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An Efficient Mechanism to Validate Offline and Online Signature Verification and Forgery Detection

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Abstract

Automatic signature verification is a well-established and an active area of research with numerous applications such as bank checks verification, ATM access, etc. This paper proposes a novel approach to the problem of automatic off-line signature verification and forgery detection. The proposed approach is based on fuzzy modeling that employs the Takagi–Sugeno (TS) model. Signature verification and forgery detection are carried out using angle features extracted from box approach. Each feature corresponds to a fuzzy set. The features are fuzzified by an exponential membership function involved in the TS model, which is modified to include structural parameters. The structural parameters are devised to take account of possible variations due to handwriting styles and to reflect moods. The membership functions constitute weights in the TS model. The optimization of the output of the TS model with respect to the structural parameters yields the solution for the parameters. We have also derived two TS models by considering a rule for each input feature in the first formulation (Multiple rules) and by considering a single rule for all input features in the second formulation. In this work, we have found that TS model with multiple rules is better than TS model with single rule for detecting three types of forgeries; random, skilled and unskilled from a large database of sample signatures in addition to verifying genuine signatures. We have also devised three approaches, viz., an innovative approach and two intuitive approaches using the TS model with multiple rules for improved performance.

Keywords: ***Off-line signature verificationForgery detectionStructural parametersFuzzy logicTS modelBank check recognition***

Introduction

Biometrics is an emerging field of technology. It makes use of unique but measurable physical, biological or behavioral characteristics to perform the identity verification of a person. Physiological biometrics is based on direct measurements of physical parts (such as fingerprint, face, iris, hand geometry etc.) of human body. Behavioral biometrics is based on the measurement of an action performed (such as signature, gait, speech, gesture etc.) by the individual. The main advantage that signature verification has over other forms of biometric technologies [1-3] is that signature is a well accepted biometric for identity verification in our society for years. The long history of trust of signature verification means that people are willing to accept a signature based biometric authentication system. But the drawback is that some people exhibit a lot of variability between different manifestations of their signature. The way a person signs his or her name is known to be characteristic of that individual. Signatures are influenced by the physical and emotional conditions of a subject. A signature verification system must be able to detect forgeries, and, at the same time, reduce rejection of genuine signatures. Also signatures evolve with time and are influenced by physical and emotional condition of the signatories [7].

Signature analysis is categorized into two modes: offline and online. In the offline signature verification, signatures are captured with a scanner or camera, saved and stored in digitized form for further processing whereas the online signature verification uses an electronic tablet and a stylus connected to a computer to extract information about a signature. It provides dynamic information like pressure

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Signature being a behavioural biometric and it is mainly used in bank checks to make transactions. Unlike physiological biometrics such as face, iris, and fingerprint, it is fraught with the problem of change over a time and it is not difficult to forge. One of the main challenges in signature verification is related to the signature variability. While signatures from the same user show considerable differences between different captures (high intra-class variability), skilled forgers can perform signatures with high resemblance to the user's signature (low intra- class variability). Signature verification aims at using such properties for making reliable authentication. However the widespread acceptance of the signature by the public makes it more suitable for certain lower-security authentication needs. However, signature verification is a challenging task due to practical constraints. For instance, MasterCard estimates a $450 million loss each year due to credit card fraud, likewise some billions of dollars being lost because of fraudulent encashment of checks. Reliable automatic signature verification could be a proper solution to reduce such losses since handwritten signatures are already involved in the credit card transactions and encashment of bank checks [4].

Importance of online Signature Verification

Signature is a special characteristic of any person. As signatures continue to play an important role in financial, commercial and legal transactions, truly secured authentication systems becomes more and more crucial.

A signature of an authorized person is considered to be the "seal of approval" and remains the most preferred means of authentication. On the other hand, the intrepidity of signature fraud continues to be on the rise dramatically. The measurements collected from a digital signature while it is being written are as unique to an individual as his DNA [5]. Signature images can be captured using a pressure-sensitive digital pad. Signature verification is natural and intuitive. The online signature gives more information than the offline signature to verify. Moreover the chances of forgery are lesser here than in the offline signatures since online signature is based on real time.

Motivation

The manual verification of signatures is based on template or sample signatures. There are a very few organizations which use the online signature verification technology to verify the signature of a given user. In a country like India, where the majority of the population still rely on the handwritten signatures [6] for all their banking needs, the scope for forgery is quite high. Therefore, online signature verification technology will not only be helpful to the users but will also make the banking system safer. Since the system only requires a digital signature tablet and an electronic pen, the infrastructure needs are also low, thus proving to be the biometric of choice.

Literature Review

The online signatures verification techniques can be classified into two broad areas:

1.Methods based on features extracted from the visible parts of the signature and

2. Methods based on features extracted from virtual strokes or individual parts of the signature(the parts that are not created but are presumed).

The widely used approaches for the signature verification include:

Dynamic time warping (DTW)

Dynamic time warping matches two signatures by aligning the pen-tip trajectories along a common time axis. Theresulting distance depends on the sequence length of the two signatures and needs to be compared with a thresholdto accept or reject the claimed identity. In this context, a major challenge for statistical analysis is the computation of a normalized distance value that is comparable between signatures of the same user as well as signatures of other user

Hidden Markov Models (HMM)

Hidden Markov Model is used to model the changes in the discrete time signal [4]. In essence, HMM is a double statistical process which is bound by Markov chain with a finite set of states and a set of probability functions

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combined with the output of an observer status. At the specific time t, the process will be in one of the states and it generates an observation symbol according to probability function corresponding to the current state.

Gaussian Mixture Models (GMM)

A GMM is a parametric probability density function represented as a weighted sum of Gaussian component densities. GMMs are commonly used in different tasks as a parametric model of the probability distribution of continuous measurements

Fuzzy modelling and neural networks

Global features of the signature like the skeleton of the pen trace and the structure of upper and lower envelope are used as shape descriptors. These are obtained by sampling upper and external points from the binary image of the signature. High pressure regions where the writer applies more pressure or emphasis are used for maximizing the correlation between the vertical and horizontal projections of the skeleton. For each of the above shape descriptors a multi- layer perception is assigned and the network is trained with a modified back propagation algorithm and the output of each individual network is combined through a fuzzy integral voter [7].

Acquisition of On-line Signatures

The First International Signature Verification Competition was established in 2004 to provide landmark on signature verification systems SVC 2004.The signature database SVC2004(Task2) is taken from the University of Science and Technology, Hong Kong[76] and used for the verification. This database consists of 40 persons each having 20 genuine datasets stored in a text file. The database has two sets of signatures, namely Task 1 and Task 2. Each signature is represented as a sequence of points , which contains X coordinate , Y co-ordinate , time stamp and pen status (pen up or down) along with the additional information like Azimuth, Altitude and pressure in Task 2. The signature is acquired from a Digital Signature Tablet [8] (WACOM STU-500 SDK) when the instrumented pen moves on the tablet. Each signature is simply represented as a set of discrete time dynamic sequences.

A total of 1600 signatures, including forgeries of different sizes is collected from a group of 40 peoples containing 6 skilled forgers. The database is divided into two kinds of forgeries: simple forgeries and skilled forgeries. In the simple forgery the imposter only knows how to spell the authentic signature whereas in the case of a skilled forgery, the imposter has an access to the genuine signature and also time to practice the imitations. The raw data available from the tablet consists of X, Y co-ordinates, pressure and time.

Fig1: Signature samples

A digital signature tablet provides the following measurements while a signature is being written:

1. **ΔX** - X co-ordinate of the signature(x_k).
2. **ΔY** - Y co-ordinate of the signature($\mathbf{y_k}$).
3. **Pressure** - The pressure value of the pen i.e. the pressure applied by the user for his or her signature(p_k). It is assumed that the digital signature tablet senses the equal force at each point of the screen.
4. **Button Status**- This keeps track of the pen movement(b_k), i.e. whether it is moving up or down with respect to time.
5. **Azimuthal angle**- The angle between the user's pen and the line perpendicular to the surface of the screen(Az_k).
6. **Altitude angle** – The angle between the users' pen and line horizontal to the surface of the screen (Az_k).

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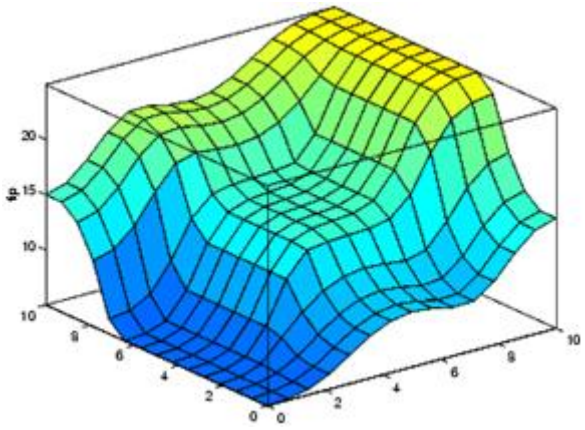
7. **Velocity** – The speed of user's signature.
8. **Acceleration**- The acceleration of the user's signature.

A sample at time t_k consists of six measurements (x_k,$\mathbf{y_k}$,p_k,b_k,Al_k,Az_k).We have not used the velocity and acceleration in this work. It may be noted that the time taken by different signatures of the same person may or may not be the same.



Takagi-Sugeno Fuzzy Model

Objectives

The following are the objectives of our thesis proposal:

1) Offline signature verification and forgery detection using checks (Angle based/CNN based).

2) Design of entropy network for off-line signature verification.

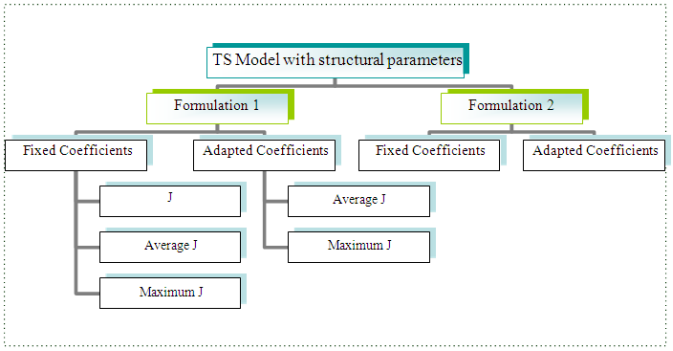
3) On-line signature verification using on-line measurements.

4) Design of entropy network for the verification of on-line signatures.

5) Development of a secure signature verification system.

Model Formulation

Since the main thrust here is to establish the genuineness of the signature thereby detecting the forgeries, we have employed the TS fuzzy model for this purpose. In this study, we consider each feature as forming a fuzzy set over large samples. This is because the same feature exhibits variation in different samples giving rise to a fuzzy set. So, our attempt is to model the uncertainty through a fuzzy model such as the TS model [9]. The overall system organization is depicted in Fig



System Organization

Issues involved in Signature Verification

Some of the issues that we want to address are the following:

1) Categorization of signatures into different types(name, graphics form).

2) Categorization of forgery into skilled and unskilled types.

3) Investigation of suitable features for off-line signature verification.

4) Development of appropriate models for representing features of off-line signatures and measurements of on-line signatures.

5) Devising different performance measures for the evaluation of models.

6) How to store signatures in a secured environment.

7) Investigation of distributed computing like Hadoop for real-time performance of verification of signatures.

Motivation:

Several approaches have been investigated. But the uncertainty in the signatures which arises due to inherent variability has not been attempted. We are therefore motivated to pursue uncertainty representation in the signatures in the case of off-line signature verification or measurements in the case of on-line signature verification. As the entropy is a measure of disorder or uncertainty, we will explore the use of entropy both for feature extraction and subsequent verification. Some studies are already available in the literatures on biometrics. Signature being a behavioural biometric, it is prone to inherent variation in handwriting. So we will explore the entropy based uncertainty representation for the signature verification [10].

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Implementation

The proposed system is applied on the Signature Database described in detail in Section 4. For implementation, we will consider two cases: In the first case, we use the simplified TS model in which the coefficients of the THEN part (Consequent) are fixed whereas in the second case we adapt the coefficients [5-9].

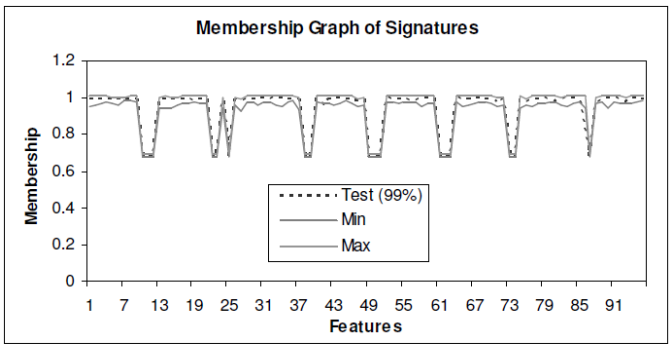
Case 1: TS model with consequent coefficients fixed

$$J = (1 - \frac{1}{L}\sum_{i=1}^{L} \mu_i)^2$$

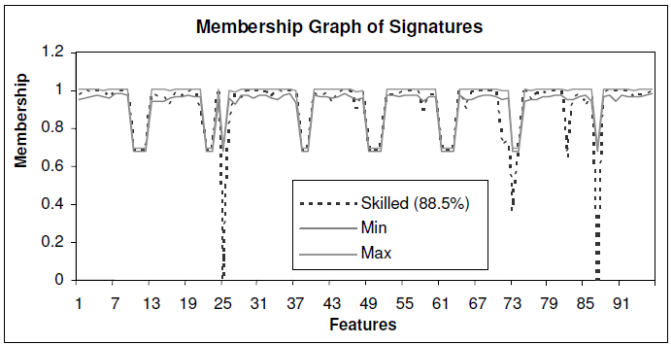
With the above performance index, we compute $\frac{\partial J}{\partial s_i}$ and $\frac{\partial J}{\partial t_i}$ in order to update the structural parameters s_i and t_i; $i=1,...,96$. Using these values, we compute the membership functions for all the features. This process is repeated for all the training samples of a person. Here, we have devised an innovative approach for the classification of all signatures (i.e., test signatures and random, skilled and unskilled forgeries) of a person.

Innovative Approach using variation in MF:

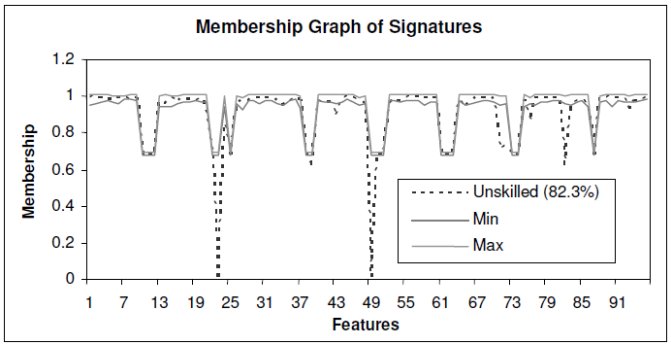
In order to know the extent of variation in the genuine signatures, we determine the maximum and minimum membership functions for each feature over all signatures in the training set. The difference between these two gives the inherent variation in the signatures of a person. We add some tolerance to the maximum and delete the same from the minimum so as to increase the range of variation in the different signatures [5]. This tolerance is meant for possible increase in the inherent variation over a time.



(a)



(b)



(c)

Membership graph of (a) genuine (b) skilled forgery and (c) unskilled forgery

We now use the inherent variation to judge the test signatures. We will also explain its utility in the testing phase. For a particular feature, if the membership value lies within the range of variation which is given by the difference of minimum and maximum thresholds, it is counted as 'true'. The total number of 'true' cases for a particular signature is divided by the total number of features (i.e., 96) to get the percentage. For example, in Fig.12a, the test signature has 99% of its features lying well within the threshold as can be seen from the membership function (i.e., 95 out of 96 features are within the range of inherent variation). The skill- forged and unskilled-forged signatures have corresponding figures of 88.5% (Fig. b) and 82.3% (Fig. c) respectively. We set the minimum limit or acceptable percentage for genuine signature at 91% referring to the output result of signature of one particular individual.

Signatures that have percentage less than 91% are treated as forged signatures. Table 3 gives the initial values of learning and structure parameters.

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Table: Initial values of the structural and learning parameters

Parameter	Simplified TS model Initial Values	TS model Initial Values
s	0.1	1
t	1.4	2
c_0	1/96	1/96
c_1	0	0
ε_1	-	0.00000001
ε_2	0.01	0.01
ε_3	0.01	0.01
Precision	**0.01**	**0.01**

Intuitive Approaches taking the average and max of J: Next, we have used the performance index given by Eqn. (12) and its derivatives to adapt the structural parameters during the training phase. These are used to determine the extent of inherent variation in terms of J in the training phase. We have tried two intuitive approaches. In the first case we have taken average J and in the second case we have taken maximum J , both serving as thresholds. The samples in the testing phase are judged by comparing their J values against the thresholds. Table 4(a) summarizes the results of forgery detection using this innovative approach. Tables 4(b) and 4(c) provide the results of forgery detection using the average J and max of J respectively. Comparing these results, we find that the innovative approach yields the best performance.

Table - Results using Formulation 1 with fixed consequent coefficients

Signature Type	Total	Accepted	Rejected
(a) *J*			
Genuine	200	200 (100%)	0 (0%)
Skilled forgery	200	0 (0%)	200 (100%)
Unskilled forgery	200	0 (0%)	200 (100%)
Random forgery	200	0 (0%)	200 (100%)
(b) *Average J*			
Genuine	200	184 (92%)	16 (8%)
Skilled forgery	200	44 (22%)	156 (78%)
Unskilled forgery	200	8 (4%)	192 (96%)
Random forgery	200	0 (0%)	200 (100%)
(c) *Maximum J*			
Genuine	200	200 (100%)	0 (0%)
Skilled forgery	200	42 (21%)	158 (79%)
Unskilled forgery	200	6 (3%)	194 (97%)
Random forgery	200	0 (0%)	200 (100%)

Conclusion

In this chapter, an offline signature verification and forgery system based on additive fuzzy modelling is presented. The handwritten signatures images are pre-processed and angle features extracted from them via a novel grid method. These features are then modelled using the Takagi-Sugeno fuzzy model, which involves two structural parameters in its exponential membership function. Each angle feature yields a fuzzy set when its values are gathered from all samples because of the variations in handwritten signatures. Two cases are considered. In the first case, the coefficients of the consequent part of the rule are fixed so as to yield a simple form of TS model and in the second case the coefficients are adapted. In this formulation, each rule is constituted by a single feature. In the second formulation, we consider only one rule encompassing all the features. Here again, we have derived two models depending on whether coefficients of the consequent part are fixed or adapted. However, this formulation is not implemented as the membership values are found to be very small for some fuzzy sets. The efficacy of this system has been tested on a large database of signatures. The verification system achieved 100% success in verifying genuine signatures and detecting all types of forgeries: random, unskilled and skilled on a signature database consisting 1200 signature samples. Simple form of TS model in the first formulation is found to be better than that with coefficients adapted. We have also demonstrated the effectiveness of the intuitive approach for signature verification over other approaches using the performance index.

References

[1]. A.K. Jain, L. Hong, S. Pankanti, "Communications of the ACM", Biometric Identification, Vol.43, No.2, pp.91-98, (2008).

[2]. A.K. Jain, Friderike D. Griess, Scott D. Connell, "On-signature verification", Pattern Recognition, Vol.35, No.12, pp. 2963--2972, Dec 2002.

[3]. H. Lei, V. Govindaraju, "A Comparative Study on the Consistency of Features in On-line Signature Verification", Pattern Recognition Letters, Vol. 26, Issue 15, November 2005.

[4]. S. A. Daramola and T.S Ibiyemi, "Efficient on-line

signature verification system", International Journal of Engineering & Technology, Vol. 10, No.4, August 2010.

[5]. B. Yanikoglu, A. Kholmatov "An Improved decision criterion for genuine/forgery classification in on-line signature verification" Sabanci University, Tuzla, Istanbul, 34956, Turkey.

[6]. M. Hanmandlu, M. Hafiz, V. K. Madasu, "Offline Signature Verification and forgery detection using fuzzy modeling", Pattern Recognition 38 ,pp. 341-356,2005.

[7]. Kour, M. Hanmandlu, and Ansari, A. Q. Ansari, "Online signature verification using GA-SVM" International Conference on Image Information Processing, pp. 1-4, 2011.

[8]. Dong, L.; Yun-Jian, G.; Xue-Yong, Z., 2010 International Conference on Computer application and System Modeling (ICCASM), On-Line Signature verification based on template matching approach and support vector data description , Vol. 12,pp. 681-685, 2010.

[9]. R. S. A. Araujo, G. D. C. Cavalcanti, and E. C. D. B. C. Filho, "On-line verification for signatures of different sizes," presented at the 10th Int.Workshop Front. Handwriting Recognition, La Baule, France, Oct. 2006.

[10]. A. Kholmatov, "Biometric Authentication using online signature", MS Thesis, Sabanci University, June 2002.

[11]. D. Impedovo, G. Pirlo, R. Plamondon "Handwritten Signature Verification: New Advancements and Open Issues", International Conference on Frontiers in Handwriting Recognition (ICFHR), 2012, 18-20 Sept. 2012, Bari, pp. 367-372.

[12]. Zhang, Z., Wang, K., Wang, Y., "A Survey of On-line Signature Verification" C. Allgrove, M. C. Fairhurst, "Majority voting for improved signature verification," in Proc. Inst. Elect. E Colloq. Vis. Biometrics, London, U.K., pp. 9-1–9-4, 2000.