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A SURVEY: OFFLINE HANDWRITTEN SIGNATURE RECOGNITION SYSTEM

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Abstract: *A rising need for personal recognition in numerous days after day applications, signature recognition is painstaking with renewed attention. A Handwritten signature is unique biometrics used even beforehand computers. Signature recognition is extensively deliberated using two approaches. On-line approach and offline approach. Offline systems are sparing applicable and trouble-free to make use of in comparison with on-line systems in many parts of the world though it is considered more difficult than on-line recognition due to the need for dynamic information. Offline signature recognition system has more attraction because of its essential for use in day-to-day life routines. This paper gives a survey of signature forgery type, features types, procedures used for features extraction and approaches used for acknowledgment in signature recognition systems.*

Keywords: *Offline signature recognition system, features extraction.*

1. INTRODUCTION

Human recognition is vital for our usual behavior such as entering any safe and sound locations besides the many other applications. To that end, higher security levels need easier user interaction which can be achieved using biometric confirmation. Biometric recognition helps us recognize people based on their mined physical or behavioral features. These features have certain properties such as uniqueness, durability, suitability, collectability, and the cost to employ any biometric. Frequently, there are two common biometric feature types-

a) Physical Features are including face, fingerprint, iris, ear, palm print, retina, hand, finger geometry and DNA. Most of these features are comparatively relentless over time.
b) Behavioral Features are including features that measure the stroke of the person such as speaking and writing. These features change over time due to elderly and other developing factors.

Signature recognition is the chore of validating an individual founded on his handwritten signature. There are two categories of signature recognition systems in the prose:

i) On-line Signature recognition System is while a signature is written onto an communicating electronic device such as a tablet and it is recite online, and matched to the signatures on file of the person to check for truthfulness. Many vital features are exploited with online signatures that are not obtainable for the offline ones.

ii) Offline Signature recognition System is while a signature is written offline such as bank checks and the system recites the image scan then authenticates it with the signatures on file for the customer.

Handwritten signatures have used as a biometric feature that recognizes individuals. It has been recognized that handwritten signatures are an actual upright quality biometric feature with a squat conflict percentage. Some signatures might be alike but there are numerous scientific mechanisms to distinguish between them and for recognition of forged signatures.

Forgeries in signature recognition systems are categorized into three types:

1. Unskilled Forgeries are signatures in which forger signs deprived of any information about name and signature shape.
2. Random Forgeries are signatures in which forger knows just the name of the signatory without any previous examples.
3. Skilled Forgeries are signatures in which forger knows the signatory name and the form of the original signature.

2. PROPOSED METHODOLOGY

The state of the skill in signature recognition follows a pattern that is like image processing as shown in figure 1.

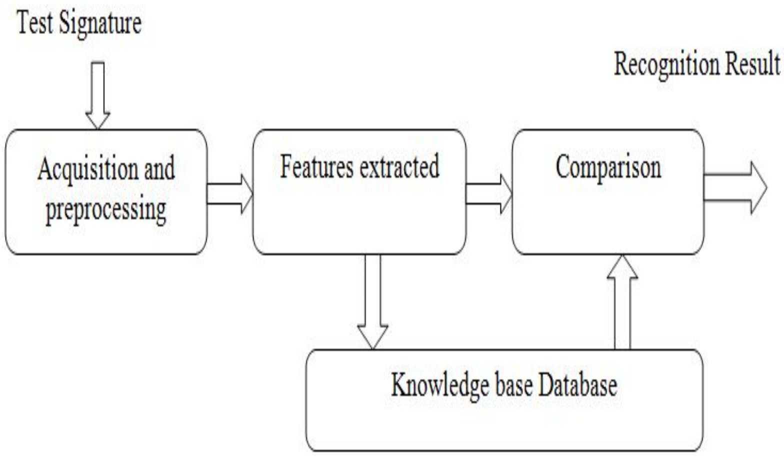

Fig 1 Signature Recognition System

The key in signatures are preprocessed, and then the individual features are extracted and warehoused in the knowledge base. In the classification phase, personal features detached from an inputted signature are compared with pattern signature deposited in the knowledge base, to check the strength of the test signature.

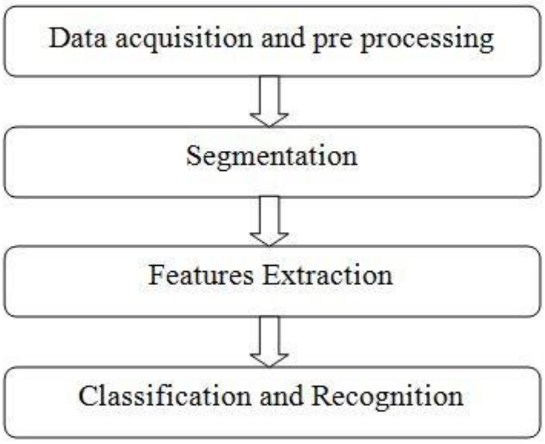

Fig 2. Workflow for a signature recognition system

2.1 Data acquisition and pre processing

A preprocessing phase is done to recuperate the signature image afterward scanning it using a scanner device. Signature preprocessing is a essential step to improve the accuracy and to decrease their computational time. It consists of the following steps

1) A noise filter (like a median filter) is applied to eliminate the noise caused by the scanner.
2) Then the image is cropped, to the bounding rectangle of the signature.
3) Transformation from color to grayscale, and then lastly to black and white.
4) Thinning the black and white image results always into the enormous information loss.

2.2 Segmentation

During segmentation phase, an image of signature is decomposed into sub-images. Segmentation refers to a procedure of dividing an image into groups of pixels which are alike with respect to some criterion, which contains of signature extraction through mining the small package that encompasses the signature data, the signature's height and width are determined, and then the signature image is cropped. Image segmentation is largely classified into two types, Local Segmentation deals by the segmenting sub images which are small windows on an entire image. Global Segmentation refers with the images containing of relatively huge number of pixels and makes predictable factor values for global segments are additional vigorous.

2.3 Feature Extraction

It is the process of removing the characteristics or attributes from an image. The accuracy of recognition in pattern systems depends mainly on the removed features. Classification of the signature recognition systems in terms of mined features are done into two kinds,

2.3.1 Global Features:

Global features describe the signature image as a entire like a length, width, density, edge points of the signature, and wavelet transforms. These features are fewer sensitive to noise and signature variations. Therefore it will not give us a high accuracy for skilled forgeries, then it would be appropriate for random forgeries and it is well to be combined with other types of features.

2.3.2 Local Features:

Which illustrate a minor area of signature image and haul out information in more details from it, it is more truthful than the global one but the computational time is high, it can be divided into two groups: statistical as well as geometrical features.

i) Statistical Features are in use from the pixel distribution of the signature image.

ii) Geometrical Features describes the geometrical uniqueness of the signature image; Geometrical features contain the aptitude to tolerate with distortion, styles deviations, rotation variations and certain degree of translation.

3. SIGNATURE RECOGNITION OUTLOOK

3.1 Template Matching

It is a course of action of pattern comparison so it is called "template matching". A test signature is matched with templates of genuine signatures warehoused in a knowledge base; the most communal methods use Dynamic Time Wrapping (DTW) for signature matching. A. Piyush and Rajagopalan [5] proposed an offline signature recognition system founded on DTW and they applied their altered DTW algorithms. The amendment was the adding of a steadiness factor. Improved results were added than using the basic DTW algorithm. Almudena [6] established an offline signature recognition system based on contour features. The features were extracted from the directional contour of the signature and the length of regions together with this between letters. For feature matching phase, each signature (set of features) was signified by probability density function and Hamming distance was used for parallel measure. MCYT database, which consists of 75 subjects, were used. The total signatures were used are 2250.

3.2 Neural Networks

This approach is extensively used in signature recognition systems, power, ease of use, capabilities in learning and generalizing are the major reasons to use this approach. When using this loom we have to configuration the Neural Network (NN) by eliminating features from signers' samples and tutoring the association between the signature and its class. Therefore the signature recognition procedure parallels this learning method. There are several methods to structure the NN training, but a very modest approach is to initially extract the feature set representative the signature (details like length, height, duration, etc.), with numerous samples from different signers. The subsequent step for the NN is to study the relationship stuck among a signature and its class (either “genuine” or “forgery”). Formerly this association has been erudite; the network can be accessible with test signatures that can be categorized as fitting to a particular signer. NNs consequently are highly appropriate to demonstrating global features of handwritten signatures. Edson [7] offered another method for off-line signature recognition uses hough transform to notice stroke lines from signature image. The Hough transform (general Radon transform) is used to get rid of the parameterized Hough space from signature skeleton as distinctive characteristic feature of signatures. In this method, the Back Propagation Neural Network is used as a tool to estimate the performance of the proposed method. The system has been experienced with 70 test signatures from different persons enlightening the recognition rate of 95.24%. Velez [8] presented the robust offline signature recognition using compression networks and positional cuttings. Each signature class was tested using the compression NN. The benefit of using compression networks is that they can take steps as auto-associative or the content addressable memories.

3.3 Hidden Markov Models

Hidden Markov Model (HMM) is solitary the most commonly used models for serial analysis in signature recognition. Handwritten signature is a order of vectors of values linked to each point of signature in its path. Coetzer [9] established a system that mechanically authenticates offline handwritten signatures via the discrete Radon transform (DRT) and a hidden Markov model (HMM). It specified the heftiness of the algorithm and the fact that simply global features are considered, the system achieves an equal error rate (EER) of 18% when only high-quality forgeries (skilled forgeries) are measured and an EER of 4.5% in the case of only casual forgeries. Justino [10] in his effort obtainable a robust system for off-line signature recognition using simple features, diverse cell resolutions and manifold codebooks in a HMM framework. The simple and random forgery error rates have been shown to be low and close of each other. A FRR of 2.83% and a FAR of 1.44%, 2.50%, and 22.67% are reported for random, casual, and skilled forgeries, correspondingly.

3.4 Statistical

The statistical knowledge is used to execute some of the statistical concepts like the relation, deviation, etc between two or more data substance to discover out a specific relation among them. Generally, it follows the proposal of Correlation Coefficients which refers to the departure of the two variables from self-determination. In signature recognition system, regular signature (template) is considered from earlier collected signatures, stored in knowledge base data, when novel input signature is recited, correlation concept is followed to find the distance between the test signature and average signature, then to make a decision if it is accepted or rejected. Debnath [11] obtainable a Statistical Approach for offline handwritten signature recognition. The algorithm projected has the elasticity of selecting the number of signatures, i.e., no-of-Sign for testing determination to generate a signature as a Avg-Sign containing the particular mean features set from the test signature set. After collecting signatures for testing, the algorithm converts them into a set of 2D arrays of binary data values-0 and 1. From these binary arrays by means of statistical methods of calculating the predictable mean an average data set. The recognition system is based on an extensive Statistical Analysis of Correlation Coefficient between bivariate data set. In implementation of projected algorithm to constant factors carry major impact on the validity of the method and the strength of the recognition lies in the efficiency of selection of these constant parameters, namely AvgSign, Threshold Value and decision value.

3.5 Structural

The chief idea in structural pattern recognition is the demonstration of patterns by means of symbolic data structure such as trees, graphs and strings. Once a forged signature comes, its figurative expression is equated with prototypes stored in database. In other librettos, Structural approach is grounded on the interpersonal group of the low-level features into higher-level structures, and then these structures are harmonized with replicas stored in database. Structural features usage modified direction and transition distance feature (MDF) which abstracts the transition locations and are grounded on the relational organization of low-level features into higher- level structures. Nguyen [12] presents the novel technique 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 procedure of the signature verification. The classifiers were skilled using genuine specimens and extra arbitrarily chosen signatures taken from the liberally available database of 3840 genuine signatures from 160 volunteers and 4800 under attack forged signatures. A distinguishing error rate (DER) of 17.78% was obtained with a SVM whilst keeping the false acceptance rate for random forgeries (FARR) below 0.16%. Ferrer [13] calculates geometric features of the signature in fixed-point arithmetic for offline verification. The proposed features are then checked with different classifiers, such as the Hidden Markov Models, the Support Vector Machines, and the Euclidean distance verifier. The results show that HMM works slightly better than SVM and the distance Euclidean verifier, but, behavior in mind that the SVM and Euclidean distance-based verifiers can be programmed in a fixed-point microprocessor, the outcome give confidence us to follow the SVM research line in arrange to built a smart card competent of detecting a simple forgery.

3.6 Wavelet- Based

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. Hou and Feng proposed [14] the process uses a wavelet-based transformation to extract the inflections of the signature curves via various scale wavelet transforms in the curving signature signals transformation. Following analysis, the appropriate scale is chosen. The zero-crossings points are mined and they are in use as the inflections of the signature. Then this signature curves are alienated into a number of parts, i.e. the strokes, according to the above inflections. The distance between the two corresponding strokes can be measured with Dynamic Time Warping algorithm. In the end, the training algorithm of the signature recognition system also the recognition method of the signatures is also introduced. The experimental result shows that this method is superior to those methods that match the whole signature curves. Samaneh and Mohsen [15] presented a method for offline Persian signature identification and recognition based on image registration and fusion. Discrete Wavelet Transform (DWT) is applied on the preprocessed signature to get high frequency sub-images, then an image reduction and fusion methods are used to create a feature matrix from sub-images. In recognition phase, for test signature; the feature matrix is compared with all feature matrixes stored in knowledge base using Euclidian distance. And then upon the specified threshold, the test signature would be accepted or rejected Larkins and Mayo [16] presented an offline signature recognition method based on adaptive feature thresholding (AFT). They converted the signature image to binary feature vector; by using the above conversion, the comparison was more accurate. That vector was based on gradient direction for each pixel from across a signature. Gradient direction gave a global features level; Spatial Pyramids were used to express a signature at deep levels, Equi-mass sampling grid with Spatial Pyramids were combined to improve the structural features. In classification phase, DWT and graph matching methods were used.

3.7 Support Vector Machine

Vahid and Hamid [17] projected an offline signature recognition using LRT and SVM. They used the LRT locally for line segments detection for feature extractions and SVM for classification. The proposed system consisted of the two models (1) Learning genuine signatures and (2) Recognition model. Preprocessing phase was shared between learning and recognition models. Feature extraction phase included the line segment detection, line segment existences validation, feature vector extraction and summarization, and feature vector normalization. Classification: in the classification phase they used SVM with Radial Basis Functions (RBF) kernel to achieve the best results. In the best case, they achieved the same 96% identification rate. Shailedra Kumar Shrivastava, Sanjay S. Gharde [18] Support Vector Machine is supervised Machine Learning technique. Support Vector Machines (SVM) is used for classification in pattern recognition widely Moment Invariant and Affine Moment Invariant techniques are used as feature extractor. Emre and Karshgil [19] presented an offline signature recognition system based on the SVM. Feature extraction phase which consists of global features, mask features, and grid features.

4. DISCUSSION

From Different recognition approaches, feature extraction & recognition rates used by different authors. It shows the details of the Feature extraction, recognition approaches of diverse authors all along with their recognition rate. Following the proportional study of various recognition approaches from signature recognition approaches, it is pragmatic that average accuracy for template matching signature recognition 56.41% which is minimum and average accuracy for statistical approach is 89.47% which is upper limit in all signature recognition approaches. In case of SVM approach signature recognition rate is 96% which is superior as compared to other approaches. SVM approach is immobile appropriate for skilled forgeries and appropriate for simple and random forgeries.

5. CONCLUSION

This system holds factual as of the amount of perspectives i.e. easiness of use, stumpy execution cost and the effortlessness of embedding the system in an organization, with no excessively disrupting or touching the obtainable operations. In this paper we present a high-tech newest method used in offline signature recognition systems. We categorize the offline signature recognition systems in terms of extracted features kind into local and global features and also we categorize local features into statistical and geometrical features. On the other hand, we recapitulate the approaches used in offline signature recognition systems, then we discuss these approaches depending on forgery type it detect, even there are many approaches used in this crisis but the accuracy motionless desires to be amplified for especially skilled forgeries.

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