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Comparative Analysis of Various Offline Signature Verification Schemes

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Abstract: **Signature verification system is one of the major research area having main application in detecting fraud in banks and other organizations. Several approaches are designed till date and all approaches have their own advantages and drawbacks. This paper shows some of the major results achieved in the last few years in the field of off-line signature verification. Based on various research papers a comparison is drawn using important factors- FAR, FRR and ERR. Finally, we have compared our own system which uses Kohonen self-organizing maps with the existing systems. Kohonen self-organizing maps are widely used in handwriting recognition systems. This research work makes use of their competitive learning power to quantify the intra-variability of the individual's signatures.**

Keywords: **Offline signature**

1. Introduction

Signature is a behavioral trait of an individual and forms a special class of handwriting in which legible letters or words may not be exhibited. The fact that the signature is widely used as a means of personal verification emphasizes the need for an automatic verification system. Verification can be performed either Offline or Online based on the application. Online systems use dynamic information of a signature captured at the time the signature is made. Off-line systems use data as a 2-D scanned image of the signature. Processing offline is complex due to the absence of stable dynamic characteristics.

Among various problems in the field of handwritten signatures, major issue is forgery. Forgery means someone attempt to copy someone else signature to steal properties of original signer [3][5]. The signature forgery can be classified into three categories:

1) Hit-or-miss Forgery: It is a very simple type of forgery and can be uncovered easily. The forger has no knowledge of the original signature and creates a signature in his own style. It is also known as Random Forgery.

2) Well-versed Forgery: In this type of forgery, the forger may be a master in imitating the original signature and may also have the knowledge about original signature that how it looks like. It is also known as Skilled Forgery.

3) Amateur Forgery: In Amateur forgery, the forger keeps an eye on the original signature and then tries to create a similar sign. Here, the forger is not an expert in forgery. It is also known as Simple Forgery. [6]

This paper presents an analysis of off-line signature verification schemes. Section II will discuss various approaches of the off-line signature verification system. Section III introduces our system and section IV will provide comparison of various existing systems. Last section concludes the paper and discusses future scope in this field.

2. Offline Signature Verification Schemes

Template Matching Approach

A process of pattern comparison is called template matching [1]. A pattern class is represented by a template which can either be a curve or an image. Template matching can be subdivided between two approaches: feature-based and template-based matching. The feature-based approach uses the features of the search and template image, such as edges or corners, as the primary match-measuring metrics to find the best matching location of the template in the source image. The template-based, or global, approach uses the entire template, with generally a sum-comparing metric (using Sum of absolute differences, Sum of Squares, cross-correlation, etc.) that determines the best location by testing all or a sample of the viable test locations within the search image that the template image may match up to.

Deng [2] developed a system that uses a closed contour tracing algorithm to represent the edges of each signature with several closed contours. The curvature data of the traced closed contours are decomposed into multi resolutional signals using wavelet transforms. The zero crossings corresponding to the curvature data are extracted as features for matching. A statistical measurement is devised to decide systematically which closed contours and their associated frequency data are most stable and discriminating. Based on these data, the optimal threshold value which controls the accuracy of the feature extraction process is calculated. Matching is done through dynamic time warping. Dynamic Time Wrapping is the most popular template matching technique for Static signature verification. The Dynamic Time Warping (DTW) algorithm which is based on dynamic programming finds an optimal match between two sequences of feature vectors.

A. Piyush Shanker and A. N. Rajagopalan[4] proposed a signature verification system based on Modified Dynamic Time Warping (DTW). Authors reported that with a threshold value of 1.5, the system has close to 0.33 acceptance rate for

casual forgeries, 19.6 acceptance rate for skilled forgeries, and about 25% rejection rate for genuine signatures. Kennard et.al [5] developed an algorithm for 2D geometric warp and obtained an EER of 26%. Liwicki et.al [6] evaluated their proposed template matching approach on offline and online Dutch and Chinese signatures and obtained acceptably good verification performance.

Structural or Syntactic Approach

The key idea in structural and syntactic pattern recognition is the representation of patterns by means of symbolic data (signatures etc.) structures such as strings, trees, and graphs [12]. In order to recognize an unknown pattern (forged signature), its symbolic representation is compared with a number of prototypes stored in a database. Structural features use modified direction and transition distance feature (MDF) which extracts the transition locations and are based on the relational organization of low-level features into higher- level structures. The Modified Direction Feature (MDF) [14] utilizes the location of transitions from background to foreground pixels in the vertical and horizontal directions of the boundary representation of an object.

Nguyen et al [15] presents a new method in which structural features are extracted from the signature's contour using the (MDF) and its extended version: the Enhanced MDF (EMDF) and further two neural network-based techniques and Support Vector Machines (SVMs) are investigated and compared for the process of signature verification. The classifiers were trained using genuine specimens and other randomly selected signatures taken from a publicly available database of 3840 genuine signatures from 160 volunteers and 4800 targeted forged signatures. A distinguishing error rate (DER) of 17.78% was obtained with the SVM whilst keeping the false acceptance rate for random forgeries (FARR) below 0.16%.

Mustafa Berkay Yilmaz, Alisher Kholmatov et. al. [16] presented an automatic offline signature verification system based on signature's local histogram representations. The signature is divided into zones using both fixed size rectangular or polar grids, where HOG and LBP features are calculated. For either of the representations, features obtained from grid zones are concatenated to form the final feature vector. Two different types of SVM classifiers are trained, namely global and user dependent SVM's, to do verification. The system performance is measured using the skilled forgery tests of the GPDS-160 signature dataset. Additionally, a classifier fusion is performed, where global and user dependent SVM classifiers are combined giving the best result of 15.08% and 17.53% equal error rate on skilled forgery test with 12 and 5 references, respectively.

Statistical approach

Using statistical knowledge, the relation, deviation, etc. between two or more data items can easily be found out. In order to find out the relation between some set of data items Correlation Coefficients are computed. In general statistical usage refers to the departure of two variables from independence. To verify an entered signature with the help of an average signature, which is obtained from the set of, previously collected signatures, this approach follows the concept of correlation to find out the amount of divergence in between them. Hidden Markov Model (HMM), Bayesian [9] these are some statistical approach commonly used in pattern recognition. They can detect causal forgeries as well as skilled and traced forgeries from the genuine ones.

The offline signature verification system proposed in [8] combines some statistical classifiers. This signature verification system consisted of three steps – the first step is to transform the original signatures using the identity and four Gabor transforms, the second step is to inter-correlate the analyzed signature with the similarly transformed signatures of the learning database and then in the third step verification of the authenticity of signatures by fusing the decisions related to each transform.

In HMM stochastic matching (model and the signature) is involved. This matching is done by steps of probability distribution of features involved in the signatures or the probability of how the original signature is calculated. If the results show a higher probability than the test signatures probability, then the signatures is by the original person, otherwise the signatures are rejected. Justino et. al. [22] used HMMs to detect random, simple and skilled forgeries. Also using a grid-segmentation scheme, three features were extracted from the signatures: pixel density feature, Extended Shadow Code and axial slant feature. They applied the cross-validation method in order to define the number of states for each HMM writer model. Using the Bakis model topology and the Forward algorithm, they obtained an FRR of 2.83% and FARs of 1.44%, 2.50% and 22.67%, for random, simple and skilled forgeries, respectively.

Offline Signature Verification Based on Pseudo-Cepstral Coefficients proposed by Jesus F. Vargas and Mioguel A.Ferrer [23]. In this technique from gray-scale images,its histogram is calculated and used as "spectrum" for calculation of pseudo-cepstral coefficients. Finally, the unique minimum-phase sequence is estimated and used as feature vector for signature verification. The optimal number of pseudo-coefficients is estimated for best system performance. FAR and FRR are observed to be 7.35 and 5.05.

Neural networks approach

The main reasons for the widespread usage of neural networks (NNs) in pattern recognition are their power (the sophisticated techniques used in NNs allow a capability of modeling quite complex functions) and ease of use (as NNs learn by example it is only necessary for a user to gather a highly representative data set and then invoke training algorithms to learn the underlying structure of the data). This learning mechanism is utilized by signature verification systems. There are many ways to implement the NN training. Simplest approach is to firstly extract a feature set representing the signature (details like length, height, duration, etc.), with several samples from different signers. The second step is for the NN to learn the relationship between a signature and its class (either "genuine"

or "forgery"). Once this relationship has been learned, the network can be presented with test signatures that can be classified as belonging to a particular signer. NNs therefore are highly suited to modeling global aspects of handwritten signatures.

K. V. Lakshmi et al. [20] proposed an Off-line Signature Verification Using Neural Networks technique. Here 3 layer neural networks have been used. i.e. input layer, a hidden layer and output layer. The 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.

Paigwar Shikha et al. [21] proposed signature verification system based on self organizing map. It 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). It is an attractive architecture for classification problems because they are capable to learn from noisy data and to generalize. 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.

Wavelet- based approach

In general, the multi-resolution wavelet transform can decompose a signal into low pass and high pass information. The high pass information usually represents features that contain sharper variations in time domain. Wavelet theory [2] is used to decompose a curvature-based signature into a multi-resolution signal. If the whole signature curves are matched, it's very hard to distinguish the genuine signatures and the forged ones effectively, because the signature curves are very complex and changeful, even the genuine signatures of the same person have very large differences.

Wavelet thinning features were used for offline signature verification using Matching Algorithm. Similarity measurement was evaluated using Euclidean distance of all found corresponding feature points. The accuracy in this case was 81.4% [24].

A combination of ART-2 and Fast Wavelet Transform (FWT) was used for signature verification [25]. In this work, FWT was employed for feature extraction. The authentic data was used for training of ART-2 net and forged data was used for verification purpose.

3. Signature Verification System Based On Kohonen Neural Network

We designed a signature verification system which uses Kohonen self-organizing map for training purpose. Kohonen self-organizing feature maps are widely used in many applications. They are unsupervised neural networks that learn competitively in an adaptive process. In the self-organizing process, we are aiming at mappings which transform a signal pattern of arbitrary dimension onto a one or two-dimensional array. The purpose of the self-organizing feature map is basically to map a continuous high-dimensional space into discrete space of lower dimension (usually 1 or 2). This enables to discover some underlying structure of the data or image.

Here, we feed feature vector as input vector and then Kohonen network will train them so that the test signatures can be recognized. Learning process of a Kohonen network involves several steps. We use Backpropagation to train this network. Basic idea is to adjust the input to match the output several time by adjusting the weights so as to bring the error of the Kohonen neural network is below acceptable level. For each training set one neuron will "win". As different neurons win for different patterns, their ability to recognize that particular pattern will be increased. An epoch (iteration) is said to be completed once all the input vectors are presented to the network. By updating the learning rate, several epochs of training may be performed. Table 1 shows neural network experimental setup.

Table 1: Neural Network Specifications

No. of layers	2
No. of input units	10
No. of output units	2
Learning rate	(0.1-0.9)
Initial weights	Randomized
No. of signatures used for training	50
No. of tested signatures	200
No. of epochs	100

Total number of 250 signatures is used for testing. Both FAR and FRR depend on the threshold taken to decide whether the signature is genuine is forged. If we choose a high threshold, then the FRR is reduced, but at the same time the FAR also increases. If we choose a low threshold, then the FAR is reduced, but at the same time the FRR also increases. We obtain a FAR of 2.8% and a FRR of 5% taking a threshold value of 75%.

4. Comparative Analysis

In evaluating the performance of a signature verification system, there are two important factors: the false rejection rate (FRR) of genuine signatures and the false acceptance rate (FAR) of forgery signatures. As these two are inversely related, lowering one often results in increasing the other. Hence, it is common to talk about the equal error rate (EER) which is the point where FAR equals FRR.

Table 2: Comparative Analysis of Offline SVS

S.No.	Offline Signature Verification Scheme		No. of Signatures	FAR	FRR	Other Parameters
1	Template Matching Techniques	Dynamic Time Wrapping (DTW)[19]	1431	20% (For skilled forgeries)	25%	EER=2%
		Modified DTW[4] (at threshold 1.5)		0.33 for Casual Forgeries, 19.6 for Skilled Forgeries	25%	EER-2%
		2D geometric warp				EER-26%
		Maximally Stable Extremely Regions (MSER) system[7]		4%	5.25%	
2.	Structural or Syntactic Approach	Support Vector Machine[10]	100		20%	
		Virtual Support Vector Machine[11]		13%	16%	
		Modified Direction Feature (MDF) [15]	3840	16%		DER=17.78%
		GSVM and USVM[16]	GPDS-160			EER=15.41%
		Structural Similarity Index Measure [18]	GPDS-100	.16 (For 15 samples)	5.12(For 15 samples)	
3	Neural Network Approach	Error Back Propagation Training Algorithm[13]	GPDS Database (1440)	12%	16.7%	CCR In Generalization =85.7
		3 Layer NN Approach[20]	50	12%	8%	
		Self Organizing Map[21]	42 samples of input data, 9 samples for testing	10%	11%	
		Kohonen self-organizing map (Proposed System)	250 samples with 50 signatures for testing	2.8%	5%	
4	Statistical Approach	Gabor Transform and Inter-Correlation[17]		2.56%	1.43%	
		Hidden Markov Method [22]	4000 genuine, 1200 forgeries	1.44% (for random forgery)	2.83%	

		Pseudo-Cepstral Coefficients[23]		7.35%	5.05%	
5	Wavelet- based approach	Matching algorithm[24]				Accuracy=81%

5. Conclusion

After studying various signature verification systems, we can conclude that since every system is using different algorithm and different number of signatures, features and evaluating criteria (see Table 2) it is difficult to check and compare the performance of such systems. However, it can be said that new approaches can still be designed by merging these techniques. The proposed system use Kohonen self-organizing map for training of feature vectors. The experimental results proved that the designed system is robust for casual and random forgeries with FAR (False Acceptance Rate) and FRR (False Rejection Rate) for the genuine samples as 2.8% and 5% respectively. Further, we are improving our research by merging fuzzy logic with Kohonen to get better results.

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