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Comparative Study of Various Signature Verification Algorithms

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Abstract - *Signature is a way of writing one's own initials or name which can distinguish his/her identity from others and can be used for authentication purposes. It is the best way of authenticating a person since each individual possesses a different style of writing. Two signatures can differ from each other in terms of the pressure exerted while signing, the shape of loops, the speed of writing, and various other features. Several algorithms have been written to verify these signatures based on different sets of features extracted as well as different classifiers used for classification. This paper compares some of such signature verification algorithms which focused on different sets of features and used different classification algorithms.*

Key Words: **Automatic Signature Verification (ASV), Minimum Distance Classification, K-Nearest Neighbor (KNN), Support Vector Machine (SVM)**

1. INTRODUCTION

Signature is one of the behavioural biometrics which is concerned with the identification of a person based on the pattern of behaviour of his/her characteristics. According to the history of biometrics, before the emergence of signatures the most familiar way for human identification was face recognition. After an increase in population, identifying a person became a challenging task, so they introduced the concept of fingerprints, palm, footprints and signature recognition.

Signature verification is categorized into two classes according to how the data is acquired, namely – offline and online. Online method is also known as Dynamic method since it captures the signature at the same moment of writing along with some extra details such as movements of pen and the pressure exerted on the paper. This method needs a special setup to record the signature.

The Offline approach is also known as Static approach. In this method the signature is captured on a sheet of paper, and is scanned using scanner to translate it into digital format.

As per the history of biometrics, the first automated signature recognition system was first developed by North America Aviation in 1965. Since then many researchers have experimented and tested different ways to enhance the efficiency and applicability of signature verification system.

2. STRUCTURE OF AUTOMATIC SIGNATURE VERIFICATION

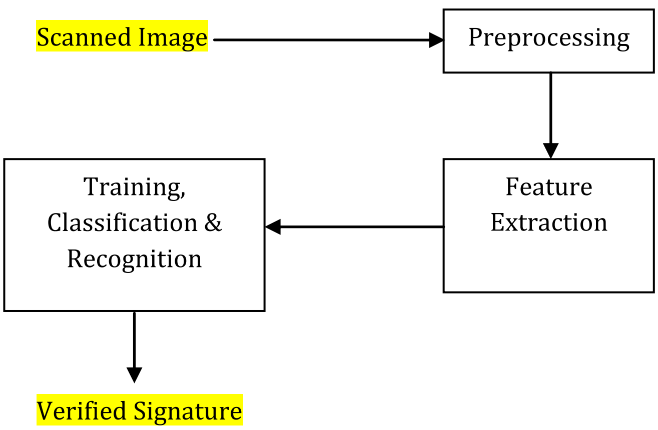

Fig -1: Structure of ASV

I. *Signature Acquisition*: The signature is converted into a digital format using an optical scanner. It can be viewed as an image of M×N pixels.

II. *Preprocessing*: This step is done to make the acquired signature ready for the next step which is feature extraction. Various researchers use variety of methods within preprocessing step that is suitable for their further feature extraction module. But the steps that are commonly followed by majority of researchers are:

i. Noise Reduction – to remove the noise that comes while scanning.

ii. Resizing – to adjust the size according to required template.

iii. Binarization – to bring all images (colored/grayscale) under one category i.e. black and white.

iv. Thinning – to take out the thickness differences of pen.

III. *Feature Extraction*: This step plays a major role in determining the accuracy and efficiency of any ASV system. Features can broadly be divided into three categories – Local features, Global features and Geometric features. Some researchers have experimented with only one kind of features while others have tried and tested several combinations of different kinds of features.

IV. *Training, Classification and Recognition*: This step basically involves the training of the system and then testing it. This step also affects the accuracy of an ASV system. With the same set of features, different classifiers yield different results.

3. SOME APPROACHES IN SIGNATURE VERIFICATION

Walter F. Nemcek and Wen C. Lin [1] have proposed a method in their paper that uses the fast Hadamard transform (FHT) to clean the signature image from unwanted noises and for feature extraction. Their approach was language independent. They have divided their research into two sets of classification experiments – first was called categorization which was done through weighted minimum distance classifier in which they had supplied genuine signatures. The other set was testing which used the same weighted classifier and tried to distinguish forged signatures from the genuine ones. From their experiment they have concluded two things – first, FHT is a useful mechanism of noise reduction and feature selection in case of two-dimensional images identification. Second, forgeries of signature can be identified. But their experiment was not suitable to identify expert forgeries.

R. M. Clark, T. Hastie and E. Kishon [2] have devised a statistical model for recognition and verification of signature by computer. Although they have worked on online signatures but they have proposed a model which is independent of dynamic features. They have majorly focused on static local and global features which include location, orientation and scale. They proposed the methods of estimating the "mean" ("average") and "variance" of a writer's signature. Their model recognizes that repeated test signatures by the same writer are similar but not identical.

In a comparative study done by Maan Ammar [3] the performances of Reference Pattern Based Features (RPBFs) and parametric features in offline signature verification have been compared. The RPBFs used in his experiment are – Horizontal and Vertical and the parametric features are – slant, high density factor, normalized global baseline etc. The unknown samples' distance was computed using Euclidean distance. Consequently, the RPBFs were better performer than parametric features which were also independent of the position of the signature on the document. He has also suggested that skilled forgeries can be fully eliminated by using only binary images.

Trevor Hastie, Eyal Kishon, Malcolm Clark and Jason Fan [4] have proposed a statistical approach to verify signatures. Along with the speed of writing they have focused on features like size, shear and rotation. Their experiment consisted of five major steps – smoothing, speed, time warping, segmentation and averaging. In order to classify a signature they have computed the least square distances on a letter basis between the two.

In another paper, Maan Ammar [5] has mentioned a method that is language independent, translation invariant and highly insensitive to the writing instrument and to the natural variability in the individual's signature. He extracted 26 features from a signature which included 4 global and 22 local features. To calculate the distance he has used weighted Euclidean distance and the verification was based on threshold values. With this approach he has lowered the average error rate to 2%.

Robert Sabourin and Jean-Pierre Drouhard [6] have suggested a two stage method. In the first stage they focused on eliminating random forgeries by considering the overall shape of the handwritten signatures. In the next stage to eliminate skilled forgeries, they have used the directional Probability Density Function (PDF) as a global feature vector along with completely connected feed forward neural network classifier. For pre-processing they have used Sobel operator for gradient evaluation, and noise removal. It was concluded that an overall increase in global performance was anticipated with this approach.

Robert Sabourin, Mohamed Cheriet and Ginette Genest [7] have conducted an experiment to verify offline signatures using an extended shadow code based approach to eliminate random forgeries. They first converted the signature image into binary image using Otsu's method. Under preprocessing step they have translated the image towards its centre based on hypercenter of inertia. Under feature extraction step, the signature is represented by 276 real numbers which is referred as extended shadow code. For classification purpose two different classifiers have been used, KNN classifier and minimum distance classifier. The KNN classifier shows a mean total error rate of 0.01% with k=1. The minimum distance classifier results into mean total error rate which was below 1%.

G. Dimauro, M. R. Grattagliano, S. Impedovo and G. Pirlo [8] have proposed a complete system to process bank cheques automatically in their paper. The part of signature verification was performed by a component-oriented analysis. A set of features were extracted from each component and then normalized. The features were – height/width ratio, number of local maxima and minima in the vertical direction, minima and maxima abscissa, negative, positive and vertical slant, the set of moduli of first 8 Fourier descriptors (obtained by Granlund approach). The verification of the entire signature was performed by combining the responses obtained for the components following a Nearest Neighbor approach. The system has shown a false-rejection error rate (type I error rate) of 11% and a false-acceptance error rate (type I1 error rate) of 3%.

Ng Geuk See and Ong llee Seng [9] have proposed a neural network approach for offline signature verification. Under preprocessing steps they captured the image and shrunk it to a standard size. The image is then translated using centroid of the image. The images were then thinned using Zhang and Suen's thinning algorithm. The vertical and horizontal projections were used as the features. A modified model of back propagation is used to reduce the learning time of the system.

Indrajit Bhattacharyaa, Prabir Ghosh and Swarup Biswas [10] proposed an offline signature verification method using Pixel Matching Technique. Their experiment was divided into two major phases – preprocessing and verification.

Preprocessing included capturing signature, removing noise, adjust property such as finding exact signature box, finding the angle and rotating it accordingly, resizing. They have used some coordinate geometry equations which make their method faster than other methods. The performance of their proposed method was compared with the existing ANN (Artificial Neural Network's) back-propagation method and SVM technique. The false acceptance rate (FAR) recorded using their experiment was 89% using ANN classifier and 84% using SVM classifier. The false rejection rate (FRR) was 11% using ANN classifier and 16% using SVM classifier.

Abdul Quaiyum Ansari, Madasu Hanmandlu, Jaspreet Kour and Abhineet Kumar Singh [11] have used segment level fuzzy modeling for online signature verification. This paper has been considered here as they have included shape features such as height, width, length, mean of x coordinates and mean of y coordinates under feature extraction section. They measured the accuracy of their experiment in terms of equal error rate (EER) that arises when FRR is made equal to the FAR by adjusting the threshold. Using user-dependent threshold as classifier they achieved an EER of 1.3%.

Karrar Neamah, Dzulkifli Mohamad, Tanzila Saba and Amjad Rehman [12] presented combination of orientation of the skeleton and gravity centre point to extract accurate pattern features of signature data in offline signature verification system. For classification purpose they have used an algorithm called as graph similarity matching algorithm. The general idea behind this algorithm is to find out how many common paths exist in both graphs. They also had used EER as the performance indicator.

Medam Manoj Kumar and Niladri Bihari Puhan [13] have found an envelope shape feature known as 'chord moments'. Central moments such as the variance, skewness and kurtosis along with the first moment (mean) are computed from sets of chord lengths and angles for each envelope reference point. The proposed chord moments adequately quantify the spatial inter-relationship among upper and lower envelope points. The moment-based approach significantly reduces the dimension of highly detailed chord sets and is experimentally found to be robust in handling non-linear variability from signature images. They used SVM classifier for classification and verification purpose and got 93.98% of accuracy.

Rashmi B. N., Dr. Vinay K. and Dr. G. Hematha Kumar [14] explored a novel approach of feature extraction from offline signatures. They have focused on features such as – end points alignment, geometrical distance metric, pruned projection features. They obtained similarity matrix using one to one pattern matching. The classification and verification is done using KNN classifier. The result is then compared with the results obtained by SIFT features. The proposed method proved to be better than SIFT.

Subhash Chandra and Sushila Maheskar [15] used geometric features along with artificial neural network classifier for offline signature verification. The features they worked on were area, centroid, even pixels, standard deviation, skewness and kurtosis. The total accuracy obtained by them using the proposed method comes out to be above 89.24%.

Srikanta Pal, Alireza Alaei, Umapada Pal and Michael Blumenstein [16] have proposed a technique based on texture features applied on Bangla and Hindi signature dataset. They used both uniform local binary patterns and local binary patterns. For classification purpose they used Nearest Neighbor technique. As a result they have achieved the maximum accuracy of 75.53%.

A table to analyze all the discussed methods at a glance is shown in Table 1.

4. CONCLUSIONS

In order to accomplish the comparative study of various signature verification algorithms, a large set of research papers by various researchers and scholars have been consulted. It is concluded that a direct performance comparison of ASV is not feasible because of the following reasons:

i. Signature Database: There is no available standard international signature database due to which each researcher uses their own signature dataset.
ii. Preprocessing steps: It is not necessary that each researcher uses the same set of steps for preprocessing phase.
iii. Feature Extraction Set: Every researcher has extracted a different set of feature for their experiment.
iv. Classifier: The methods used for training and testing the system for signature verification purpose is different.

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REFERENCES

[1] Walter F. Nemcek, Wen C. Lin, "Experimental investigation of automatic signature verification." IEEE, Vol. 4, Issue 1, Jan. 1974, pp. 121-126

[2] Clark RM., Hastie T., Kishon E., "A model for comparing signatures." Systems, Man and Cybernetics, Vol. 1, Issue 1, Nov. 1990, pp. 326-330

[3] Maan Ammar, "Performance of parametric and reference pattern based features in static signature verification: a comparative study." Pattern Recognition, Vol. 1, Issue 1, June 1990, pp. 646-648

[4] Trevor Hastie, Eyal Kishon, Malcolm Clark, Jason Fan, "A model for signature verification." IEEE, Vol. 1, Issue 1, Oct. 1991, pp. 191-196

[5] Maan Ammar, "Elimination of skilled forgeries in offline systems: a breakthrough." IEEE, Vol. 1, Issue 1, Aug. 1992, pp. 415-418

[6] Robert Sabourin, Jean-Pierre Drouhard, "Off-line signature verification using directional PDF and neural networks." IEEE, Vol. 1, Issue 1, Aug. 1992, pp. 321-325

[7] Robert Sabourin, Mohamed Cheriet, Ginette Genest, "An extended shadow-code based approach for off-line signature verification." Document Analysis and Recognition, Vol. 1, Issue 1, Oct. 1993, pp. 1-5

[8] Dimauro G., Grattagliano MR., Impedovo S., Pirlo G., "A system for bankchecks processing." Document Analysis and Recognition, Vol. 1, Issue 1, Oct. 1993, pp. 454-459

[9] Ng Geok See and Ong Hee Seng, "A neural network approach for offline signature verification." IEEE, Vol. 1, Issue 1, Oct. 1993, pp. 770-773

[10] Indrajit Bhattacharyaa, Prabir Ghosh, Swarup Biswas, "Offline signature verification using pixel matching technique." International Conference on Computational Intelligence: Modeling Techniques and Applications, Vol. 1, Issue 1, Sept. 2013, pp. 970-977

[11] Abdul Quaiyum Ansari, Madasu Hanmandlu, Jaspreet Kour, Abhineet Kumar Singh, "Online signature verification using segment level fuzzy modelling." Institution of Engineering and Technology Biometrics, Vol. 3, Issue 3, Sept. 2014, pp. 113–127

[12] Karrar Neamah, Dzulkifli Mohamad, Tanzila Saba, Amjad Rehman, "Discriminative features mining for offline handwritten signature verification." 3D Research Express, Vol. 5, Issue 2, Jan. 2014, pp. 1–6

[13] Medam Manoj Kumar, Niladri Bihari Puhan, "Off-line signature verification: upper and lower envelope shape analysis using chord moments." Institution of Engineering and Technology Biometrics, Vol. 3, Issue 4, Dec. 2014, pp. 347–354

[14] Rashmi BN., Vinay K., Hematha G. Kumar, "A novel approach to signature verification and identification." International Conference on Computer Communication and Informatics, Vol. 1, Issue 1, Jan. 2016, pp. 1-3

[15] Subhash Chandra, Sushila Maheskar, "Offline signature verification based on geometric feature extraction using artificial neural network." Recent Advances in Information Technology, Vol. 1, Issue 1, Mar. 2016, pp. 1-5

[16] Srikanta Pal, Alireza Alaei, Umapada Pal, Michael Blumenstein, "Performance of an off-line signature verification method based on texture features on a large Indic-script signature dataset." Document Analysis Systems, Vol. 1, Issue 1, Apr. 2016, pp. 72–77

Table -1: Chart showing the Existing Methods for Signature Verification

References	Feature Extraction Method	Classifier	Accuracy %
[1]	Hadamard Transform (Karhunen-Loeve) and Fast Fourier transform	Minimum Distance Classifier	82%
[3]	Parametric and Reference Pattern based features	Minimum Distance Classifier	82.25%
[4]	Slowly varying affine transformations such as size, rotation and shear	Least square distances	Not mentioned
[5]	4 Global features and 22 Local features	Weighted Euclidean distance measure	98%
[6]	Directional Probability Density function	Neural Network classifier	95.93%
[7]	Extended Shadow Code	KNN (k=1), Minimum Distance Classifier	97%
[8]	Minima and maxima abscissa, height/width ratio, negative, vertical and positive slant, number of local maxima and minima in the vertical direction, the set of the moduli of the first 8 Fourier descriptors derived from the boundary of the component	Nearest Neighbor approach	89%
[9]	Vertical and Horizontal projections	Neural Network classifier	Not mentioned
[10]	Pixel matching technique	ANN and SVM	89% and 84% respectively
[11]	Height, width, length, mean of x coordinates and mean of y coordinates	User-dependent threshold	Not mentioned
[12]	Combination of orientation of the skeleton and gravity centre point	Graph Similarity Matching algorithm	Not mentioned
[13]	Chord moments	SVM	93.98%
[14]	Geometrical distance metric features, end points alignment and pruned projection features, vector of angle and one existing SIFT features	KNN	98.60%
[15]	Geometric features namely area, centroid, standard deviation, even pixels, kurtosis and skewness	ANN	89.24%
[16]	Texture features	Nearest Neighbor	66.18% (Bangla), 75.53% (Hindi)