Analyzing the Progression in the Identification of Offline Handwritten Signatures

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Abstract

A signature is observed as one of the important biometrics for verifying the identity of human beings as every individual has his/her unique signature. Therefore, a signature is widely used as a Personal identification tool for the automatic verification system. Signatures done by an authorized person is only considered a valid signature. Biometrics can be differentiated into two areas: Behavioral and Physiological. Behavioural includes signature verification, keystroke dynamics, etc. and Physiological includes fingerprint, iris characteristics, etc. There are two different types of signature verification techniques i.e. Static (Offline) and Dynamic (Online). The signatures done by a person on paper or a document are termed offline or static signatures and they need to be scanned or captured by the camera for a digital copy, whereas the signatures done by a person using a stylus on a tablet fall under the category of Online or dynamic signatures. In this paper, a brief overview of Offline signature Recognition and verification techniques for reducing forgeries to maintain security are discussed.

Keywords - Biometric System, Signature Recognition, Signature Verification, Forgery.

1. Introduction

There are two different types of signature verification techniques i.e. Static (Offline) and Dynamic (Online). Static signature is observed as one of the important and convenient biometric methods for identifying and verifying the identity of human beings as that is unique for every person [1]. A signature is a handwritten identification of any individual's name, nickname, or identity mark that a person writes on documents as proof of identity. A signature is a behavioural biometric as it depends on criteria like mood, fatigue, etc. Biometrics is always with an individual and it cannot be forgotten or misused. Signature verification has an edge over other biometric techniques like a fingerprint, voice and iris recognition, etc. as biometric characteristics of the individual are not freely transferable, and cannot be lost, stolen, or broken [2]. The selection of one of the biometric solutions depends on the following different factors [3]:

- Level of security required
- Accuracy

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- Acceptability by User
- Cost and implementation time
- Convenience
- Usability

Handwritten signatures are used as biometrics in transaction authentication like in banking, bank cheques, and credit cheques. The other areas where signature recognition and identification are: User login in computer or Personal Digital Assistant (PDA), access control and property Dealing, etc. [4].

Handwritten static signatures may be composed of special characters, and symbols used to differentiate and authenticate one human from another. In this verification system, a captured image is stored in a computer in form of a JPEG or other image format file. The problem is to compare the user signature with a sample database of signatures. The signature identification rate of online mode is higher than in offline mode, but the dynamic mode has a major drawback in that it's online. So, it cannot be used in some important areas as the individual is not physically present in the place of signing and front of the authority. Static signature identification systems need to be designed with care to achieve the desired accuracy.

A forged signature is a similar signature to of original signature but not original. Forgeries are categorized into three different categories i.e. Random, Simple and Skilled [5] [6].

1. **Random Forgery:** When any individual uses his/her way to copy the actual sign to create a forgery, it is known as a random forgery. It can be easily judged by the naked eye. Such forgeries are not based on any prior knowledge of the actual signature.
2. **Simple Forgery:** When any individual is new to forgery and does not have any experience to forge the actual sign, it is known as a simple forgery. It can also be easily judged by the naked eye as in the case of Random Forgery. Such forgeries are based on ideas about the signature from the name of the authentic signer. These forged signatures may or may not look like the original - partially or even totally.
3. **Skilled forgery:** When an individual is an expert in forging the actual sign with knowledge and prior experience, then such forgeries made are called expert or skilled forgeries. Such forged signatures are most difficult to identify with the naked eye or also using any verification system due to the exact replication of the original signature. Skilled forgery is the most difficult to detect compared to the other two forgeries.

To verify and measure the standard performance of the proposed system, False Rejection (Type 1 errors) and False Acceptance (Type 2 errors) are computed for the effectiveness of the static signature verification

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system. It verifies if a signature is original or forged. The system performance is calculated by following three measures: [6] [7]

1. **False Rejection Rate (FRR):** It is the probability of original signatures not being accepted as false by the system i.e. the percentage when the proposed system incorrectly rejects as a failure after comparing the input signature with the sample signature in the database.
2. **False Acceptance Rate (FAR):** It is the probability of fake signatures accepted as original signatures by the system i.e. the percentage when the proposed system incorrectly accepts the signatures as correct after comparing the test sample with the non-matching set of signatures in the database.
3. **Equal Error Rate (EER):** When at a particular defined set threshold value, FRR is equal to FAR. It is Equal Error Rate (EER).

2. Applications of Signature Recognition and Verification System

A signature is seen as one of the crucial biometric methods for proving the identity of human beings as every person has his/her unique signature. It is therefore accepted that signature is widely used as a means of Personal identification tool for the automatic verification system. Static signatures are used in different areas. The signature indicates the acceptance by an individual as his/her physical presence for the work and a mark of authenticity. Therefore, offline signatures are used conveniently in various areas like in government and other official documents. Handwritten signatures are used as biometrics in transaction authentication like in banking, bank cheques, and credit cheques. The other areas where signature recognition and identification are: User login in computer or Personal Digital Assistant (PDA), access control and property Dealing, Visa application and academic certificates, etc.

The major area where handwritten signature requires more security is in Financial Institutions that deal with Banking transactions [8] like

1. **Cheques:** A cheque needs a person's signature as a mark of authentication. It is a very cumbersome and labour-oriented job for banks to authorize and verify each cheque for its signature and authenticate it. As there is a large number of transactions in day-to-day banking, it becomes a very time-consuming process and also compromises the security that a customer expects. So, the solution to overcome this situation is correct static signature recognition and verification.
2. **Credit Cards:** The purchases are done using a credit card and also need a static signature verification system. Credit card transactions are growing day by day including monetary transactions based on signatures only. Therefore, it

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needs some security system. The implementation of a static signature authorization system can add more security to an existing system. Credit cards are a digital mode of payment but the major drawback is that they do not check the originality of a customer for authentication purposes. The solution to overcome this drawback is also the implementation of a signature recognition and verification system. This makes the signature identification process more authentic and secure.

3. Signature Verification Process

Handwritten signature processing can be used for two different purposes:

1. Identification (Recognition)
2. Verification (Authentication)

Signature Identification: The biometric recognition of any person's signature depends on the data input in form of a signature that is scanned from a document using a scanner, camera, or other imaging devices. Then that scanned image is compared with an available dataset of signatures. The four different properties of an off-line signature are [9]

- ✓ Authenticity of the signer: An offline signature permits verification of an individual's identity.
- ✓ Integrity: The signature makes sure that the signed document has its integrity by authenticating that the document is not modified in any way.
- ✓ Acceptance: The signature indicates the acceptance by an individual of his/her physical presence at the work and also accepts the terms defined in a document. It is a mark of authenticity.
- ✓ Non-Refusal: The above three factors in combination make sure that no individual can deny his/her signatures

Signature verification is a result about the available signature is genuine or forged.

Signature Recognition and verification consist of different sub-parts that are preprocessing of input signature, feature extraction, classification, and verification [1].

4. Literature Survey

In this section, work of several researchers is mentioned here.

Bhattacharya *et al.* [2] proposed a method of static handwritten signature recognition and verification using the Pixel Matching Technique (PMT). It is used to verify the signature of an individual with the sample signature available in the database. The performance of this proposed system is comparable to the existing Artificial Neural Network (ANN) back propagation technique and Support Vector Machine (SVM). The signature database includes 8 signatures in original and forgery each from an individual signer. It is verified that signature verification using PMT proved that the True Acceptance rate is 0.94 which is comparable to other techniques like ANN where

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the True Acceptance rate is 0.98 and in SVM True Acceptance rate is 0.78.

Bansal *et al.* [7] proposed a contour matching algorithm that specifies the basic feature patterns in a sample signature. The various pattern Matching classifiers for static signature verification are also discussed. To test the system, 75 random users were selected. The results proved a success for 66 users' signatures from the given 75 users on using this proposed system. Then these accepted 66 users were authenticated against 1176 different signatures. The results of FAR in the case of Random Forgery is 0.08% and for simple and skilled forgery it is 13.02%. On implementing this system, FRR is found to be 2.64%.

A new offline handwritten signature recognition and verification based on the Contourlet Transform (CT) feature extractor is proposed by Pourshahabi et al. [9]. Experimental results of the proposed system proved reliable independent of the signer's nationality for Persian and English signatures. The first experiment has been performed on a Persian signature database that includes 20 classes and 30 signatures per class i.e. 600 signatures in all. Each class consists of 10 genuine signatures for training, 10 genuine signatures for testing, and 10 skilled forgery signatures. Then another experiment has been performed on an English signature database that includes 22 classes and 42 signatures per class i.e. 924 signatures in all. Each class consists of 10 genuine signatures for training, 20 genuine signatures for testing, 6 casual forgery signatures, and 6 skilled forgery signatures. The identification rate calculated from the Persian signature database is 100% and from the English signature database is 93.2%. The rates of verification FAR and FRR are 14.5% and 12.5% respectively for the Persian skilled forgery set, whereas 22.72% and 23.18%, for the English skilled forgery set

In [10] Sigari et al. proposed another method of static handwritten signature recognition and verification based on the Gabor wavelet transform. The basic idea behind its development is to prepare a simple and robust technique for feature extraction based on the Gabor wavelet transform so as to reduce the dependency on the signer's nationality. To verify and analyze the designed system's performance different experiments are performed on Persian, Spanish, Turkish, and South African signatures databases respectively. The first experiment has been performed on a Persian signature database that includes 20 classes and 30 signatures per class i.e. 20 genuine and 10 expert forgery signatures per class. 600 signatures in total. In Signature Identification, the Correct Classification Rate (CCR) is 100% which is similar to the above-mentioned technique in [1] i.e. Gabor wavelet transform, and in Signature Verification Equal Error Rate (EER) is 15%. The second experiment has been performed on a Turkish signature database that includes 40 classes and 12 signatures per class i.e. 8 genuine and 4 forgery signatures per class. 480 signatures in

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total and 30 different persons in addition to genuine signers signed the forgery signatures. The results of signature Verification EER is 9%. Another experiment was performed on a Spanish signature database that includes 38 classes and 6 signatures per class i.e. 228 signatures in all. In Signature Identification, the CCR is 77.3%. The final experiment was performed on a South African signature database that includes 22 classes. In each class, there are 10 actual signatures for the training set and 20 actual signatures, 6 expert forgery signatures, and 6 simple forgery signatures for testing purposes. The database contains 924 signatures in total. The results of signature Verification in case of simple forgery and expert forgery's EER is 6.3% and 16.8% respectively. It is therefore accepted that this system is more worthy in case of expert forgery signatures.

Sulong *et al.* [11] proposed a method of Offline Handwritten signature identification using the Adaptive Window Positioning Technique (AWP). This method along with signature identification also emphasizes on the individuality of the signer. The signature database includes 4870 signature samples from 90 different individuals. It then compares the different features of the test signature with the signer signature using a suitable classifier. The results of offline handwritten signatures verification concluded that the AWP is certified to be an efficient and trustworthy method. The results were tested on a sample of 1200 signatures taken from 40 signers. The results of the AWP technique come to be far better when compared with other methods like Graph Matching, Adaptive Feature Thresholding, High-Pressure Polar Distribution, etc. The FAR is 8.68%, the FRR is 6.12% and the ERR is 7.40%.

In [12] and [13], Armand *et al.* have proposed an Off-line Signature Verification method using the Enhanced Modified Direction Feature and Neural-based Classification. The proposed feature extractor consists of Gradient, Structural, and Concavity features. The results computed after the verification process is 78%. Various techniques were used for offline signature verification like Support Vector Machines (SVMs) and Hidden Markov Models (HMMs). SVM proved to be more favorable than HMM. For the classification of signatures, a combination of the MDF and some properties like centroid, length, surface area, and skew are implemented. To identify signature verification accuracy a Resilient Backpropagation (RBP) neural network and RBF (Radial Bias Function) network were contrasted. A database of 2106 signatures that includes 936 actual and 1170 forged signatures for the testing process. The results computed after verification are 91.21% for RBF and 88.0% for RBP.

Armand *et al.* [14] analysed the results of Enhanced Modified Direction Feature (EMDF) after implementation on single and multiple neural networks. The database of 2376 signatures was used to perform a trial of the

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proposed method. It includes the signatures of 44 individuals and for each person, there are 24 valid samples and 30 forged signatures. The identification accuracy rate calculated for a single neural network is 89.77% and on implementing multiple neural networks, the identification error rate calculated is 1.16%.

In [15], advanced techniques have been proposed for Off-line Signature Verification using Enhanced Modified Direction Features (MDF) in Conjunction with Neural Classifiers and Support Vector Machines. The MDF and Extended MDF are used to extract the structural properties from the signature's contour image. Then for the off-line signature verification process, neural network-based techniques and SVM are used. These classifiers were tested and trained on actual signatures and randomly selected signatures available in the open database. This open database includes 3840 actual signatures of 160 volunteers and 4800 copy signatures. The results concluded for an error rate is 17.78 %.

The work reported in [16] used global features for the off-line signature verification problem based on the corners of a signature and its expectation for escalating the process of automated signature verification. The first universal feature is obtained from the total 'energy' a signer uses to design their signature. The second feature uses data from the vertical and horizontal estimates of a signature on the area between keystrokes in the image, and the height/width of the signature. The results proved to be favorable for offline signature verification on the integration of the above features with the Modified Direction Feature (MDF) and the ratio feature. To verify the proposed system the global available database gpds SIGNATURE is used. The system is tested using the Support Vector Machine (SVM) classifier on 12 original signatures and 400 random copy signatures. The results computed with an AER of 17.25%, and the FAR for random forgeries is 0.08%.

Pushpalatha *et al.* [17] proposed an offline signature verification with random and skilled forgery detection using polar domain features and a multi-stage classification regression model. The authors used a polar feature descriptor that includes Radon Transform and Zernike Moments for signatures. Then Multiclass Support Vector Machine (SVM) is used for signature verification. Finally, to get a regression score, Regression is implemented on all the signatures available in the database and for Log Likelihood, Hidden Markov Model is used for computations. The database consists of 50 signatures each from 100 users i.e. 5000 signatures in all. The authors used 10 signatures for training purposes i.e. 1000 signatures and 40 signatures for testing purposes i.e. 4000 in all. The results are accepted and successful in signature classification only if the regression score and Log Likelihood distance deviation are less than 5%. Signature verification results proved the accuracy of 98%. The FAR is .8%. The proposed system identified skilled forgery

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and Random forgery with an accuracy of 71% and 76% respectively.

Prachi Chauhan *et al.* [18] have explored a system for static digital signature recognition and verification using Artificial neural networks (ANN). To prepare the script GUIDE method available in the MATLAB toolbox was used. Firstly all the attributes to be tested were coded and then those codes were used in the script. The ANN when used for pattern matching tasks on all the signatures that are not part of the database, proved to be successful in identifying and verifying the same. The process of signature recognition and verification is done by comparing its feature vector with the database images. The results derived are more reliable when the neural network is used on larger databases. This approach is more efficient in signature verification.

In [19] and [20], Pansare and Bhatia have also discussed handwritten signature verification using neural networks. The database used for training and testing contains 1440 signatures in all. It constitutes signatures from 30 individuals where each person does 24 original valid signatures and 24 copy sample signatures. For training purpose, a sample of 19 signatures of 30 persons is used for feature extraction using a neural network. The Correct Classification Rate (CCR) after training the defined signature samples using a neural network gave 100% results in signature recognition and classification. The CCR gets lower to 82.66% in the case of testing the neural network approach on new signatures that were not earlier trained for.

Mahmud *et al.* [21] worked on an offline signature verification system based on modified feature analysis and ANN. For quick signature identification and verification from extracted features, the authors used multi-dimensional features of a neural network classifier and for training, they used resilient backpropagation NN. Finally, for testing purposes, they worked on cross-validation techniques. Different signatures were taken from 30 individuals for verification purposes. Each person contributed with 10 signatures. The system is trained for 10 genuine and 5 duplicate signatures for each individual. The accuracy ranges from 78% to 94%.

Abughfa *et al*. [22] developed a static signature verification system using image processing and Hu Moment. They developed a signature certification system using a digital image to validate offline signatures. The proposed system on a trial basis was used on 1050 signatures in all. It included 300 original signatures, 90 forged, and 660 redundant signatures. The system was able to achieve success on 959 signatures from 1050 total signatures. Out of the remaining 91 signatures, 90 were declined as it was forged. The ERR calculated for the proposed system is 08.67% and the identification rate is 91.3% which is far better than the expectations of the authors.

Bharadi and Kekre [23] have used cluster-based global features as well as grouping-based

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features that are a multi-algorithmic handwritten signature recognition system. For the horizontal and vertical pixel distribution authors used Walsh transformations. A signature database contains 984 signatures of 75 individuals with 12 signatures per person. There are 8 signatures used as a threshold value for any computation and left out four are used as original signatures for testing. The authors also collected 125 skilled forgery signatures, and 30 casual or unskilled forged signatures for testing. So, in total 1139 signatures were available in the database for testing purposes. The results calculated after implementation is FAR is 2.5%, EER is 3.29% with an overall signature recognition authenticity of 95.08%.

The authors in [24] also worked on an offline signature verification system for better results. The proposed method uses different statistical features to identify signatures that help in recognizing and differentiating signatures of different individuals. This method is also able to identify all three variants of forgeries i.e. random forgery, unskilled forgery, and skilled forgery. The database used to test the proposed system includes 60 original and 67 forged signatures. After implementing the proposed system on the set database the performance as per FAR and FRR parameters justified that the designed system is the best algorithm for signature verification. The said system is able to overcome the limitations due to factors like the angle of inclination, region of interest, and scaling factors. It therefore can be termed as the modified handwritten signature verification method.

The work reported in [25] developed pixel based handwritten signature verification system. The proposed system is the fastest and easy method to identify and validate signatures. Firstly, the signature image is acquired and then it is divided into a 2-dimensional array from which the hexadecimal RGB value of each pixel is computed. The total match percentage is calculated. The threshold value is 90%. If the matched value is more than 90% it is said to be valid otherwise invalid. They developed this signature verification system as a web-based application for open access to all such that any signature can be authenticated from anywhere. The database includes 35 signatures onto which the proposed system is tested. According to the authors, the results of the proposed system after implementation were found to be excellent. The average execution time of the proposed system for signature verification is 0.00003545 seconds only.

Hafemann *et al.* [26] discussed writer independent feature learning for handwritten signature verification using Deep CNN. The authors surveyed a variety of handcrafted feature extractors, graphology, computer vision, signal processing, etc. They believed in the use of Deep CNN to learn features in a writer-independent style. The system is tested on global available database sets i.e. GPDS-960 and Brazilian PUC-PR. The GPDS-960 dataset includes the signatures of 881 persons with 24

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actual signatures and 30 forgeries per user. Another Brazilian PUC-PR dataset includes signatures from 168 persons and forgeries for the first 60 persons. The results proved to be good when implemented on GPDS and more promising on the Brazilian PUC-PR dataset. It achieved low ERR. Further, in [27], analyzed features for Off-line Signature Verification using Deep CNNs. The authors surveyed a variety of handcrafted feature extractors, graphology, texture descriptors, etc. To the advancement of previous research [26], the improved performance of the range of architectures is explored. This proposed system is also implemented on the same databases. The results then proved to be much better than previous results. The results calculated an EER of 2.74%. The system proved that model is successful in differentiating signatures that have a separate global appearance. It fails when forged signatures are very similar to original signatures.

Ranjan Jana *et al*. [28] have also introduces an offline signature verification system for validating the signatures and differentiating between original signatures and forged signatures. The different methods were developed by various researchers that use clustering methods like K-means, fuzzy c-means, and hierarchical clustering for the classification of features. The authors have proposed a new method of feature extraction and signature classification by calculating a Euclidian distance. The verification results after implementation on the sample dataset give an accuracy of 100 %. The EER gets lower in the case of large databases.

5. Conclusion

Handwritten signatures is one of the most commonly accepted personal identification tools for automatic verification system. The off-line signatures is one of the most widely accepted means to verify transactions and then authenticate them for their originality in contrast with other available physiological methods like fingerprints, iris scanning, etc. In financial institutions where number of banking transactions i.e. cheques, are large in number to be processed after authentication within limited time, is often time consuming. This helps in the development of static signature verification systems. The vital contribution of this survey is to get an idea of different handwritten signature recognition and verification methodologies that are followed currently with respect to its specifications, merits, demerits and its FAR, FRR, EER as well as accuracy. It is noticed that the FAR of the skilled forgeries is very high due to similarity in the structure and shape of skilled and original signatures. Therefore, the signature verification accuracy is required to be improved for skilled forgeries with respect to FRR and FAR. It is also observed that there is an insufficient number of sample signatures from each person for training and testing of the static system. The results will be more accurate

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if we collect the large number of sample signatures from the signers at different gaps of time. It will also help to identify the intrapersonal signature variations more consistently and accurately. A larger sample signature database can reduce FAR as well as FRR with increase in accuracy.

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