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OFFLINE SIGNATURE VERIFICATION AND RECOGNITION METHODS: A REVIEW

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Abstract: Due to rapid developments in financial, commercial and legal transactions, truly secured authentication becomes more and more crucial. Signatures continue to play a vital role for authentication of person as well as document over the other biometrics. A number of signature recognition strategies have been proposed for personal identification in the past. This paper attempts to survey off-line signature recognition & verification methods using different classifiers. Authors focus on offline approaches, where the signature is captured and presented to the user in an image format. Available literature elaborates statistical methods, template matching, Hidden Markov Models, Neural Networks, Dynamic Time Wrapping, Support vector machines and hybrid approaches. The pros and cons of each of them are studied to explore opportunities for future research.

Keywords: Dynamic Time wrapping, Hidden Markov Models, Neural Networks, Support Vector Machines, Statistical approach, Template matching

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INTRODUCTION

Signature verification and recognition is an emerging area of research. In past few years, we have seen many ambiguous large-scale efforts based on different personal characteristics of a human being. The most common characteristics used for authentication include voice, lip movements, hand geometry, face, odor, gait, iris, retina and fingerprint [2]. All of these psychological and behavioural characteristics are called biometrics.

The paper is structured as follows: This section describes present scenario for signature recognition system, including biometric security and choice of signature as a preferred biometric by users. This is followed by section II that presents a brief background of the said domain covering essential components of a typical signature recognition and verification system. Section III elaborates most commonly used classification methods used for the problem of signature recognition. A detailed review and survey of related work enables authors to identify challenge in the said field that are listed in Section IV followed by depicting opportunities for future researchers in conclusion.

The biometrics is most commonly defined as measurable psychological or behavioural characteristic of the individual that can be used in personal identification and verification. The driving force of the progress in this field is, above all, extensive spread of internet and electronic transfers in modern society. Therefore, considerable number of applications is concentrated in the area of electronic commerce and electronic banking systems.

The biometrics significantly dominates traditional authentication techniques such as passwords, PIN numbers, smartcards etc. This fact that biometric characteristics of the individual are not easily transferable, are unique of every person, and cannot be lost, stolen or broken emphasizes the choice of one of the biometric solutions.

The factors that affect choice of biometrics are user acceptance, level of authentication required, correctness, efficiency and cost and deployment time.

Signature verification emerged in past few decades benefit the advantage of being highly accepted by potential customers. Signature recognition has a long history, which goes back to the appearance of the writing itself. Furthermore, the use of signature recognition as an authentication method is that most of the modern portable computers and personal digital assistants (PDAs) use handwritten inputs, thus there is no need in invention of principally new devices for biometric information collection [33, 34].

II .Background

The first signature recognition system was developed in 1965. Signature recognition research continued in the 1970s, focusing on the use of static or geometric characteristics (what the signature looks like) rather than dynamic characteristics (how the signature was made). Interest in dynamic characteristics surged with the availability of better acquisition systems accomplished through the use of touch sensitive technologies. In 1977, a patient was awarded for a“personal identification apparatus” that was able to acquire dynamic pressure information.

In 1991, the Sandia National Laboratories produced a performance evaluation Of Biometrics devices.(http://infoserve.sandia.pdf/cgibin/techlib/access-control.pl/1991/910276.pdf), a report that evaluates the relative performance of multiple biometric devices, including dynamic signature. In 1999, Report of Biometrics In-house Test (www.epa.gov/cdx/cromerrr/propose/biometric_dmrrpt.pdf), an operational pilot in New York State sponsored by the Environmental Protection agency, evaluated the interoperability of signature recognition hardware with existing user drivers and operating systems and found numerous interoperability problems. Even though these test represent the most recent government evaluations of notable scale, the information cannot be considered conclusive because of the age of the tests.

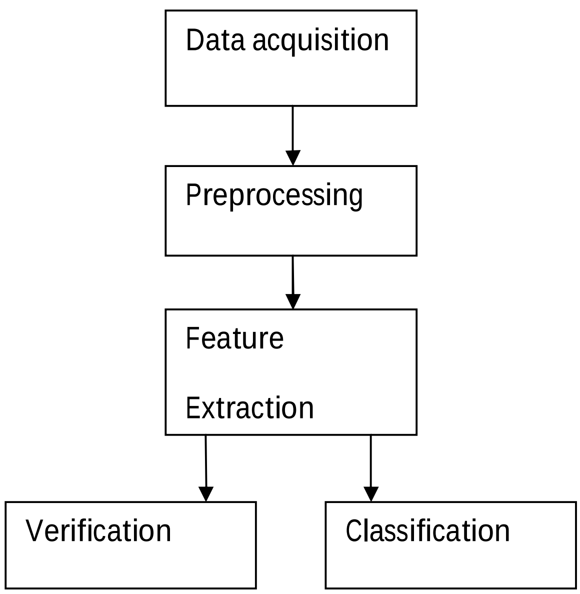

Figure 1: Typical signature recognition system

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The input to the system is categorized as online signatures and offline signatures. As stated above, online signatures characterizes dynamic features (time dependent) that contribute additional input for classification. Whereas offline signature verification and recognition is relatively challenging, as it doesn't provide time domain information which may help classifier to enhance recognition results. This paper focuses on review of offline signature verification and recognition systems where the input data to system are genuine signatures of users. The genuine signatures are collected over a period of three months to account for variations in the signatures with time.Fig.1 depicts a typical signature verification system that is made up by consecutive phases of data acquisition, pre-processing, feature extraction, training and verification. There have been numerous approaches for data acquisition, pre-processing, feature extraction, Verification and classification [1, 3, and 4]. This survey however emphasizes on classification approaches to signature verification and recognition for fraud detection.

A. Evolution of New Techniques

The four best known approaches for pattern recognition are template matching, statistical classification, structural or syntactic matching and neural networks [(33)]. Template matching is one of the simplest and earliest approaches to pattern recognition where a template typically, a 2 dimensional shape or a prototype of the pattern to be recognized is available. The pattern to be recognized is matched against the stored template while taking into account all allowable pose and scale changes.

Statistical Pattern Recognition (SPR) is based on the Bayes decision theory and is instantiated by classifiers based on parametric and nonparametric density estimation [29]. Its principles are also important for better understanding and implementing neural networks, Support Vector Machines (SVMs), and multiple classifier systems [30].

Unlike statistical methods that are based on class-wise density estimation, neural networks, SVMs are based on discriminative learning, that is, their parameters are estimated with the aim of optimizing a classification objective. Discriminative classifiers can yield higher generalization accuracies when trained with a large number of samples.

For structural pattern recognition, two methods that have been widely used are: attributed string matching and attributed graph matching. Despite that the automatic learning of structural models from samples is not well solved; structural recognition methods have some advantages over statistical methods and neural networks. They interpret the structure of characters, store less parameters, and are sometimes more accurate.

As character recognition research and development advanced, demands on handwriting recognition also increased because a lot of data such as addresses written on envelopes; amounts written on checks, names, addresses, identity numbers, and dollar values written on invoices and forms were written by hand and they had to be entered into the computer for processing. But early character recognition techniques were based mostly on template matching, simple line and geometric features, stroke detection, and the extraction of their derivatives. Such techniques were not sophisticated enough for practical recognition of data handwritten on forms or documents. To cope with this, the standards committees in the United States, Canada, Japan, and some countries in Europe designed some handprint models in the 1970s and 1980s for people to write them in boxes. Hence, characters written in such specified shapes did not vary too much in styles, and they could be recognized more easily by character recognition machines, especially when the data were entered by controlled groups of people, for example, employees of the same company were asked to write their data like the advocated models. Sometimes writers were asked to follow certain additional instructions to enhance the quality of their samples, for example, write big, close the loops, use simple shapes, do not link characters, and so on. With such constraints, recognition of handprints was able to flourish for a number of years. Neural networks are considered to be pragmatic and somewhat obsolete compared to SVMs but actually, they yield competitive performance at much lower training and operation complexity [28]. Nevertheless, for neural classifiers to achieve good performance, skilled implementation of model selection and nonlinear optimization are required. Potentially higher accuracies can be obtained by SVMs and multiple classifier methods.

B. Recent Tends and Movements

As the years of intensive research and development went by, computers became much more powerful than before. People could write the way they normally did, and characters need not have to be written like specified models, and the subject of unconstrained handwriting recognition gained considerable momentum and grew quickly. As of now, many new algorithms and techniques in preprocessing feature extraction, and powerful classification methods have been developed.

III. Classification approaches

In the area of signature verification, especially offline, different technologies have been used and still the area is being explored. In this section we review some of the recent papers on offline signature verification. The approaches used by different researchers differ in the type of features extracted, the training method, and the classification and verification model used [5].

The performance of a signature verification or recognition system is generally evaluated according to the error representation of a two-class pattern recognition problem, the error representations are False Rejected Ratio (FRR) and False Acceptance Ratio (FAR). [6, 7, 8 and 9]. Most methods of pattern recognition can be applied here.

There has been substantial research work carried out in the area of signature recognition and verification. An offline signature verification system using Hidden Markov Model is proposed [1]. In [5] a handwritten signature verification system, based on Neural 'Gas' vector quantization is proposed. Other recent approaches to signature recognition and verification include: the use of Modified Direction Features which generated encouraging results, researching significant accuracy rate cursive signatures. A Support Vector Machine approach based on geometrical properties of the signature is proposed in [10] with global features. Various classifiers have been successful in off-line signature verification, with Support Vector Machines (SVMs) providing and overall better result than all others such as Hidden Markov Models.

Fig. 2 briefly elaborates different classification approaches for the task of signature recognition and their salient features.

A. Statistical Approaches

This approach exploits statistical information, the relation, deviation, etc between two or more data items can easily be found out. Most common method to find out the relation between some set of data items is correlation coefficients.

In general statistical usage refers to the departure of two variables from independence. To verify a test signature with the help of reference signature, which is obtained from the data set of, previously collected signatures, this approach follows the concept of correlation to find out the amount of divergence in between them.

A unique method is proposed in [10]. In this approach various features are extracted which include global features like image gradient, statistical features derived from distribution of pixels of a signature and geometric and topographical descriptors like local correspondence to trace of the signature. The classification involves obtaining variations between the signatures of the same writer and obtaining a distribution in distance space. For any questioned signature the method obtains a distribution which is compared with the available known and a probability of similarity is obtained using a statistical KolmorogorvSmirnov test [10]. This method does not use the set of forgery signatures in the training/learning.

B. Template Matching

A method is proposed for the detection of skilled forgeries using template matching [11]. This is based on the optimal matching of the one-dimensional projection profiles of the signature patterns and the other is based on the elastic matching of the strokes in the two-dimensional signature patterns. A test signature to be verified with the help of positional variations that are compared with the statistics of the training set and a decision based on a distance measure is made. Both binary and grey-level signature images are tested.

C. Hidden Markov Model

Hidden Markov Model (HMM) is one of the most widely used models for sequence analysis in signature verification. Handwritten signature is a sequence of vectors of values related to each point of signature in its trajectory [32]. Therefore, a well-chosen set of feature vectors for HMM could lead to the design of an efficient signature verification system. These models are stochastic models which have the capacity to absorb the variability between patterns and their similarities. 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.

In paper [12], a system is introduced that uses only global features. A discrete random transform which is a sinograph is calculated for each binary signature image at range of 0 – 360, which is a function of total pixel in the image and the intensity per given pixel calculated using non overlapping beams per angle for X number of angles. Due to this periodicity, it is shift, rotation and scale invariant. A HMM is used to model each writer signature.

D. Neural Networks

Paper [13] presents structure features from the signatures contour, modified direction feature and additional features like surface area, length skew and centroid feature in which a signature is divided into two halves and for each half a

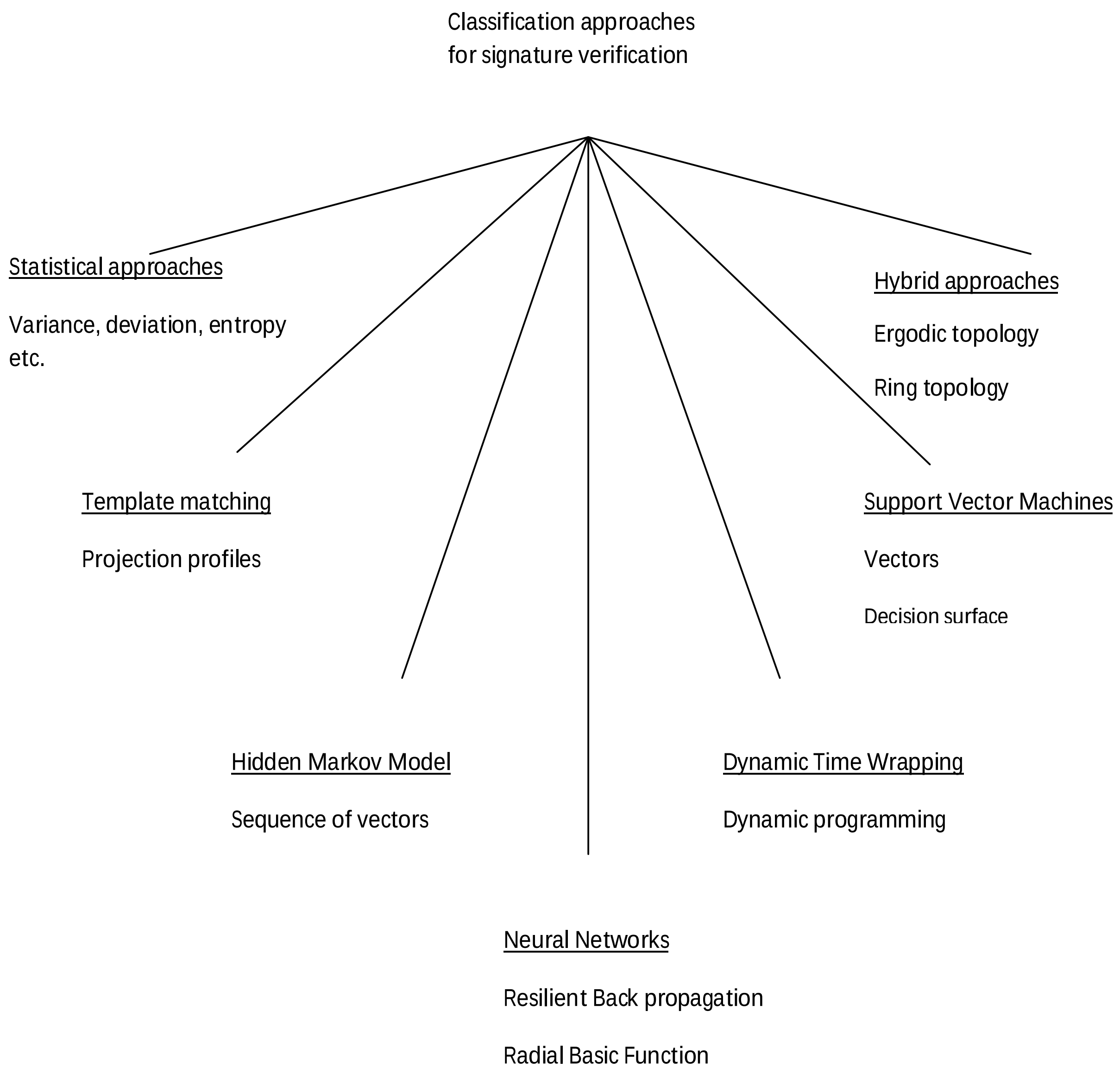

Figure 2: Classification and recognition methods for signature recognition

position of the centre of gravity is calculated in reference to the horizontal axis. For classification and verification two approaches are compared the Resilient Back propagation (RBP) neural network and Radial Basic Function (RBF) are used for recognition and verification.

E. Dynamic Time Wrapping (DTW)

DTW is one of the most commonly used and best performing approaches in signature verification. DTW compares two sequence of different lengths using dynamic programming, giving the minimum of a given distance value. Since two signatures usually vary in length, DTW turns out to be quite suitable for the task of signature verification. DTW is always combined with other methods to improve the performance. In the First International Signature Verification Competition [14], a DTW-based principal component analysis (PCA) method won the first place [15].

Aside of PCA, minor component analysis (MCA) is also combined with DTW for on-line signature verification [16]. Signatures are represented as sequences and used DTW for sequence matching [15]. DTW is first employed to partition signatures, and then adopted multivariate autoregressive model to extract features of signatures [17]. Instead of warping the whole signature, an approach attempts to warp a selected set of extreme points to be more adaptive [18]. An enhanced DTW, which enhanced the separability between genuine and forged signatures, is found in [19].

F. Support Vector Machines (SVMs)

SVM is another effective approach for data separation. SVM maps vectors in a low dimensional space where they cannot be directly separated into a higher dimensional space where they can. The separating hyper plane is then mapped back into the original space as the decision surface. Use of SVM, comparing to PCA and Bayesian decision method is presented [20]. SVM is also used to fuse HMM and MLP [21]. A new kernel for SVM based on longest common subsequence for on-line signature verification is explored by [22].

G. Hybrid approaches

Some hybrid approaches are explored that are found suitable for on-line signature verification since it is highly adaptable to personal variability [23]. The topologies of HMM frequently resorted to include left-to right, ergodic and ring. Left-to-right is the most commonly adopted topology in signature verification, such as in [24]. The study of ergodic topology can be found in [25]. Same as DTW, HMM is also combined with other techniques to improve the performance.

The combination of HMM and autoregressive models is proposed [26]. Furthermore combination of HMM and multi-layer perceptron (MLP) neural network is used.

IV. Challenges and constraints

Survey of related work by various researchers shows that the field of offline handwritten signature recognition is still an open problem due to challenges and constraints posed by nature of this task. The inherent challenges that are identified are as follows:

- In contrast to on-line systems, recognition task is challenging in offline systems due to unavailability of dynamic information as, writing speed, stroke length, and pressure applied.
- It is hard to segment signature strokes due to highly stylish and unconventional writing styles.
- There is large intra-personal variation due to nonrepetitive nature of variation of the signatures, because of age, illness, geographic location and the emotional state of the signer.
- poor image quality, lack of robust preprocessing and normalization and high similarity between different strokes may pose difficulty in achieving high recognition rates.

V. Opportunity for future research

Review of most commonly classification approaches to signature recognition enables authors to choose neural network as a suitable tool for implementation. Learning ability, adaptation and simplicity of use are the main reasons for the widespread usage of neural networks (NNs) in pattern recognition. The basic idea is to extract a feature set representing the signature e.g. 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.

VI .Conclusion

Signature recognition can be easily integrated into existing systems because of the availability and prevalence of signature digitizers and the public's acceptance. A need for continued improvements in current products will help drive the development and application of this technology.

This paper reviews the recent developments in the domain of offline signature verification and summarizes representative works in this field. Although numerous literature is available [27] on feature extraction techniques, dynamic features, as well as complex features this paper focuses only on classifiers used in emerging applications. Based the features, pattern recognition, like DTW, HMM and SVM can be adopted to fulfill the task of off-line signature verification. Since the process of generating signatures is complex, which is sensitive to the psychological state and external conditions, with limited number of samples, signature verification will remain a challenging problem in the near future.

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