ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 3, Issue 3, March 2014

A Survey on Off-line signature Recognition and Verification Schemes

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ABSTRACT: The signature Recognition and verification system is used to recognize and verify individual's handwritten signature. Now a day's handwritten signature is one of the most widely accepted personal attributes for identity verification. Signature verification provides authorization in financial and business transaction. Signature verification finds its application in the field of net banking, passport verification system, provides authentication to a candidates in public examination from their signatures, credit cards, bank cheques. Therefore it has long been the target of fraudulence. Therefore, with the growing demand for processing of individual identification faster and more accurately, the design of an automatic signature system is needed. This paper represents a brief survey on different off-line signature recognition and verification methods.

KEYWORDS: Verification, Recognition, Forgeries, Handwritten Signature, Neural networks, Systems, Off-line signature Recognition and Verification.

I.INTRODUCTION

Handwritten signature is one of the most widely accepted personal attributes for identity verification. The major area of research on signature verification is in the field of pattern recognition and image processing. It is also widely used in the fields of finance, access control and security. Handwritten signature has long been the target of frauds. Therefore, with the growing demand for processing of individual identification faster and more accurately, the design of an automatic signature system is needed. Signature verification system is categories in two separate classes that is off-line signature verification system and online signature verification system.

1. Off-line verification [1]:
In off-line verification system verification is performed off-line. Data acquisition been done by scanning individual handwritten signature. That scanned signature will be used for signature verification process.

2. On-line Verification [1]:
In on-line verification system verification is performed on-line. Here data acquisition done by touch screen, digitizer and stylus. This instrument will generate dynamic values such as location, pen pressure, co-ordinate values, speed of signature or time etc.

No	Off-line Verification	On-line Verification
1.	Verification depends upon analysed image of person's signature.	Verification depends upon capturing and analysing the real-time signature, as the person signing it.
2.	Having a lot of noise included.	Zero noise included.
3.	Information obtained slightly.	Information obtained by varying.
4.	Fast verification process.	Faster than offline verification.
4.	Fairly high degree of accuracy.	Very high degree of accuracy.

Table 1: Comparison of Off-line Verification and On-line Verification [1]

II. SIGNATURE VERIFICATION CONCEPT

A handwritten signature is personal attribute ment to be used for identification. The signature verification processes of any person have to be done by analysis of his or her signature. Through which a system can differentiate a genuine signature from a forgery signature [2].
There are two type of error that will define the precision of the signature verification system that is FAR (False Acceptance Rate) and FRR (False Rejection rate).

FRR (False Rejection rate) [3]
The percentage of genuine signatures rejected from genuine signature tested as forgery which is called False Rejection Rate.

$$\text{FRR} = \frac{\text{No. of Genuine Signatures Rejected}}{\text{No. of Genuine Signatures Tested}}$$

FAR (False Acceptance Rate) [3]
The percentage of forgery signatures accepted from forgery signature tested as genuine which is called false acceptance rate.

$$\text{FRR} = \frac{\text{No. of Forgery Signatures accepted}}{\text{No. of Forgery Signatures Tested}}$$

III. TYPES OF FORGERIES

In handwritten signature verification the forgeries may be categories in 3-type given below [4].
1] Random forgery:
The signature uses the name of a person randomly in his own style to write a forgery known as the simple forgery or random forgery. In majority cases this forgery occurs, although they are very easy to detect even by naked eye.
2] Unskilled forgery:
The signers sign the person's signature in his own style without any knowledge of spelling. This type of forgery is known as unskilled forgery.
3] Skilled forgery:
The forgeries are created by professional person who have experience in copying the signature called skilled forgery.
Based on the various skilled levels of forgeries, it can also be divided in to six different subsets:
1) Random forgery 2) Causal forgery 3) Simulated forgery
4) Unskilled forgery 4) Targeted forgery 6) skilled forgery

IV. METHODS OF OFFLINE SIGNATURE VERIFICATION

There are so many methods have been developed for signature verification (SV) and recognition. Here are some convenient approaches and optimized methods are discussed below. This paper represents a brief survey of recent work on off-line signature verification and recognition system. Different existing approaches are discussed and compared along with their FRR and FAR.

1. Neural network approach:
K. V. Lakshmi et al. [5] proposed an Off-line Signature Verification Using Neural Networks technique. Artificial neural network (ANN) is also well known as neural network (NN). Neural network consisting of small processing unit which is basically has been modelled on human nerves system [1]. Here 3 layer neural networks have been used. I.e. input layer, a hidden layer and output layer. Here output layer will take binary decision based on predefined threshold. The input is accepted the magnitude of the output is greater than threshold otherwise input is rejected. Here, total 50 signatures are used for testing the model with first 25 signatures as genuine and rest 25 signatures as forgery. Neural network Training tool is used for simulations using the following specifications. Batch Processing by least mean square estimate. No. of NN layers: 3 Activation function of hidden layer = Log-sigmoidal Activation function of output layer

ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 3, Issue 3, March 2014

= linear No. of inputs, n = 8 No. of neuron in hidden layer, m = 20 No. of output = 1(b/w 1 and 0) Learning rate, lr = 0.08 No. of epochs = 25. An FRR 8%and 12% FAR was achieved [5].

2. Support Vector Machine:
Mandeep Kaur Randhawa at al. [6] Sharma proposed Off-line Signature Verification with Concentric Squares and Slope based Features using Support Vector Machines method. Support Vector Machines (SVMs) are machine learning algorithms that uses a high dimensional feature space and estimate differences between classes of given data to generalize unseen data [1]. SVM can be used to solve multi-class problem. The main task is to find a hyper plane between two classes. Which maximizes the distance from either class to hyper plane and distinguish the largest possible number of points belonging to the same class on same side? The vectors near the hyper plane are called 'support vectors'. The main Here 3 kernels have been used i.e. polynomial kernel, Radial basis functional kernel and linear kernel. Here, total 1000 signatures are used for testing the model with first 600 signatures as genuine and rest 400 signatures as forgery. Using polynomial kernel an FRR 3.33% and FAR 3.75, Using Radial basis functional kernel an FRR 1.66% and FAR 1.25%, using linear kernel an FRR 4.10% and FAR 2.50% was achieved.

3. SVM-DSmT Combination for Off-Line Signature Verification:
Nassim Abbas et al. [7] proposed SVM-DSmT Combination for Off-Line Signature Verification method. Here associate features based on Radon and ridgelet transforms for each individual system. Outputs of SVM classifiers are combined through a decision rule using the DSmT. For recognition and verification 3 systems have been used that is Random transform –SVM, Ridgelet transform-SVM and PCR5 (Proportional conflict redistribution).Database consists of 1320 genuine and1320 skilled forgery signatures that was build from 55 users. At threshold value 10 for Random transform –SVM FRR 7.72% and 7.72%, for Ridgelet transform-SVM FRR 7.72% and 7.72%FAR, for PCR5 FRR 5.45% and 5.45% was achieved.

4. Virtual support vector machine:
Samuel Audet et al. [8] proposed Offline Signature Verification Using Virtual Support Vector Machines. Support Vector Machines (SVMs) are machine learning algorithms that use a high dimensional feature space and estimate differences between classes of given data to generalize unseen data [1].For virtual support vector machine, the support vectors found during the course of the training of an SVM classifier are sent back to the image processing module to undergo invariant transformation before retraining .here 10 person with 16 genuine signatures and 200 random forgeries for training using linear kernel was taken and got 15% FAR and 15% FRR for Fixed parameter C=1024.

5. SOM (Self Organizing Map) and MLP (Multi-layer Perceptron):
Paigwar Shikha et al. [9] proposed Neural Network Based Offline Signature Recognition and Verification System. Artificial neural network (ANN) is also well known as neural network (NN Neural network consisting of small processing unit which is basically has been modelled on human nerves system [1]. Teuvo kohenon was first introduced self organizing map. Self Organizing Map is a kind of artificial neural network which is suitable to clustering tasks which can be useful to solve pattern recognition problems. The mappings are built by means of a process of competitive and unsupervised training (or learning).SOM is single layered architecture.
Where as MLP (Multi-layer Perceptron) is multilayered architecture. It is an attractive architecture for classification problems because they are capable to learn from noisy data and to generalize. Architecture of Multi-layer Perceptron was developed by Rosenblatt in the late 1950's. It is different from SOM because of layer and also it learns and behaves so that suitable for different type of problem. MLP is three layered architecture which consists of an input layer, a hidden layer and an output layer [9].
Here 70% or 42 samples of input data for training, 15% or 9 samples for testing and 15% or 9 samples for validation is used. For no. of iteration 103, 12.5% FAR, 10% FRR and 22.5% TER was achieved for SOM. For no. of iteration 103, 8.5% FAR, 11% FRR and 18.5% TER was achieved for MLP. The learning capabilities of MLP is better than MLP because MLP have multilayered architecture [9].

6. Back propagation neural network:
Nilesh Y. Choudhary et al. [10] proposed Signature Recognition & Verification System Using Back Propagation Neural Network Artificial neural network (ANN) is also well known as neural network (NN). Neural network consisting of small processing unit which is basically has been modelled on human nerves system [1]. Here Invariant

ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 3, Issue 3, March 2014

Central Moment and Zernike Moments used as a feature extraction method. Back propagation method is probably the easiest to implement, while preserving efficiency of the network. Back propagation layer usually use 3 layer architecture i.e. input layer, output layer and hidden layer. Here 672 images of database was created by 56 people are used for both training and testing. Since 8 (out of 12) input vectors for each image were used for training purposes,
There are only 224 (56*4) input vectors (data sets) left to be used for the test set. The back propagation network recognize 56 signatures correctly which results 100% recognition rate.

7. Fuzzy modeling concept:
Madasu Hanmandlua et al. [11] proposed Off-line signature verification and forgery detection using fuzzy modeling. The proposed method based on takagi-sugeno (TS) model. Here signature detection and signature verification process performed by angle feature extracted from box approach. Each feature corresponds to a fuzzy set. The features are fuzzified by an exponential membership function involved in the TS model, which is modified to include structural parameters. The structural parameters are taking in to account of possible variations due to handwriting styles and to reflect different moods. The membership functions constitute weights in the TS model. The optimization of the output of the TS model with respect to the structural parameters yields the solution for the parameters. There are two TS models have been used. First is TS model with multiple rules and second is TS model with single rule. TS model with multiple rules is better than TS model with single rule for detecting three types of forgeries; random, skilled and unskilled from a large database of sample signatures in addition to verifying genuine signatures.
There are 600 genuine signatures, 200 skilled forgeries, 200 unskilled forgeries and 200 random forgeries taken. For genuine signatures 62.5% accepted 37.5% rejected, for skilled forgeries 34%accepted 66% rejected, for unskilled forgeries 25.5% accepted 74.5 % rejected, for random forgeries 25% accepted 75% rejected

8. Novel feature extraction method:
Dr. Daramola Samuel et al. [12] proposed novel feature extraction technique for off-line signature verification system. We accepted Biometric characteristic for personal and document authentication as handwritten signature of a person. Verification results based on local or global features extracted from signature under processing. Excellent verification results can be achieved by comparing the robust features of the test signature with that of the user's signature using appropriate classifier [12][13][14].
Here proposed method of feature extraction is novel feature extraction method .Total numbers of 500 signatures made up of 200 genuine signatures, 100 random forgeries, 100 simple forgeries and 100 skilled forgeries are tested. For simple forgeries, random forgeries and skilled forgeries FAR is 0%, 0% and 1% respectively and FRR for genuine signature is 0.5% we achieved.

9. Four Speed Stroke Angle approach:
L.Basavaraj et al. [15] proposed Offline-line Signature Verification and Recognition: An Approach Based on Four Speed Stroke Angle. Different pixels of single thickness lines are obtained in the pre-processing stage and separated based on angle orientation. Here standard method extracts only the angles 0, 45, 90,135. The Four Speed Stroke Angle approach extracts the dynamic features of static image that is speed of stroke, intensity of the stroke. Here image is divided in to four speed levels that are binary, the histogram of the thinned gray, threshold points and intensity level of an image. The four speeds – divided stroke images are applied with the method of Stroke Angles and the count of pixels in each angle are taken. Based on the number of matching of the counts, classification is performed which decides whether the signature under test is genuine or forged. Here collected data contains 100 users' genuine and forged signatures. For stroke angle (without speed division) FAR is 26.78% and FRR is 18.75%. For stroke angle with four-speed division FAR is 16.5 % and FRR is 14.5%. And combine result is 13.78% FAR and 14.15% FRR.

10. Hidden markov model:
Neural network consists of small processing unit which is basically modelled on human nerves system [16]. The implementation of hidden markov models for signature verification has been done by Coetzer and Preez [17] using the global features of a signature. Using combination of global features and local features extracted from signature image other researchers, Kashi proposed the same method [18].HMM is easy to implement. HMM have limitation such as difficulty in determining best algorithm that can be used for modeling. Using 440 genuine signatures from 32 writers with 132 skilled forgeries we get 16% FAR and 22.5% FRR.

11. Signature Envelope and Adaptive Density Partitioning approach:
Vahid Malekian et al. [19] proposed Rapid Off-line Signature Verification Based on Signature Envelope and Adaptive Density Partitioning. Adaptive density partitioning is the other novel and effective feature extraction technique. In this method, the pre-processed image is split into four partitions through its centre of gravity. Each quadrant is then divided into four equal parts. This way signature is split into sixteen segments. Envelope signals obtained based on the centre of gravity. Multi-layer perceptron architecture is used. Multi-layer perceptron (MLP) neural network has been among the most widely satisfactorily applied classifiers for handwritten signature verification problems [20]. The database contains 900 signatures collected from 45 people. Since generally signatures signed by the same person may vary in different trials, each individual was asked to provide 10 samples in multiple sessions over up to 2 weeks period. 10 forged specimens for each person were collected. For recall test 0.47% FAR and 0.36% FRR and generalization test 5.3% FAR and 4.0% FRR was achieved.

12. Confidence voting method
Juan Ramo´n Rico-Juan et el. [21] proposed Confidence voting method ensemble applied to off-line signature verification method. A new approximation to off-line signature verification is proposed based on two-class classifiers using an expert decisions ensemble. Different methods to extract sets of local and a global feature from the target sample are detailed. Also normalization by confidence voting method is used in order to decrease the final equal error rate (EER). Each set of features is processed by a single expert, and on the other approach proposed, the decisions of the individual classifiers are combined using weighted votes. Using 1500 training set and 750 testing set obtained an EER of 6.3 and 2.31 % as the best results in skilled and random forgeries, respectively.

V. PERFORMANCE EVALUATION OF DIFFERENT APPROACHES WITH RESULT

FAR and FRR are the evaluation parameter for any signature verification system. Some of the convenient approaches with associated results are shown in table 2.
FRR- False Rejection Rate
FAR-False Acceptance Rate

Sr. No.	Approach	Input	FRR	FAR
1.	3 layer neural network approach	Using 50 signatures that containing 25 genuine and 25 forgeries	8%	12%
2.	SVM based approach	Using 1000 signatures that containing 600 genuine and 400 forgeries	1.66%	1.25%
3.	SVM-DSmT Combination	1320 genuine and 1320 forgery build from 55 users	7.72%	7.72%
4.	V-SVM approach	Using 10 person with 16 genuine signatures and 200 random forgeries	15%	15%
5.	SOM approach	Using 42 samples of input data 9 samples for testing and 9 samples for validation	11%	10%
6.	MLP approach	Using 42 samples of input data 9 samples for testing and 9 samples for validation	11%	8.5%
7.	Fuzzy modeling approach	Using 600 genuine signatures, 200 skilled forgeries, 200 unskilled forgeries and 200 random forgeries	6.6%	3.4%
8.	Novel feature extraction approach	Using 500 signatures made up of 200 genuine signatures, 100 random forgeries, 100 simple forgeries and	0.5%	1%

ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 3, Issue 3, March 2014

		100 skilled forgeries		
9.	Four Speed Stroke Angle approach (without speed division)	Using 100 users' genuine and forged signatures	18.75%	26.78%
10.	Four Speed Stroke Angle approach (with speed division)	Using 100 users' genuine and forged signatures	14.5%	16.5%
11.	Hidden markov model approach	Using 440 genuine signatures from 32 writers with 132 skilled forgeries	22.5%	16%
12.	Signature Envelope and Adaptive Density Partitioning approach	Using 900 signatures collected from 45 people	4.0%	5.3%

Table 2: Performance evaluation of different approaches with result

VI.CONCLUSION

This paper represents a brief survey of recent work on off-line signature verification and recognition system. Different existing approaches are discussed and compared along with their FRR and FAR.

In the field of signature verification lots of work has been already done. Here MLP approach, Fuzzy modeling approach, Hidden markov model approach are good approaches But there are still many challenges in research area. The non-repetitive nature of variation of the signatures, because of illness, age, geographic location and perhaps the emotional state of the person, accentuates the problem. The other major problem with this area is, for security reasons, not easy to create database of a real document.

The results obtained in signature recognition and verification is not very high and more research on off-line signature verification is required.

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