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A SURVEY FOR OFFLINE SIGNATURE VERIFICATION AND RECOGNITION TECHNIQUES USING IMAGE PROCESSING

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Abstract— Signature Verification is the examination of a signature as it is widely used as a means of personal verification to discriminate between original and forged samples of a signatory. It offers two different types of schemes those are offline (static) and online (dynamic) verification techniques. Offline systems work on the scanned images while online systems use dynamic information of a signature captured at the time the signature is made. On comparing both offline systems found to be more complex due to the absence of stable dynamic characteristics and also due to highly stylish and unconventional writing styles despite that they are designed because of several benefits like systems does not requires signer's attendance as it is already stored in database. The aim is to lower down the false acceptance rate (FAR), false rejection rate (FRR) average error rate (AER) and equal error rate (EER). In this paper we reviewed and compared some popular existing verification techniques, their results and methods of feature extraction.

Keywords- offline/online signature verification and recognition; techniques used; feature extraction; image processing.

I. INTRODUCTION

A Biometric system is a pattern recognition system which determines a user by assuring the legitimacy of a specific feature or behavioral characteristic possessed by the user. The signature verification has an advantage over other forms of biometric techniques like fingerprint, voice and iris recognition, heart sound etc. A Signature is a hand written depiction of someone's name, nickname or any other identifying mark that proof his or her identity. It will have some intrapersonal variation even when it comes from a same person due to geographical factors, age, emotional state, illness or due to any other reason as well as interpersonal variation means differences between originals and forgeries. Forgeries are then further classified into three different categories namely Random, Simple and Skilled.

a) *Random forgery*: The signer uses his/her own style to forge the victim sign to create a forgery is known as random forgery. It is very easy to recognize by the naked eye. These signatures are not based on any knowledge of the original signature.

b) *Simple forgery*: The signer does not have any prior experience to forge the victim sign for forgery is known as simple forgery. It is also very easy to detect by the human eye. These are based on an assumption of how the signature looks like by knowing the name of the signer.

c) *Skilled forgery*: It is the most difficult than rest of all forgeries. The signer is an expert and has prior experience to copy the victim sign to make forgery or in other words it is an imitation of the original signature. It is very hard to recognize by eye even by the verification system.

II. PROCESS METHODOLOGY

There are three major steps used for signature verification and recognition and each of these steps consists of many methods that contribute to improved results. Following steps are:

a) *Data acquisition:* Paper based signature is first converted into a digital image by scanning and then it is used for verification purpose.

b) *Preprocessing of image:* It is the most important step in signature verification and recognition that exists for the manipulation and modification of images. Its successful implementation produces improved results and higher accuracy rates.

Different levels of processing are:

1. *Elimination of background:* Threshold method is used to extract the signature from the background of a signature. All pixels of signature are converted to "1" and rest of pixels those are belongs to background of signature convert to "0".
2. *Noise reduction*: Noise reduction filter is employed to the binary signature to do this job. It removes the single black pixels on the white background. Defects removal, image enhancement and quality achieved.
3. *Width normalization:* A given signature is then resized for proper dimensions because the signature may vary between interpersonal and intrapersonal.
4. *Thinning:* Thinning removes the thickness differences that can occur because of different pens.

c) *Feature Extraction:* Feature extraction techniques play vital role to improve the accuracy of signature verification system. This process identifies and differentiates an individual signature from another. It can be achieved by employing different type features such as global features, geometric features, texture features.

A. VARIOUS GEOMETRIC FEATURES ARE LISTED BELOW:

- Measure of Pen pressure
- Measure of writing movement
- Measure of stroke formation
- Slant
- Height
- Aspect ratio
- Eccentricity, Area, Centre of Gravity,
- Kurtosis and Skewness.

B. VARIOUS GLOBAL FEATURES INCLUDE:

- Color
- Aspect ratio
- Moment invariant

C. VARIOUS TEXTURE FEATURES INCLUDE:

- Coarseness
- Contrast
- Directionality
- Roughness
- Entropy
- Wavelets, fractals

D. MISCELLANEOUS FEATURES

- Height Width Ratio
- Scale Invariant Area
- Calculation of Centroid

III. RELATED WORK

Neural Networks Approach: It is a field of artificial intelligence that aims to imitate the way a human brain works. It consists of interconnected processing elements neurons that work together to produce an output. The number of neuron connections is extensive in nature and process the information parallel rather than in series or in sequential form. It has a unique property that it can still perform most of its functions even if some of the neurons are not functioning. They learn through training on a large number of data, which enables them to create a pattern of time that they will use later. They are highly reliable when trained using a large amount of data.

C. Quek et al. [1] proposed a pseudo-outer product based on the fuzzy neural network (POPFNN-TVR) driven signature verification system. This five layer structure used learning ability, generalization ability and high computational ability and extract different features of an image like Reference pattern based features, Global baseline, Pressure features and Slant features which are used as elements of training vector later on. They claimed an average of 22.4% EER.

Pansare and Bhatia [2] also make the use of neural network for performing signature verification. They studied the relationship between signature and classes based on signature verification extraction. They employed features like contour, surface area and length skew. Its limitation is that it cannot be used for systems that can receive data in time series.

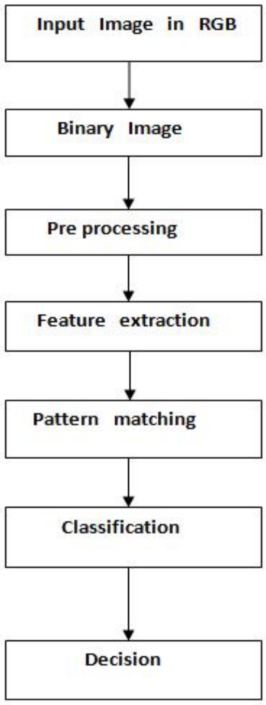

Fig. 1. Work flow of process

Karouni, Ali, Bassam Daya and Samia Bahlak [3] employed a mechanism to verify offline signature by using shape based geometric features such as Eccentricity, Area, Center of Gravity, Kurtosis and Skewness. It proposed better output only for small amount of training data.

Papamarkos, N., and H. Baltzakis [4] imply the OCON (One class one network) structure in each of the global, texture and grid features. They employed a simple Euclidean norm along with ALOPEX algorithm to determine the originality of a given signature. One combiner is used along with these to combine three different sets of neural network. It reported an average FRR and FAR of 3% and 9.8%.

Support Vector Machine: These are machine learning algorithms which use high dimensional space feature and estimate differences between classes of given data to account on unseen data. Although SVM algorithm has an excellent ability in generalizing the given image but has a limitation of determining which kernel to be used, classification using SVM requires considerable time and space. They are used for regression and classification by analyzing data and recognizing patterns. It is first invented by Vladimir Vapnik in 1995. It is a special case of Tikhonov regularization, they can minimize the empirical classification error and maximize the geometric margin simultaneously thus it is also called as maximum margin classifier. It separated the data into two groups, one that belongs to class and other consists of feature vectors not belonging to the training class.

E. J. Justino et al. [5] compared the capabilities of SVM and HMM taking a set of static features such as pixel density and gravity centre and pseudodynamic features such as slant and stroke curvature and demonstrates that SVM is more promising then HMM.

l. Maritinez et al. [6] compared parameters such as Contour measure, Contour following, Region grouping and direct image. It reported an error rate of 11.13%, 12.19%, 20.14%, 11.28% respectively.

V. Kiani et al. [7] used Radon Transform as a feature extractor and SVM as a classifier. They used Radon Transform locally for line segments detection and feature extraction, against using it globally. It reported FRR of 19%, FAR of 2% and 22% for casual and skilled forgeries.

Hidden Markov Model: It is a statistical model in which the system being modeled is assumed to be a Markov process with hidden parameters. In this model state is not visible but the output is state dependent. Its aim is to discover hidden parameters from the observable parameters, which are then further utilized for signature verification. It has a limitation of difficulty in determining best algorithm that can be used for modeling. Considering Viterbi algorithm has good performance but requires a lot of resources both in terms of time and space.

E. J. Justino et al. [8] first performed an offline signature verification using HMM involving the use of scales with square cells, presented a learning process for segmentation. For this purpose they used an automatic derivation process of the decision threshold in their matching process. It reported an average error rate (AER) results of 0.46% and 0.91% respectively.

E. J. Justino et al. [9] observed intrapersonal variations in a given signature considering both static and pseudodynamic features. It reported a FRR of 2.8% and FAR of 1.44%, 2.50% and 22.67% respectively for random, casual, skilled forgeries.

J. Coetzer et al. [10] employed both Discrete Radon Transform and HMM on Stellenbosch data set containing 924 2-D based signatures from 22 writers reporting EER of 4.5% and 18% on casual and skilled forgeries respectively.

Modified Direction Feature: This technique extracts direction information from a given image. The principal is to look out for transitions between background and foreground pixels in a given image. It was first discovered by M. Blumenstein et al. It extracts both location transitions and direction transitions for more advanced calculation.

S. Armand et al. [11] performed an experiment using the combination of MDF with other features like Centroid(C), Trisurface(T) and Length(L). The best result reported with a verification rate of 91.12%.

S. Armand et al. [12] used Radial basis function (RBF) network and Resilient Back-propagation (RBP) neural network in comparison with Enhanced MDF (EMDF). Verification rates of 91.21% and 88.0% were obtained using RBF and RBP respectively.

S. Armand et al. [13] observed their EMDF using both on single and multiple neural networks. Experiment was performed on 2376 signatures from 44 sets of signatures (24 genuine and 30 forgeries sample each set). Single Neural Network achieved a verification accuracy rate of 89.77% while Multiple Neural Networks achieved a verification error rate of 1.16%.

IV. OTHER RELATED WORK

M. H. Sigari et al. [14] proposed a simple and robust Gabor wavelet transform technique carried out for noise reduction and signature image normalization by size and rotation after preprocessing. For this purpose a virtual grid is placed on an image then gabor wavelet coefficients with different directions and frequencies will be calculated on each grid points and fed into a classifier. It results an EER of 17.125%.

M. B. Yilmaz et al. [15] local histogram features like histogram of oriented gradients (HOG) and histogram of local binary patterns (LBP). SVMs are then used for classification of these two different approaches. It reported an EER of 15.41% in skilled forgery test.

Bharadi and Kekre [16] employed global as well as grouping based features for the determination of pixel information. They use Walsh transform to the horizontal pixel distribution and vertical pixel distribution. It achieve FAR of 2.5%, EER of 3.29% with an accuracy of 95.08%.

Bansal, Gard, and Gupta [17] proposed a contour matching algorithm, used to track the basic pattern in a given signature and verify it. They use vector quantization method to extract critical point and then apply the matching algorithm. It reported FAR of 0.08% in case of random forgery and 13.02% in case of simple and skilled forgery.

TABLE I. Performance comparison of various offline signature recognition system

Sr.	Approach	FAR(%)	Accuracy
1	Back-Propagation Neural Network Prototype[18]	10.00%	
2	Generic Algorithm[19]	01.80%	86.00%
3	Virtual Support Vector Machine[20]	13.00%	
4	Wavelet Based verification[21]	10.98%	
5	Smoothness Index Based Approach[22]	3.13%	79.00%
6	Signature recognition using clustering technique[23]	2.5%	95.08%
7	Exterior Contours and Shape Features[24]	06.90%	93.80%

V. CONCLUSION

The major contribution of this paper is the briefing of offline signature verification and recognition methodologies currently adapted considering their specifications, advantages and disadvantages with their respective FAR, FRR, Accuracy, EER, AER. Experimental results and the comparative analysis on the standard dataset reveal the performance of different offline signature verification schemes that are tabulated in section V. Out of them Genetic Algorithm and Signature Recognition using clustering technique are found to be more efficient in terms of FAR and accuracy respectively.

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