature extraction with applications to signature verification," in *Proc. SPIE*, vol. 5676, pp. 76–83, Jan. 2005.

[31] B. Wirtz, "Stroke-based time warping for signature verification," in *Proc. 3rd Int. Conf. Doc. Anal. Recognit. ICDAR-3*, Montreal, QC, Canada, Aug. 1995, vol. 1, pp. 179–182.

[32] M. A. Ferrer, J. B. Alonso and C. M. Travieso, "*Offline geometric parameters for automatic signature verification using fixed-point arithmetic*", IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 27, No. 6, June 2005.

[33] J. Coetzer, B. M. Herbst and J. A. Du Preez, "Offline signature verification: A comparison between human and machine performance," in *10th Int. Workshop Front. Handwriting Recognit. IWFHR 01*, La Baule, France, Oct. 2006.

[34] H. Baltzakis, N. Papamarkos, "*A new signature verification technique based on a two-staged neural network classifier*," Engineering Applications of Artificial Intelligence, 2001, vol. 14, pp 95-103.

[35] G. Rigoll and A. Kosmala, "A systematic comparison between on-line and offline methods for signature verification with hidden Markov models," in *14th International Conference on Pattern Recognition*, 1998, pp. 1755–1757.

[36] S. Srihari, A. Xu and M. Kalera, "Learning strategies and classification methods for offline signature verification", in *Proceedings of the 9th International Workshop on Frontiers in Handwriting Recognition*, 2004, pp. 161–166.

[37] M. I. Malik, M. Liwicki, L. Alewijnse , W. Ohyama, M. Blumenstein and B. found, " ICDAR2013 Competitions on Signature Verification and Writer Identification for On and offline Skilled Forgeries (SigWiComp2013)," in *12th International Conference on Document Analysis and Recognition ICDAR*, 2013.

[38] M. A. Abdala and N. A. Yousif, "*Offline signature recognition and verification based on artificial neural*," Network Eng & Tech. Journal, Vol.27, No.7, 2009.

[39] S. Armand, M. Blumenstein and V. Muthukkumarasamy, "Off-line signature verification based on the modified direction feature," in *The 18th IEEE International Conference on Pattern Recognition ICPR'06*, 2006.

[40] T. Ito, W. Ohyama, T. Wakabayashi and F. Kimura, "Combination of signature verification techniques by SVM," in *International Conference on Frontiers in Handwritten Recognition ICFHR*, 2012.