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Writer-Independent Handwritten Signature Verification based on One-Class SVM Classifier

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Abstract— **The limited number of writers and the lack of forgeries as counterexample to construct the systems is the main difficulty task for designing a robust off-line Handwritten Signature Verification System (HSVS). In this paper, we propose to study the influence of writer's number using conjointly the curvelet transform and the One-Class Support Vector Machine (OC-SVM), which takes in consideration only genuine signatures. The design of the HSVS is based on the writer-independent approach. Experimental results conducted on the standard CEDAR and GPDS datasets demonstrate that the proposed method allows achieving the lowest Average Error Rate with a limited number of writers.**

Keywords— ***One-class support vector machines, hard and soft threshold, signature verification, curvelet transform.***

I. INTRODUCTION

Biometric recognition is described as an automatic identification of an individual person. Hence, several biometric modalities have been proposed in the last decades, which are based on physiological and behavioral characteristics depending on their nature. Physiological characteristics are related to anatomical properties of a person, and include for instance face, fingerprint, iris and hand geometry. Behavioral characteristics refer to how a person performs an action, and include typically voice, signature and gait. Hence, the choice of a biometric modality depends on several factors such as non universality, non permanence, intra-class variations, poor image quality, noisy data and matcher limitations [1], [2], [3].

Handwritten signature occupy a very special place in this wide set of biometric traits. This is mainly due to the fact that handwritten signature have long been established as the most wide spread means of personal verification. Signatures are generally recognized as a legal means of verifying an individual's identity by administrative and financial institutions. Moreover, verifying by signature analysis requires no invasive measurements and people are familiar with the use of signature in their daily life [4].

The handwritten signature can be verified using two acquisition modes: the online mode and the off-line mode. The design of the handwritten signature verification systems (HSVS) based on the off-line is more difficult comparatively to the online mode since many desirable characteristics as the velocity, the pressure and so on are not available during the acquisition. The offline signature verification system depends only on the feature selected from the signature image [5].

Generally, an offline HSVS is composed of three stages: acquisition, preprocessing, feature generation and classification [6]. In this work, we are interested on the classification stage where many methods have been developed in the last decades such as Template Matching, the Statistical Models as the Neural Networks and the Hidden Markov Models, and the Structural Models [5] as the Binary Class Support Vector Machines (Bi-SVM) [6]. More recently, the One-Class Support Vector Machine (OC-SVM) has been used for the offline signature verification, which has proved its efficiency comparatively to the Bi-SVM [7].

Usually, two approaches are used for verifying a handwritten signature, which are based on writer-dependent and writer-independent [8]. The first approach consists to select parameters for each writer during the construction of the signature model. Although this approach allows providing less error, however, it requires selecting at each time the parameters of the classifier. This problem is solved by the second approach where it does not need to recompute the parameters for a new writer. This approach consists to find the optimal parameters of the system by using a set of writers through training, validation and testing their signatures. When a new writer is added to the system, no parameters are found. Therefore, a few samples of signatures are sufficient for generating its model. Indeed, the validation step is not performed which makes the system more flexible. Indeed, this approach assumes that all users have the same parameters [9], which can be considered as writer-independent handwritten signature verification.

We propose, in this paper, a design of the writer-independent (WI) HSVS by using conjointly the curvelet transform and the OC-SVM, which takes into consideration only genuine signatures for constructing the signature model. Using only genuine signatures are occurred for example in the bank. Indeed, when a new client is enrolled in the bank, she/he asked to supply only the genuine signature samples. Hence, the WI-HSVS design is nowadays a crucial challenge when considering only genuine signatures in the context of the WI. Furthermore, the second problem relies on the required number of writers for generating an efficient HSVS. Hence, we discuss in this paper the performance of the WI-HSVS when reduced signatures are available.

The remaining of this paper is organized as follows. Section 2 briefly reviews One-Class Support Vector Machine. Section 3 presents the design of HSVS. Section 4 reports all the experiments performed on CEDAR and GPDS datasets. Finally, the conclusion is presented in the last section.

II. Review of One-Class Support Vector Machine

One-Class SVM (also known as single-class classification or novelty detection) is a learning algorithm developed by Schölkopf [10]. One-class classification allows classifying just one-class objects, and distinguishing it from all other possible objects. Objects can be classified well by the classifier, but the others will be classified as outliers [5].

The concept of the OC-SVM consists to find a hyper sphere in which the most of learning data are included into a minimum volume. More specifically, the objective of the OC-SVM is to estimate a function $f_{oc}(x)$ that encloses the most of learning data into a hyper sphere $R_x = \{x \in R^d \setminus f_{oc}(x) > 0\}$ with a minimum volume where d is the size of feature vector [11]. $f_{oc}(x)$ is the decision function, which takes the following form [4]:

$$f_{oc}(x) = sgn\{\sum_{i=1}^{m} \alpha_i \ K(x, x_i) - \rho\} \quad (1)$$

m is the number of training data and α_i are the Lagrange multipliers computed by optimizing the following equations:

$$\min_\alpha \left\{\frac{1}{2} \alpha_i \alpha_j K\left(x_i, x_j\right)\right\} \quad (2)$$

Subject to

$$0 \leq \alpha_i \leq \frac{1}{\nu m} \quad (3)$$

$$\sum_i^m \alpha_i = 1 \quad (4)$$

ρ defines the distance of the hyper sphere from the origin. ν is the percentage of data considered as outliers. $K(.,.)$ defines the OC-SVM kernel that allows projecting data from the original space to the feature space [12].

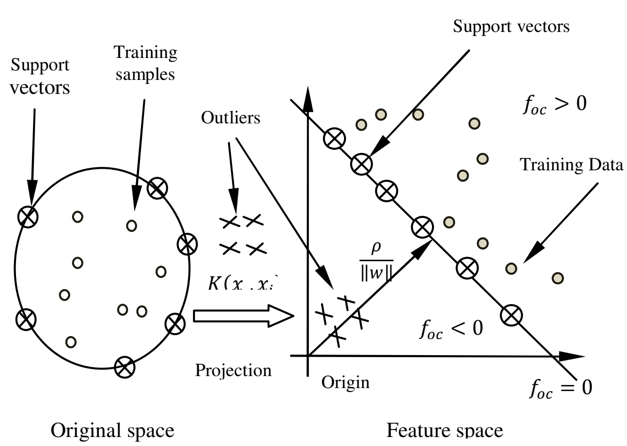


Fig. 1. Data classification based on OC-SVM

A pattern x is then accepted when $f_{oc}(x) > 0$. Otherwise, it is rejected. Various kernel functions can be used as polynomial or Radial Basis Function or multilayer perceptron [13]. Usually, the RBF is the most used kernel, which allows determining the radius of the hyper sphere according the parameter γ. It is defined by:

$$K(x, x_i) = \exp\left(-\gamma d(x, x_i)\right) \quad (5)$$

such that: $d(x, x_i) = \|x - x_i\|^2$ and γ is the kernel parameter.

Fig. 1 shows how the data are separated from the origin into the feature space when using the decision function.

A. *Parameter selection of the OC-SVM*

Two parameters should be tuned to design the OC-SVM, which are the percentage of outliers(ν), the kernel parameter (γ). The optimal parameters are found during the training, and validation steps.

When a new writer is added to the system, we assume that it has the same parameters as the writer used during the construction of the model.

III. Design of the HSVS

A. *Description of the HSVS*

During generating of the model, K genuine and L forged signatures are available for each writer. Genuine signatures are subdivided randomly into three sub-sets namely M, N and P genuine signatures. M and N signatures are used for training and validating the model of the OC-SVM whilst P genuine and L forged signatures are used for finding the optimal threshold t_{opt} from the FAR and FRR curves. In our case, the optimal threshold is defined as the Half Total Error Rate according the following equation:

$$t_{opt} = HTER = \frac{FAR+FRR}{2} \quad (6)$$

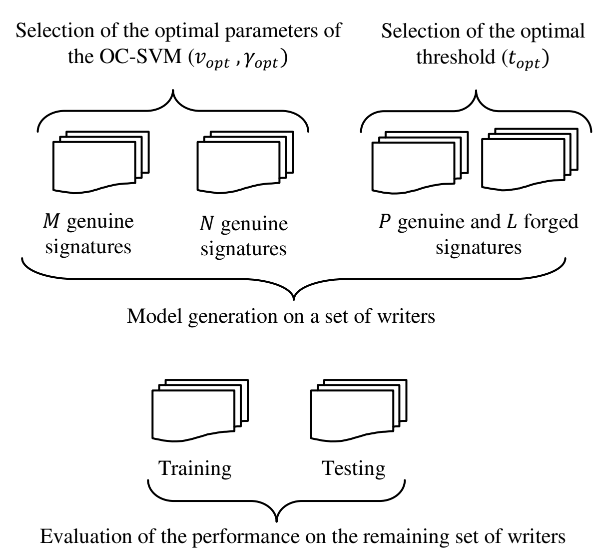


Fig. 2. Model generation and evaluation process

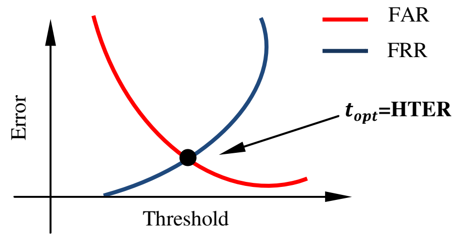


Fig. 3. The choice of the threshold from FAR and FRR curves

Fig. 3 shows the concept of finding the optimal threshold from FAR and FRR curves. After finding the optimal parameters, the second step involves to evaluate the performance of the classifier.

B. Threshold Tuning

The OC-SVM is designed to separate a class from other classes. Theoretically, a signature x is correctly classified when the decision function $f_{oc}(x)$ is positive. Implicitly, the threshold is fixed to zero. This approach can be considered as a hard thresholding. Indeed, some signature samples near to the hyper plan into the feature space are not accepted. In order to relax this constraint, we propose a soft thresholding for reducing the misclassification. Therefore, we adopt the following decision rule [7]:

$$x \in \begin{cases} Accepted & if\ f_{oc}(x) \geq t \\ Rejected & otherwise \end{cases} \tag{7}$$

t defines the threshold computed according the following equation:

$$t = m_f + k\sigma_f \tag{8}$$

IV. Experimental Results

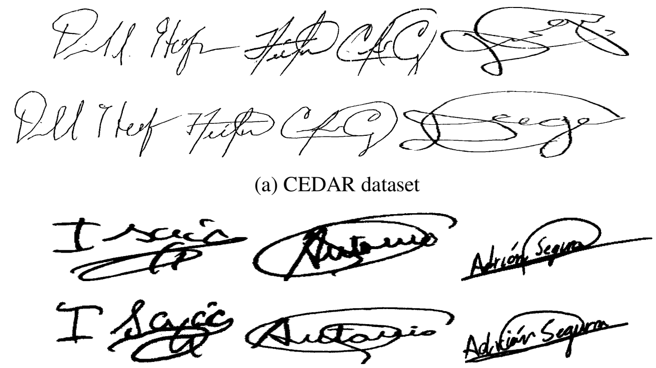
A. Dataset

In this work, we use two datasets for evaluating the performance of the HSVS based on the OC-SVM. The first one is performed on the Center of Excellence for Document Analysis and Recognition (CEDAR) signature dataset containing 55 writers [14], each one has 24 genuine and 24 forgery signatures. The signatures from the different writers are scanned at 300 dpi. The second one is performed on the ”Grupo de Procesado Digital de Senales" (GPDS) signature dataset [15] containing 300 writers each one has 24 genuine and 30 forgery signatures, respectively. Fig. 4 shows some samples of signatures, the first line represents the genuine signature; in contrast, the second line represents the forged signature for the two datasets.

B. Feature Generation

In the proposed system, features of the handwritten signatures are generated by using the curvelet transform which is recently developed by Candès and Donoho [16].

The curvelet transform was developed specifically for edges representation and other singularities along curves, which make it much more efficiently than traditional transforms, i.e. using many fewer coefficients for a given accuracy of reconstruction.



(a) CEDAR dataset

(b) GPDS dataset

Fig. 4. Samples of signatures from three writers

The curvelet transform has been widely used in several applications such as pattern recognition [17] and image compression [18], More recently, it has been successfully used for off-line handwritten signature retrieval [19]. Hence, the generation of feature vector generation was based on calculating the energy and the standard deviation of the curvelet coefficients. In our case, features are generated by calculating only the energy of the curvelet coefficient of the signature image

C. Results

1) Finding the optimal threshold

For each writer, we consider 8 genuine signatures for training the OC-SVM, 8 genuine signatures for validation and 8 genuine and all forged signatures for finding the optimal threshold. The optimal threshold (t_{opt}) is selected from FAR, FRR versus threshold curves which is defined as the Half Total Error Rate

2) Influence of the writer’s number

The main problem for designing the HSVS is the adequate selection of the writer’s number for constructing the OC-SVM model. Therefore, we study the influence of the number of writers to generate model, the signature dataset is composed as follows:

- CEDAR dataset: Initially, we consider 5 writers to generate model and the remainder of the dataset is used for evaluating the performance of HSVS. Then, for each run, we add 5 writers and we repeat the evaluation for the rest of writers
- GPDS dataset: Initially, we consider 100 writers to generate model and the remainder of the dataset is used for evaluating the performance of HSVS. Then, for each run, we add 25 writers and we repeat the evaluation for the rest of writers.

Fig. 7 and Fig. 8 show the influence of the writer’s number on the error rate for the CEDAR and GPDS datasets.

We clearly can note that the lowest error rate is obtained by the optimal threshold which represents the lowest HTER selected in the construction of the model. Furthermore it is

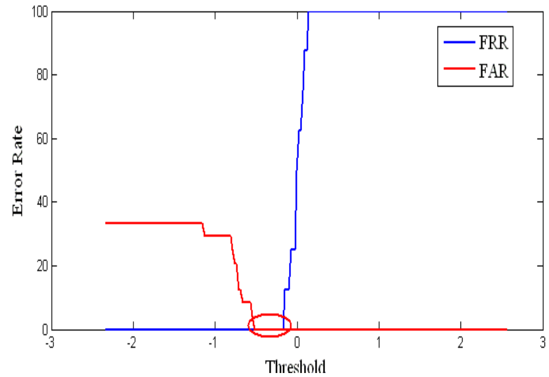


Fig. 5. ROC curve for the generation model using CEDAR dataset

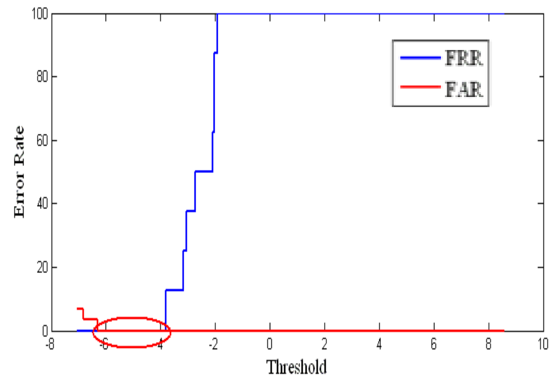


Fig. 6. ROC curve for the generation model using GPDS dataset

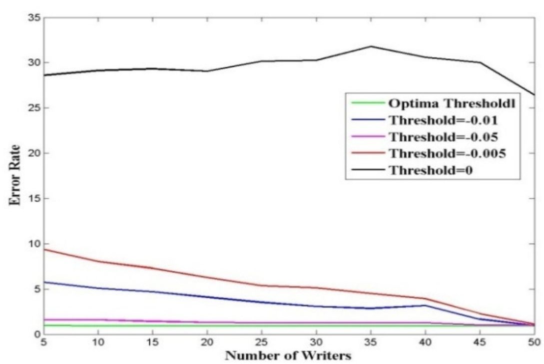


Fig. 7. Error rate according the number of writer by using CEDAR dataset

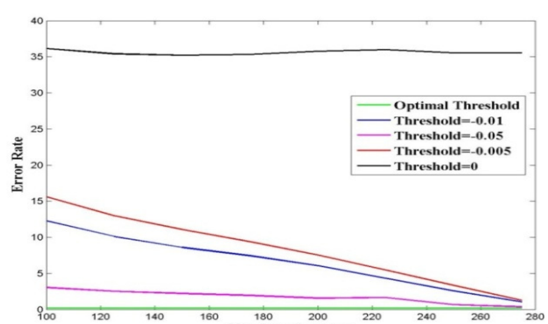


Fig. 8. Error rate according the number of writer using GPDS dataset

independent to the number of writers. On the other hand, we see that the remainder threshold values depend strongly to the number of writers and take its lowest error with the highest number of writers, except the hard threshold, which presents the highest error rate regardless the number of writers used for generating the model.

3) *Results for fixed number of writers*

The second part consist to select a fixed number of writer to generate the model and store the setting, with the same parameters we evaluate the performance of the others writers in order to achieve the lowest performance of classifier. The signature dataset is composed as follows:

- CEDAR dataset: 25 writers are selected randomly for generating the model and 30 writers for evaluating the performance of the system.
- GPDS dataset: 150 writers are selected randomly for generating the model and 150 writers for evaluating the performance of the system.

In order to appreciate the effective use of the proposed method with a fixed number of writers, various thresholds are selected to compare; which are the hard and the soft threshold. The hard threshold is computed when the decision function equal to 0, whilst the soft threshold is selected from FAR and FRR curves.

Tables 1 and 2 report FRR, FAR and AER obtained for the CEDAR and GPDS datasets, respectively. We clearly can note that the best performance is reached when the optimal threshold is selected from FAR and FRR curves. Hence the AER is 0.91% for a threshold equal to -0.174 and for other thresholds: -0.05, -0.01 and -0.005, the AER is 1.25%, 3.41% and 5.34%, respectively for the CEDAR dataset. Whilst for

TABLE I. RECOGNITION PERFORMANCES OBTAINED FOR DIFFERENT THRESHOLDS USING CEDAR DATASET

Threshold	*FRR (%)*	*FAR (%)*	*AER (%)*
0.000 (Hard threshold)	32.50	30.27	31.38
-0.005	9.54	1.14	5.34
-0.010	5.68	1.14	3.41
-0.050	0.68	1.82	1.25
-0.174	**0.00**	**1.82**	**0.91**

TABLE II. RECOGNITION PERFORMANCES OBTAINED FOR DIFFERENT THRESHOLDS USING GPDS DATASET

Threshold	*FRR (%)*	*FAR (%)*	*AER (%)*
0.000 (Hard Threshold)	59.26	10.81	35.04
-0.005	22.06	0.07	11.06
-0.010	17.15	0.07	8.61
-0.050	4.28	0.14	2.21
-3.237	**0.00**	**0.35**	**0.17**

TABLE III. ERROR RATE (%) PROVIDED BY THE PROPOSED SYSTEM AND THE STATE OF THE ART ON CEDAR AND GPDS DATASETS

Dataset	*Method*	*Classifier*	*AER (%)*
CEDAR	*Srihari et al [20]*	SVM	9.30
	Kumar et al [21]	Neural network	8.33
	Proposed method	OC-SVM	0.90
GPDS	*Ferrer et al [22]*	HMM	2.75
		Euclidean distance	5.13
		SVM	2.56
	Proposed method	OC-SVM	0.17

the GPDS dataset, the AER is 0.17% when the threshold is equal to -3.232. In contrast, the hard threshold yields a higher AER since the threshold is equal to 0. Indeed, the obtained AERs are 31.39% and 35.04% for CEDAR and GPDS datasets, respectively.

C. Comparative Analysis

Tables 3 reports AERs provided by various systems using both CEDAR and GPDS datasets. Comparisons with other systems are difficult because of the type (genuine and forgery) selected during the designing step of the HSVS. For CEDAR dataset, we can note that our proposed system provides better performances in terms of AER comparatively to other systems, which use genuine and forged signatures during the designing step. In contrast, in our approach, we use only genuine and forged signatures for designing HSVS and the thresholding. Srihari et al [20] provided a study between a writer-dependent and writer-independent for two-class and one-class classification using different classifiers as: Distance Threshold, Distance Statistics, Naive Bayes and SVM. They use One-Class where forgeries for the individual writers are unavailable and two-class where genuine and forgeries are available, Kumar et al [21] proposed to describe the shape of the signature in terms of spatial distribution of blacks pixels using the neural network AER is 9.30 % and 8.33% by using SVM and neural network, respectively. AER is 0.9% when using our system.

For GPDS dataset, Ferrer et al [22] proposed offline signature verification using different configurations of Local Binary Pattern (LBP) and by using classifiers (nearest classifier with histogram intersection and Chi-square similarity measure and LS-SVM with linear, Radial Basic Function, histogram intersection and Chi-square Kernel). Error rates are 2.75%, 5.13% and 2.65% when using HMM, when using Euclidean distance and SVM classifiers, respectively. When using our system, the obtained error rate is 0.17%.

V. Conclusion

In this paper, we proposed an effective use of the OC-SVM for off-line handwritten signature verification using only genuine signatures. The main advantage of the proposed HSVS is that it allowed designing the HSVS using few writers and signatures. It allowed also defining an only optimal threshold from genuine and forged signatures, which should be carefully adjusted. When a new writer is presented to the system, the same parameters of the OC-SVM are used without finding the optimal threshold.

The obtained results conducted on CEDAR and GPDS datasets show that the proposed HSVS provided interesting performances comparatively to the state of the art.

In continuation to the present work, the next objective consists to explore the writer-independent concept based on the similarity and dissimilarity measures for designing the HSVS.

References

[1] S. Adebayo and T. Samuel lbiyemi, "Offline Signature Recognition using Hidden Markov Model", *International Journal of Computer Application*, vol. 10. no. 2, 2010.

[2] N. Abbas and Y. Chibani, "SVM-DSMT Combination for the Simultaneous Verification of Off-line and On-line Handwritten Signatures, *International Journal of Computational Intelligence and Applications,* vol. 11, no. 3, 2012.

[3] F. Leclerc and R. Plamondon, "Automatic Signature Verification: The State of the Art 1989-1993*", Pattern Recognition and Artificial Intelligence, special issue on signature verification, 8(3), pp. 643-660*, June 1984.

[4] R. Plamondon and S. N. Srihari, "On-line and off-line handwriting recognition: A comprehensive survey", *IEEE Trans. PAMI,* vol. 22, no. 1, pp. 63–84, 2000.

[5] F. Camci and R. B. Chinnam, "General support vector representation machine for one-class classification of non-stationary classes", *Pattern Recognition, vol. 41, pp. 3021-3034*, 2008.

[6] D. Impedovo and G. Pirlo, "Automatic Signature Verification: The State of the Art", *IEEE Transactions on the systems,* vol. 38, no. 5, 2008.

[7] Y. Guerbai, Y. Chibani and N. Abbas, " One-Class versus Bi-Class SVM Classifier for Off-line Signature Verification", *Proceedings of IEEE Conference on Multimedia Computing and Systems,* 10-12 May 2012, Tangiers, Morocco.

[8] L. Batista, E. Granger, R. Sabourin, "Dynamic Selection of Generative-Discriminative ensembles for off-line signature verification *", Pattern recognition*, vol. 45, 2012, pp.1326-1340.

[9] D. Bertolinia, L. Oliveirab, E. Justiona, and R. Sabourin, "Reducing Forgeries in Writer Independent Off-line Signature Verification through ensemble of Classifiers". *Pattern Recognition*, vol. 43, 2010, pp. 387-396.

[10] B. Schölkopf, J. Platt, J. Shawe-Taylor, A. Smola and R. Williamson."Estimating the support of a high dimensional distribution", *Neural Computaion*, vol. 13, no.7, 2001, pp. 1443-1472.

[11] A. Rabaoui, D. Manuel, Z. Lachiri and N. Ellouze, "Improve One-Class SVM Classifier for Sounds Classification ", *Proceedings of IEEE Conference on Advanced Video and Signal Based Surveillance, London, United Kingdom* , 2007.

[12] C. Bergani, L. S. Oliveira, A. L. Koreich and R. Sabourin,"Combining Different Biometric Traits with One-Class classification", *Signal Processing* , vol. 89, 2009, pp. 2117- 2127.

[13] Vapnik, *The Nature Of Statistical Learning Theory*, Springer, 1995.

[14] M. Kalera, B. Zhang, and S. Srihari, "Offline Signature Verification and Identification Using Distance Statistics*", International Journal of Pattern Recognition and Artificial Intelligence*, vol. 18, no.7, 2004, pp. 1339-1360,

[15] L.E. Martinez, C.M. Travieso, J.B. Alonso, and M. Ferrer,Parametrization of a forgery Handwritten Signature Verification using SVM", *IEEE 38th Annual 2004 International Carnahan Conference on Security Technology,* 2004, pp. 193-196.

[16] E. Candès, D. Donoho, "Curvelets: A Surprisingly Effective Nonadaptive Representation of Objects with Edges", *Saint-Malo Proceedings*, 2000, pp. 1-10.

[17] K. Feng, Z. Jiang, W. He and B. MA,"A recognition and novelty detection approach based on Curvelet transform, nonlinear PCA and SVM with application to indicator diagram diagnosis", Expert Systems with Applications, vol. 38, no. 10, 2011, pp. 12721-1272.

[18] Li, Q. Yang and R. Jiao, "Image compression scheme based on curvelet transform and support vector machine", *Expert Systems with Applications*, vol. 37, 2009, pp. 3063-3069.

[19] M. S. Shirdhonkar and M. Kokare, "Off-Line Handwritten Signature Retrieval using Curvelet Transforms", *International Journal of Computer.*

[20] S. N. Srihari, A. Xu and M. K. Kalera, "Learning Strategies and Classification Methods for Off-line Signature Verification", *IWFHR '04 Proceedings of the Ninth International Workshop on Frontiers in Handwriting Recognition*, 2004.

[21] R. Kumar, J. D. Sharma and B. Chanda, Writer-independent off-line signature verification using surroundedness feature. "*Pattern Recognition Letters*", vol. 33, 2012, pp. 301-308.

[22] A. Ferrer, J. F. Vargas, A. Morales and A. Ordóñez, " Robustness of Offline Signature Verification Based on Gray Level Features", *IEEE Transactions on Information Forensics and Security*, vol. 7, no.3, 2012.