International Journal of Applied Engineering Research ISSN 0973-4562 Volume 13, Number 12 (2018) pp. 10931-10938

Multiple Classifier System for Writer Independent Offline Handwritten Signature Verification using Elliptical Curve Paths for Feature Extraction

[1]Ashok Kumar and [2]Karamjit Bhatia

[1]Research Scholar, Department of Computer Science, Gurukula Kangri Vishwavidyalaya, Haridwar, India.
& Associate Professor, Departement of Computer Applications, Invertis University, Bareilly, India.

[2]Professor, Department of Computer Science, Gurukula Kangri Vishwavidyalaya, Haridwar, India.

Abstract

Various offline handwritten signature verification systems using writer independent approach are proposed by the researchers in last few years using numerous perspectives, like feature extraction techniques, feature selection techniques, classifiers used to develop the system etc. Despite the progressions in this framework, building classifier that can isolate the genuine and skilled forgery signatures is still a tough task. In this work, multiple classifier system is proposed to develop the writer independent offline handwritten signature verification system. To train the classifiers of multiple classifier system, feature vectors of the training set are partitioned into subsets and classifiers are trained using these subsets to preserve the diversity. The pixels lying on the elliptical curve paths are used to extract the features from genuine and forgery signature images. Two scenarios are proposed for the performance analysis. In the first scenario, the classifiers are trained using genuine signature and random forgery signature samples whereas genuine and all types of forgeries specifically random, unskilled and skilled forgery signatures are utilized for the training process of the classifiers in the second scenario. Signature database of 150 writers is used to perform the experiments. False rejection rate 8.33 and false acceptance rate 0.00, 0.00 and 1.67 for random, unskilled and skilled forgeries, respectively are reported as the best result of the experiments.

Keywords: Multiple classifier system, offline handwritten signature verification system, writer independent approach, support vector machine, elliptical curve feature set.

INTRODUCTION

The handwritten signature of a person is a significant form of biometric trait used to verify a person's uniqueness in administrative, financial, and legal areas. Handwritten Signature Verification (HSV) research problem is divided into online and offline research areas [1]. In online research problems, a special input device is used to acquire the signature of the persons and the dynamic features like inclination, the order of strokes, pen's position etc. are captured. In this study, offline signature verification research problem is focused, where the signatures are collected using a white paper sheet and optical scanner is used to convert the signature image into a digital image. Due to inaccessibility of dynamic information, the development of competent offline HSV system is a hard task. For developing HSV system the forgeries set is divided into three forgery subsets to be specific random, unskilled, and skilled. The genuine signature of a different writer is considered as a random forgery for a genuine writer. In unskilled (also called simple) forgery creation process, the genuine writer's name is known to the forger whereas the forger knows the genuine signature of the writer and has practiced the genuine signature many times to create skilled (also called simulated) forgery [2]. The genuine signature of a writer and all types of forgeries are shown in Figure 1. In HSV framework, False Rejection Rate (FRR) and False Acceptance Rate (FAR) are two performance metrics which are generally utilized to assess the performance of a HSV system. The percentage of genuine signatures of writer acknowledged as forgery signature by the system is known as FRR whereas FAR is calculated as the percentage of forgery signatures of writer acknowledged as a genuine signature. In literature, another term called Average Error Rate (AER) or Mean Error Rate (MER) which is the average of FRR and FAR is also reported. In this work, FAR is computed for Random Forgery (FARR), Unskilled Forgery (FARU) and Skilled Forgery (FARS) signatures. Two approaches namely- Writer Dependent (WD) and Writer Independent (WI) are utilized to develop offline HSV framework [3]. In WD approach, a personal model is built for every writer on the basis of two dissimilar classes, *Class1* and *Class2*, where genuine signature samples of a specific writer constitute *Class1* whereas *Class2* consists of forgery signature samples. The WD approach suffers from two major drawbacks, first, it requires to include a vast number of genuine samples and second, its incapability to absorb a new writer without generating a new personal model for the writer. On the other hand, WI approach (also called global model) requires a single model to manage all writers and is proficient to absorb unknown writer without retraining the model. The prime advantage of WI approach is that one can build reliable model even few number of genuine signature samples are available.

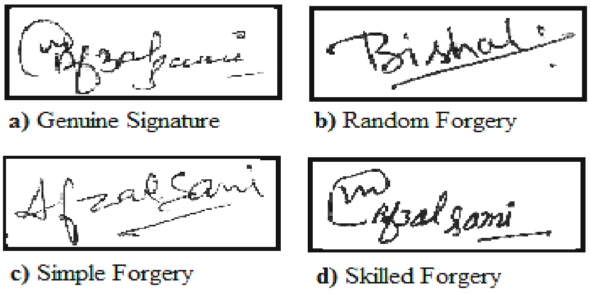

Figure 1: Genuine and forgery signatures

In WI approach, the feature vector of the questioned signature is compared with feature vectors of reference signatures to classify the questioned signature as genuine or forge. To perform classification process, the dissimilarity between the feature vector of questioned signature Q and the feature vector of reference signatures R_k (k = 1, 2, …,n) is computed. The dissimilarity representation concept is introduced by E. Pekalska et. al. [4] and is based on the idea that dissimilarities among the same class objects are less as compared to those among objects belonging to different classes. The difference between the feature vector of the reference sample and feature vector of the questioned sample is computed as $D_i = |FR_i - FQ_i|$ to create dissimilarity vector. Dissimilarity feature vector is fed to the classifier to get the partial decision. Finally, fusion strategy is used to combine the partial decisions to obtain a final decision as shown in Figure 2.

The aim of this planned research effort is to offer the Multiple Classifier System (MCS) and a competent approach for feature extraction to reduce the FAR for unskilled and skilled forgeries. Two objectives of this work are: (1) the approach will absorb well the handwritten signature of unknown writers without retraining the model; (2) the approach will reduce AER by reducing FAR for unskilled as well as skilled forgeries. To develop the WI offline HSV system, two features specifically (1) Mean of the pixel intensities, and (2) Number of transitions among the pixels intensities (1 to 0 or 0 to 1) from the pixels of the signature image lying on the elliptical curve path is computed. In this manner, two feature sets namely- Mean Feature (M - Feature) and Number of Transitions (T - Feature) sets are extracted from the signature image by taking the elliptical curve paths of various radiuses. The reason behind using the elliptical curve paths centered on the center of signature images is that in most of the signature images the density is high at the center of signature images and decreases as move far from the center of the signature image. Further, generally the center portion of the signature image is more complex as compared to other portion of the signature image. Forgers mainly focus the starting and ending part of the signature image rather than the center of the signature image to make the forgery. So the center part of the signature image may be more beneficial as compared other portion to distinguish between genuine and skilled forgery signature image. Then again, the size of the signature images is generally rectangular; consequently, the elliptical curve paths may be more useful to extract the features from signature images as compared to other curve paths such as circular curve paths.

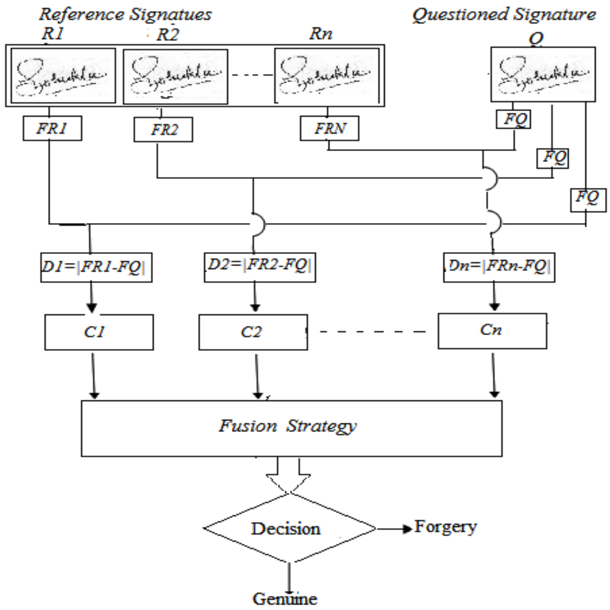

Figure 2: Writer independent approach for offline HSV system

The signature database of 150 writers is used to develop the system. Two multiple classifier systems are proposed in this study, first one is generated by Support Vector Machine with Polynomial Kernel (SVMP) classifiers and other is generated by Support Vector Machine with Quadratic Kernel (SVMQ) classifiers. The training set is partitioned into k partitions using k fold cross-validation technique [5] to create the MCS of k diverse classifiers and same training algorithm is utilized to train all classifiers of MCS. Two scenarios (Scenario I and Scenario II) are utilized to train the classifiers of MCS. In Scenario I, genuine and random forgery signature samples are utilized to train the classifiers of MCS whereas Genuine Signature (GS), Random Forgery (RF), Unskilled Forgery (UF) and Skilled Forgery (SF) samples are utilized to train the classifiers of MCS in Scenario II. To test the classification accuracy of the developed system, UF and SF signature samples are used in both scenarios. These multiple classifier systems aim at classifying the handwritten signature of writers as genuine or forged.

LITERATURE REVIEW

Writer independent approach is not widely used as compared to the WD approach to developing the offline HSV system. The writer independent approach was proposed by Santos C. et. al. [4]. The researchers used this approach with Neural Network (NN) and graphometric features to develop WI offline HSV system and claimed AER 8.02. Bertolini D. et. al. [3] improved the performance of WI offline HSV system through a pool of SVM classifiers and graphometric features. Authors claimed AER 6.28 through their experiment. Rivard

D. et. al. [6] utilized two grid-based techniques specifically Directional Probability Density Function (DPDF) as well as Extended Shadow Code (ESC) to extract the features from the signature images and acquired AER 5.19 through SVM classifier. An approach based on surroundedness features and two classifiers, namely- NN and SVM to broaden the WI offline HSV system is proposed by Kumar R. et. al. [7]. Authors claimed classification accuracy by 86.24. Eskander S. et. al. [8] used the spatial distribution and additionally orientation of stroke features to develop the WI offline HSV system and claimed AER 5.38 using SVM classifier. To develop the WI offline HSV system, Swanepoel J. et. al. [9] proposed Dynamic Time Wrapping (DTW) as well as Discrete Radon Transform (DRT) features and claimed AER 4.93. Eskander G. et. al. [10] claimed a more secure, accurate and less complex offline HSV system using the SVM classifier and reported AER 7.24. Offline WI system for HSV with the lessened number of references against questioned signature samples is reported by Hamadene A. et. al. [11]. The researchers utilized Contourlet Transform (CT) and Directional Code Co-event Matrix (DCCM) as features and acquired AER 18.42 through one-class SVM classifier. Hafeman L. et. al. [12] used SVM - RBF classifier and obtained AER 3.96 through experiments.

RESEARCH METHODOLOGY

The major steps used to develop the MCS for WI offline HSV in this work are: the creation of a signature database, pre-processing of signature images, feature extraction, the creation of a dissimilarity feature vector set, the creation of multiple classifier system, and training and testing of MCS.

a) Creation of Signature Database

1. Samples of handwritten signatures are collected from 150 students of undergraduate and postgraduate courses of an institute on the A4 white paper sheet. Each student signed 20 genuine signatures.
2. To acquire the unskilled forgery and skilled forgery signature samples, two forgers are chosen for each genuine writer to sign 5 unskilled as well as 5 skilled forgery signatures on A4 white paper sheet. In this manner, total 10 unskilled and 10 skilled forgery signature samples per genuine writer are collected.
3. All A4 white paper sheets of genuine and forgery signature samples are scanned by scanner at 600 dpi to convert the signature images into digital form.

In this manner, the signature database of 150 writers incorporates genuine, unskilled forgery and skilled forgery signature samples of writers. Signature samples of 90 writers are used in training and remaining signature samples of 60 writers are used in testing phase.

b) Pre-processing of the Signature Images

1. To eliminate the noise, all signature images are passed through winner filter.
2. All signature images are converted into binary images using threshold calculated by means of Otsu's method [13].
3. All signature images are cropped and resized to the image of size 256 x 512

c) Feature Extraction

In the proposed approach, the performance of two feature sets namely M – Feature vector set and T – Feature vector set is analyzed to develop the WI offline HSV system. The feature vectors of both sets contain global as well as local features. The procedure of M – Feature vector set and T – Feature vector set extraction is presented as follows.

1. To extract global features, 127 elliptical curve paths of various radiuses within a whole signature image of size 256 x 512 are used as shown in Figure 3.
2. The mean of intensities of the pixels and the number of transitions between pixel intensities of the pixels lying on the elliptical curve path are calculated. In this manner, a global mean feature vector (M_W) and a global number of transitions feature vector (T_W) of length 127 each is obtained from 127 elliptical curve paths.
3. To extract local features, each signature image is partitioned into four equal parts namely- Upper Left (UL), Upper Right (UR), Lower Left (LL) and Lower Right (LR) of size 128 x 256 pixels and 63 elliptical curve paths of various radiuses for each part are used as shown in Figure 4.
4. The mean of intensities of the pixels lying on the elliptical curve path is calculated for each part. In this way, local mean feature vectors M_{UL}, M_{UR}, M_{LL}, and M_{LR} of length 63 each are obtained. Likewise, local number of transition feature vectors T_{UL}, T_{UR}, T_{LL}, and T_{LR} of length 63 each are obtained from 63 elliptical curve paths by computing the number of transitions between pixel intensities of the pixels lying on the elliptical curve path.
5. Finally, global and local mean feature vectors M_W, M_{UL}, M_{UR}, M_{LL}, and M_{LR} are combined to find the M – Feature vector of length 379. Similarly, T – Feature vector of length 379 is obtained by combining the global and local number of transition feature vectors T_W, T_{UL}, T_{UR}, T_{LL}, and T_{LR}.
6. Repeat steps 1 to 5 for each genuine and forgery signature sample of the signature database to obtain the M – Feature vector set and T – Feature vector set.

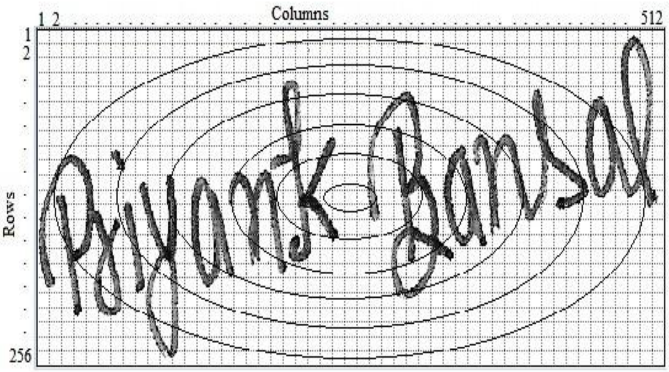

Figure 3: Elliptical curve paths in whole signature image

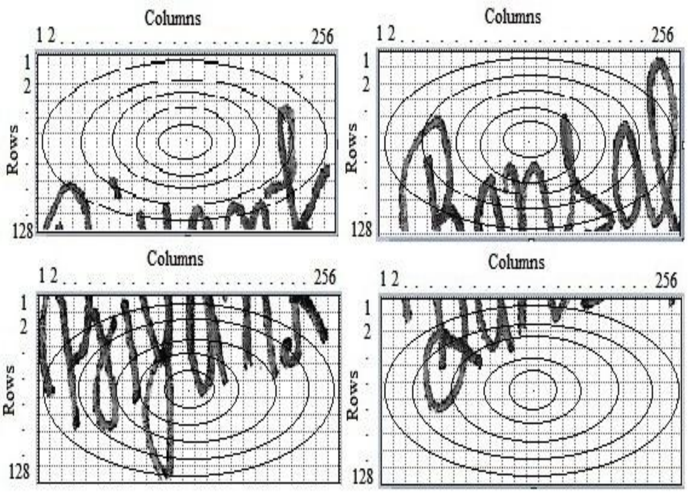

Figure 4: Elliptical curve paths in UL, UR, LL, and LR signature sub images

d) Creation of Dissimilarity Feature Vector Set

In this study, training and testing of MCS are performed using Dissimilarity Feature (DF) vector set. The DF vector set contains two subsets namely- Positive Feature Vector (PFV) subset and Negative Feature Vector (NFV) subset. In the training phase, two Scenarios (Scenario I and Scenario II) are proposed. In Scenario I, only GS and RF feature vectors are used. To create PFV subset, dissimilarity among 7 GS feature vectors of the writer is computed. In this way, 21 DF vectors per writer are obtained. This resulted in 1890 DF vectors from 90 writers. To generate NFV subset, the dissimilarity between 5 GS feature vectors of the first 5 writers and 5 GS feature vectors of 85 writers from the remaining training set is computed. In this way, 2125 negative feature vectors are obtained. Finally, the DF vector set of 4015 dissimilarity feature vectors (1890 positive feature vectors plus 2125 negative feature vectors) is used to train the classifiers of MCS.

In Scenario II, GS feature vectors are used to generate PFV subset and RF, UF, and SF feature vectors are used to generate NFV subset. The PFV subset of 1890 feature vectors is obtained from 90 writers by computing the dissimilarity among 7 GS feature vectors of the writer. The dissimilarity between 3 GS feature vectors of the first 5 writers and 3 GS feature vectors of 85 writers from the rest of training set is computed to obtain 1275 negative feature vectors using RF feature vectors. To create 810 negative feature vectors using UF feature vectors, the dissimilarity between 3 GS and 3 UF feature vectors of the writer is computed. In the same way, the dissimilarity between 3 GS and 3 SF feature vectors of the writer is computed to obtain 810 negative feature vectors using SF feature vectors. Finally, the DF vector set of 4785 dissimilarity feature vectors (1890 positive feature vectors plus 2895 negative feature vectors) is used to train the classifiers of MCS.

To test the performance of MCS, the feature vectors of UF and SF along with GS and RF feature vectors are used for both scenarios. The required number of GS, RF, UF, and SF feature vectors to create the PFV and NFV subsets are dependent on the reference signatures used for the questioned signature.

e) Creation of Multiple Classifier System

To create the multiple classifier systems, two classifiers namely- support vector machine with polynomial kernel and support vector machine with quadratic kernel classifier are used. To generate the MCS, k fold cross-validation method is utilized and the value of k is taken 5, 10, and 15 in this study. In this way, MCS of 5 SVMP classifiers, MCS of 10 SVMP classifiers, MCS of 15 SVMP classifiers, MCS of 5 SVMQ classifiers, MCS of 10 SVMQ classifiers, and MCS of 15 SVMQ classifiers are created.

f) Training and Testing of Multiple Classifier System

All created multiple classifier systems are trained using DF vector sets. To generate DF vector sets, M – Features vector set and T – Features vector set are utilized for both scenarios. In this way, total 24 trained multiple classifier systems are obtained. Then, the performance of all trained multiple classifier systems is evaluated using 7, 9, 11, 13, and 15 Reference Signatures (RS).

EXPERIMENTAL RESULTS

MATLAB 2013a is used to perform the experiments using 150 writers database. Performance of all trained multiple classifier systems is evaluated in terms of FRR, FARR, FARU, FARS and AER metrics using max, mean and majority votes fusion strategies but mean fusion strategy has reported better results.

The performance of MCS of 5 SVMP classifiers and MCS of 5 SVMQ classifiers of Scenario I using DF vector set of M – Feature vector set and T – Feature vector set are presented in Table 1 and Table 2, respectively whereas Table 3 and Table 4 present the performance of the Scenario II using DF vector set of M – Feature vector set and T – Feature vector set, respectively. The comparison of the performance between the proposed WI offline HSV system and the existing WI offline HSV systems in terms of FRR, FARR, FARU, FARS, and AER is presented in Table 5.

Table 1: Performance of Multiple Classifier Systems of Scenario I using M - Feature Set

MCS	RS	FRR (%)	FARR (%)	FARU (%)	FARS (%)	AER (%)
SVMP	7	3.33	0.00	8.33	21.67	8.33
	9	5.00	0.00	8.33	20.00	8.33
	11	1.67	0.00	8.33	20.00	7.50
	13	1.67	0.00	8.33	20.00	7.50
	15	1.67	0.00	8.33	20.00	7.50
SVMQ	7	6.67	0.00	11.67	18.33	9.17
	9	5.00	0.00	10.00	21.67	9.17
	11	0.00	0.00	10.00	21.67	7.92
	13	0.00	0.00	11.67	23.33	8.75
	15	0.00	0.00	10.00	23.33	8.33

Table 2: Performance of Multiple Classifier Systems of Scenario I using T - Feature Set

MCS	RS	FRR (%)	FARR (%)	FARU (%)	FARS (%)	AER (%)
SVMP	7	1.67	0.00	8.33	26.67	9.17
	9	0.00	0.00	8.33	25.00	8.33
	11	0.00	0.00	8.33	23.33	7.92
	13	0.00	0.00	8.33	23.33	7.92
	15	0.00	0.00	8.33	21.67	7.50
SVMQ	7	5.00	0.00	8.33	16.67	7.50
	9	3.33	0.00	10.00	20.00	8.33
	11	1.67	0.00	10.00	20.00	7.92
	13	1.67	0.00	10.00	21.67	8.33
	15	1.67	0.00	10.00	25.00	9.17

The performance of MCS of 10 SVMP classifiers, MCS of 15 SVMP classifiers, MCS of 10 SVMQ classifiers and MCS of 15 SVMQ classifiers of Scenario I using DF vector set of M – Feature vector set and T – Feature vector set in terms of AER is shown in Figure 5 and Figure 6, respectively . The performance of MCS of 10 SVMP classifiers, MCS of 15 SVMP classifiers, MCS of 10 SVMQ classifiers and MCS of 15 SVMQ classifiers of Scenario II using DF vector set of M – Feature vector set and T – Feature vector set in terms of AER is shown in Figure 7 and Figure 8, respectively.

Table 3: Performance of Multiple Classifier Systems of Scenario II using M - Feature Set

MCS	RS	FRR (%)	FARR (%)	FARU (%)	FARS (%)	AER (%)
SVMP	7	15.00	0.00	3.33	6.67	6.25
	9	13.33	0.00	3.33	10.00	6.67
	11	8.33	0.00	3.33	6.67	4.58
	13	10.00	0.00	3.33	6.67	5.00
	15	11.67	0.00	3.33	6.67	5.42
SVMQ	7	21.67	1.67	8.33	10.00	10.42
	9	21.67	1.67	8.33	8.33	10.00
	11	16.67	0.00	8.33	8.33	8.33
	13	18.33	0.00	8.33	8.33	8.75
	15	15.00	0.00	8.33	8.33	7.92

Table 4: Performance of Multiple Classifier Systems of Scenario II using T - Feature Set

MCS	RS	FRR (%)	FARR (%)	FARU (%)	FARS (%)	AER (%)
SVMP	7	10.00	0.00	0.00	1.67	2.92
	9	11.67	0.00	0.00	1.67	3.33
	11	10.00	0.00	0.00	1.67	2.92
	13	8.33	0.00	0.00	1.67	2.50
	15	8.33	0.00	0.00	1.67	2.50
SVMQ	7	16.67	1.67	5.00	5.00	7.08
	9	16.67	0.00	5.00	6.67	7.08
	11	13.33	0.00	5.00	5.00	5.83
	13	13.33	0.00	3.33	5.00	5.42
	15	11.67	0.00	3.33	8.33	5.83

The performance of MCS of SVMP classifiers is better than MCS of SVMQ classifiers for both scenarios and for both M – Feature vector and T – Feature vector sets. The multiple classifier systems of scenario I reported better results in terms of FRR as compared the multiple classifier systems of scenario II whereas the multiple classifier systems of scenario II reported better results in terms of FARU, FARS, and AER as compared to the multiple classifier systems of scenario I.

The multiple classifier systems of scenario I are trained using only genuine and random forgery signature samples consequently they are not able to classify well the questioned signature samples of UF and SF signature samples therefore FARU and FARS are very high for Scenario I as compared to Scenario II.

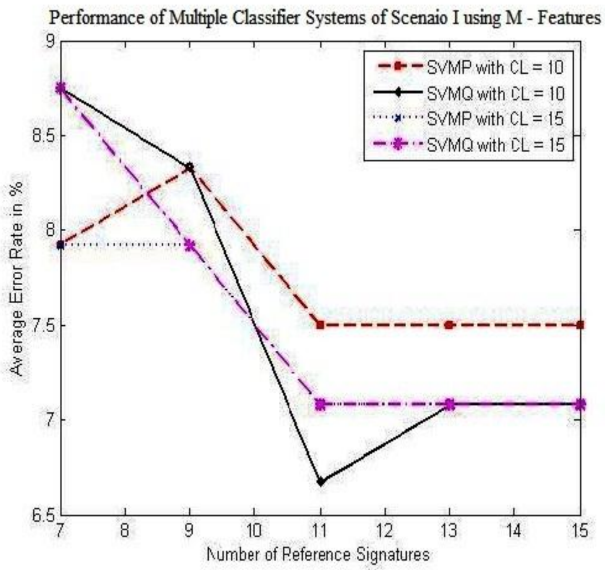

Figure 5: Performance of multiple classifier systems of Scenario I using M - Feature set in terms of AER

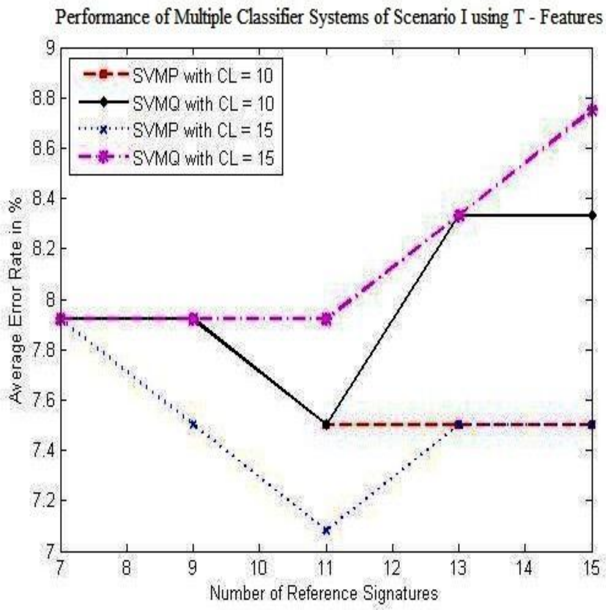

Figure 6: Performance of multiple classifier systems of Scenario I using T - Feature set in terms of AER

The multiple classifier systems of scenario II are trained with genuine and all types of forgery signature samples consequently they are able to classify the questioned signature samples of UF and SF signature samples very well subsequently FARU and FARS are very low for Scenario II as compared to Scenario I. The performance of the multiple classifier systems with 10 or 15 classifiers is slightly better than as compared to multiple classifier systems with 5 classifiers in few cases. If the number of classifiers in MCS is increased, the training and testing time of MCS will increase. Consequently, the training and testing time of MCS with 10 or 15 classifiers will be more as compared to MCS with 5 classifiers.

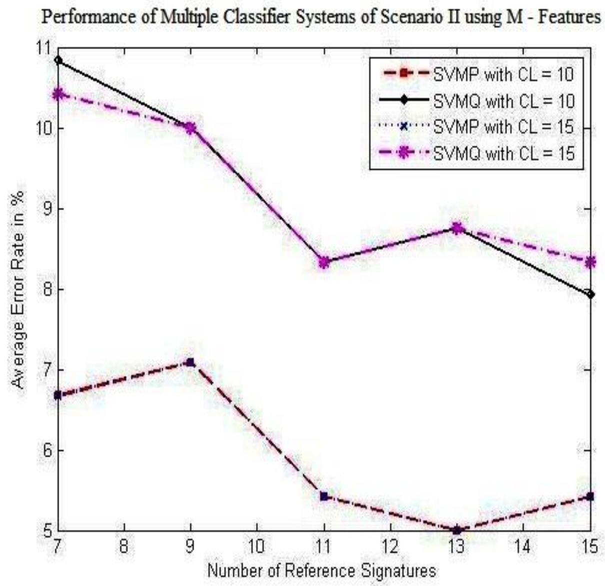

Figure 7: Performance of multiple classifier systems of Scenario II using M - Feature set in terms of AER

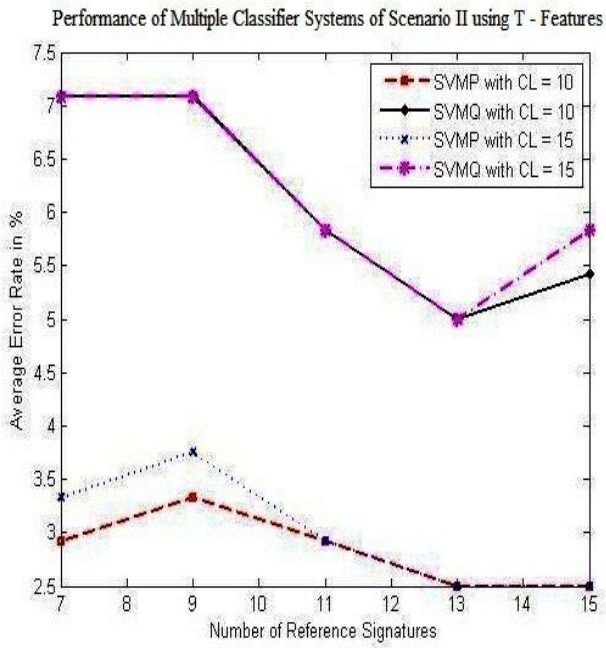

Figure 8: Performance of multiple classifier systems of Scenario II using T - Feature set in terms of AER

For Scenario I, the lowest AER 6.67 is obtained through the experiment performed using DF vector set of M - Feature vector set along with MCS of 10 SVMQ for 11 reference signatures whereas, in Scenario II, the experiment performed using DF vector set of T - Feature set along with MCS of 5 SVMP is reported lowest AER 2.50 for 13 reference signatures.

Table 5: Comparison of Existing and Proposed Writer Independent HSV Systems

SN	Authors	Classifiers	Feature Set(s)	FRR (%)	FARR (%)	FARU (%)	FARS (%)	AER (%)
1	Santos C. et. al. [4] (2004)	Neural Network	Graphometric Features	10.33	4.41	1.67	15.67	8.02
2	Bertolini D. et. al. [3] (2010)	SVM	Graphometric Features	11.32	4.32	3.00	6.48	6.28
3	Rivard D. et. al. [6] (2011)	SVM	ESC & DPDF	9.77	0.02	0.32	10.65	5.19
4	Kumar R. et. al.[7] (2012)	NN & SVM-RBF	Surroundedness Features	13.76	-	-	13.76	13.76
5	Eskander G. et. al. [8] (2012)	SVM	ESC & DPDF	7.73	0.016	0.17	13.50	5.38
6	Swanepoel J.et. al. [9] (2012)	LDF &QDF	DRT & DTW	-	-	-	-	4.93
7	Eskander G. et. al. [10] (2013)	SVM	ESC & DPDF	14.36	0.02	0.35	14.24	7.24
8	Hamadene A. et. al. [11] (2016)	OC-SVM	CT & DCCM	-	-	-	-	18.42
9	Hafemann L. et. al. [12] (2016)	SVM-RBF	CNN	2.17	0.17	0.50	13.00	3.96
10	Proposed Approach	MCS of SVMP	T – Feature Set	8.33	0.00	0.00	1.67	2.50

CONCLUSION

The study aimed at proposing a writer independent offline HSV system with reduced FARU, FARS, and AER. The writers involved in the testing process are not included in the training process and the MCS used in this study is able to classify the genuine and forgery signature samples of the testing set very well without retraining. This implies that developed MCS for WI offline HSV is capable of absorbing the signature of an unknown writer without retraining. It is observed from the experiments, FARU and FARS are high when classifiers of MCS are trained using only genuine signature and random forgery signature samples whereas FARU and FARS are reduced but FRR is increased when unskilled forgery and simulated forgery signature samples are involved along with genuine signature and random forgery signature samples in the training of classifiers of MCS.

It is observed from the experiments, the performance of the experiment using T- Feature set along with MCS of SVMP classifiers for Scenario II is better than as compared to other experiments of this study in terms of the FARU, FARS, and AER. It is also observed from the experiments that the performance of MCS is varied for both feature sets as well as for both types of classifiers (SVMP and SVMQ) used to create the MCS. Consequently, it is concluded that the performance of MCS depends on the classifiers and feature set used to develop the WI offline HSV system.

From the comparison between proposed and existing WI offline HSV systems, it is evident that proposed WI offline HSV system using MCS of SVMP classifiers along with T-Feature set under Scenario I outperform the existing WI offline HSV systems in terms of FARU, FARS, and AER. It is, therefore, concluded that efficient multiple classifier system for WI offline HSV system with reduced FARU, FARS, and AER can be developed using SVMP classifiers and T -Feature set.

REFERENCES

[1] Oliveira L., Justino E., and Sabourin R., 2007, “Offline signature verification using writer indepen-dent approach”, Proc. IEEE International Joint Conference on Neural Networks, Orlando, Florida, USA, pp. 2539 – 2544.

[2] Justino E., Bortolozzi F., and Sabourin R., 2001, “Offline signature verification using HMM for random, simple and skilled forgeries”, Proc. 6th International Conference on Document Analysis and Recognition, Seatlle, WA, USA, pp. 1031-1034.

[3] Bertolini D., Oliveira L., Justino E., and Sabourin R., 2010, “Reducing forgeries in writer independent offline signature verification through ensemble of classifiers”, Elsevier Journal of Pattern Recognition, vol. 3, no. 1, pp. 387 – 396.

[4] Santos C., Justino E., Bortolozzi F., and Sabou-rin R., 2004, “An offline signature verification method based

on the questioned document expert's approach and a neural network classifier", Proc. IEEE 9th Int'l Workshop on Frontiers in Handwriting Recognition, Washington, DC, USA, pp. 498 – 502.

[5] Zhang P., 1993, "Model selection via multi-fold cross validation", Annals of Statistics, vol. 21, no. 1, pp. 299 – 313.

[6] Rivard D., Granger E., and Sabourin R., 2011, "Multi feature extraction and selection in writer independent offline signature verification", International Journal on Document Analysis and Recognition, vol. 16, no. 1, pp. 1 – 21.

[7] Kumar R., Sharma J., and Chanda B., 2012, "Writer independent offline signature verification using surroundedness feature", Pattern Recognition Letters, vol. 33, no. 3, pp. 301–308.

[8] Eskander G., Sabourin R., and Granger E., 2012, "Adaptation of writer independent systems for offline signature verification", Proc. International Conference on Frontiers in Handwriting Recognition, Bari, Italy, pp. 434 – 439.

[9] Swanepoel J., and Coetzer J., 2012, "Writer specific dissimilarity normalisation for improved writer independent signature verification", Proc. IEEE International Conference on Frontiers in Handwriting Recognition, Bari, Italy, pp. 391- 396.

[10] Eskander G., Sabourin R., and Granger E., "Hybrid writer independent writer dependent offline signature verification system", IET *Biometrics,* vol. 2, no. 4, pp. 169– 181, 2013.

[11] Hamadene A. and Chiban Y., 2016, "One class writer independent offline signature verification using feature dissimilarity thresholding", IEEE Transactions on Information Forensics and Security, vol. 11, no. 6, pp. 1226- 1238.

[12] Hafemann L., Sabourin R., and Oliveira L., 2016, "Writer independent feature learning for offline signature verification using deep convolutional neural networks", Proc. International Joint Conference on Neural Networks, Vancouver, Canada, pp. 2576 – 2583.

[13] Vala H., and Baxi A., 2013, "A review on Otsu image segmentation algorithm", International Journal of Advanced Research in Computer Engineering & Technology, vol. 2, no. 2, pp. 387 – 389.