MULTIPLE CLASSIFIER FOR ON-LINE SIGNATURE VERIFICATION SYSTEM

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ABSTRACT

With the increase of advance development in security technology, many major corporations and governments start employing modern techniques to identify the identity of the individual. These include the adoption of a system such as on-line signature and handwriting verification application for banking systems, public sectors, as well as for documents and checks. To achieve better solutions, multimodal biometric system needs to be employed since this system exploits more than one psychological or behavioral at verification process. This work presents a signature verification system as behavioral system to ensure that the currency authentication is preserved by validating the genuine signature. This study developed signatures by applying multiple classification techniques. These include Artificial Neural Network (ANN), Support Vector Machine (SVM) and pearson correlation. These techniques are combined with fusion techniques, i.e., ordinal structure module of fuzzy and Or gate to determine the signature either it is real or forge. The average of the values we have it after applying multiple classification techniques is calculated, and the results are compared with the pre-defined threshold prior to decision making of either the signature is genuine or not. After collect many samples and calculate the final result we calculate the error rate for FRR and FAR to compare it with previous study. After calculated the error rate we found 2% for False Rejection Rate (FRR) and 0% for False Acceptance Rate (FAR), so the result for these study it’s better than previous one.

ABSTRAK

`Dengan peningkatan memajukan pembangunan di teknologi keselamatan, banyak syarikat besar dan kerajaan mula menggunakan teknik-teknik moden untuk mengenalpasti identiti individu. Ini termasuk pengadopsian sistem seperti on-line pengesahan tandatangan dan tulisan tangan aplikasi untuk sistem perbankan, sektor awam, serta dokumen dan cek. Untuk mencapai penyelesaian yang lebih baik, sistem biometrik Multimodal perlu untuk dipekerjakan kerana sistem ini memanfaatkan lebih daripada satu psikologi atau perilaku dalam proses pengesahan. Karya ini menyajikan sebuah sistem pengesahan tanda tangan sebagai sistem perilaku untuk memastikan bahawa mata wang yang diawetkan dengan pengesahan memvalidasi tanda tangan asli. Studi ini dibangunkan tanda tangan dengan menerapkan beberapa teknik-teknik pengelasan. Ini termasuk Artificial Neural Network (ANN), Support Vector Machine (SVM) dan korelasi Pearson. Teknik-teknik ini digabungkan dengan teknik gabungan, iaitu, modul struktur ordinal kabur dan Atau gerbang untuk menentukan tanda tangan baik itu nyata atau dipalsukan. Rata-rata dari nilai-nilai yang kita miliki setelah menerapkan beberapa teknik pengelasan dihitung, dan hasilnya berbanding dengan ambang batas yang telah ditetapkan, sebelum turun keputusan baik tanda tangan asli atau tidak. Selepas mengumpul banyak sampel dan mengira hasil akhir kita menghitung tingkat kesalahan untuk fRr dan FAR untuk membandingkannya dengan pengajian dahulu. Setelah dihitung tingkat kesalahan kami menemukan 2% untuk Penolakan Salah Rate (fRr) dan 0% untuk Penerimaan Salah Rate (FAR), sehingga hasil kajian ini lebih baik daripada sebelumnya.

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CHAPTER 1

INTRODUCTION

1.1 Introduction

Biometrics refers to the automatic identification of a person based on his/her physiological or behavioral characteristics. Biometrics can be defined as the science and technology of measuring and statistically analyzing biological data. Physiological characteristics are based on measurements and data derived from direct measurement of a part of the human body. Fingerprints, hand geometry, and retina, iris, and facial images (Orlans, et al., 2003) are leading physiological biometrics (Figure 1.1). Behavioral characteristics are based on an action taken by a person. Behavioral biometrics is based on measurements and data derived from an action, and indirectly measure the characteristics of the human body. Signatures, voice recordings (which also has a physiological component), and keystroke rhythms are leading behavioral biometric technologies.

The terms "Biometrics" and "Biometry" have been used since early 20th century. It refers to the field of statistical and mathematical methods that are applicable to data analysis problems in the biological sciences. Recently, these terms have also been used to refer to the emerging field of information technology devoted to automated identification of individuals using biological traits especially for authentication purposes.

Biometrics is nowadays an important area receiving continuously growing interest. The increasing needs for security make biometrics become valuable world-wide. This method of identification is preferred over traditional methods for various reasons:

- The person to be identified is required to be physically presented at the point-of-identification.
- Identification based on biometric techniques obviates the need to remember a password or carry a token.

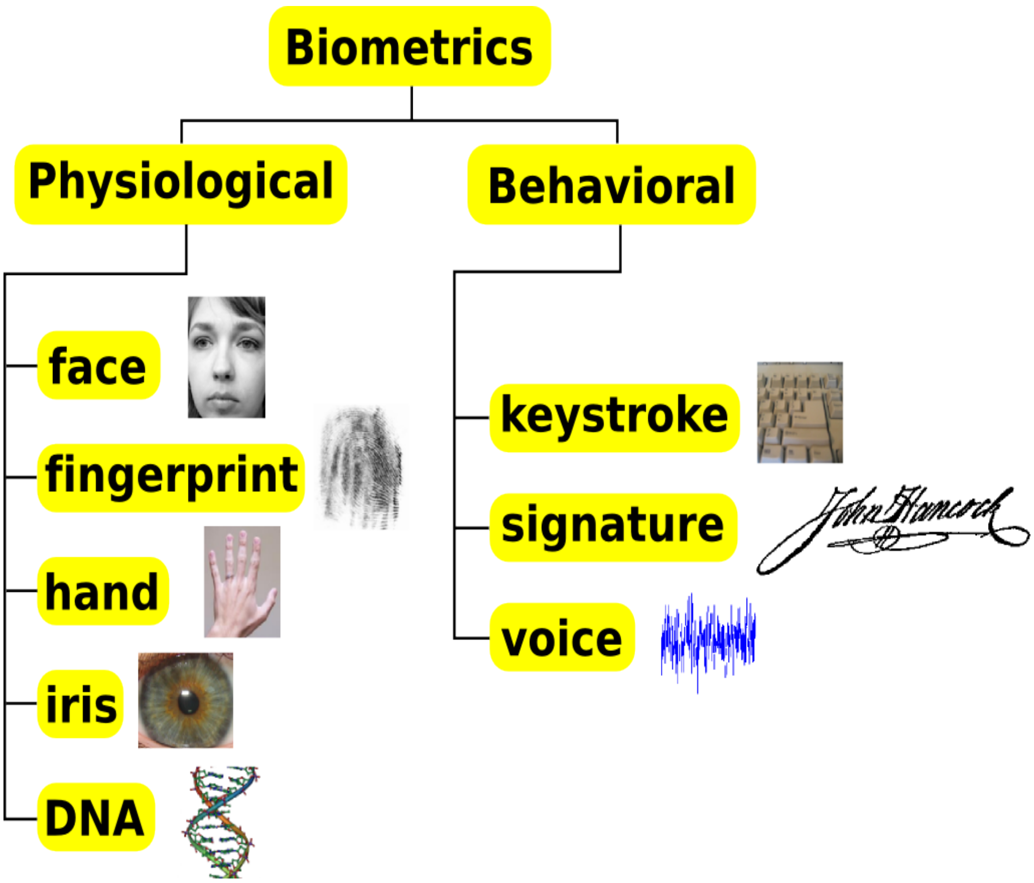

Figure 1.1 Behavioral characteristics

1.2 Problem Background

Since decade, the problems that were faced by human are how to verify the identity of the individual and belongings. These involved from the invention of the ring which crafted name on it, followed by the use of rolled fingerprint, signature and subsequently identifying through iris technology.

The development of signature technology began with handcrafted writing and ended with the digital signature. But for the digital signature, human does many programs to support the signature verification. These programs are validated by calculating the error rate: False Rejection Rate (FRR) and False Acceptance Rate (FAR).

Signature verification is designed to verify subjects based on the traits of their unique signature. As a result, individuals who do not sign in a consistent manner may have difficulty enrolling and verifying their signatures verification. This is due to the requirement of the enrolment that need to have series of signatures that are similar for better verification. During this verification, many characteristics must remain constant to determine the confidence level for the granted authorized person. As a result, individuals with muscular illnesses and people who write their initial might result in higher False Rejection Rate (FRR). FRR measures the likelihood that a system will incorrectly reject an authorized user. Since many users are unaccustomed to signing on a tablet, some digital signatures may differ to their signatures on ink and paper. Thus, inviting increasing number of false rejection. There also a lot of people who can counterfeit the signature very well; consequently the result have high False Acceptance Rate (FAR), since the system can accept as an authorized user. Hence, this study will propose a solution to solve the above issues by reducing the FRR error rate. Table 1.1 illustrates the previous studies on reducing the FRR and FAR of signature verification system.

Table 1.1 Related previous results on real time signature verification of error rate

Year	Comment / Method	Error %	
		FRR	FAR
1993	Signal Autoregressive (Mohan Krishnan, et al., 2007)	4	0
1995	Siamese neural network (Isabelle Guyon, et al., 1995)	5	20
1997	Signal correlation: DB (Nawla, 1997)	7	1
2001	Wavelet / BPNN (Dariusz Z. Lejtman, et al., 2001)	0.1	0
2001	Position, Pressure, inclination / Matching (T. Ohishi, et al., 2001)	2.4	1.3
2001	Dynamic Features of pressure / Dynamic Program Matching (Tanabe, et al, 2001)	6	6
2002	String Matching	2.8	1.6
2002	Wavelet-based / DTW (SILVA, et al.,2002)	30	0
2003	Stroked Based Feature / probabilistic distribution (Tong Qu, et al., 2003)	6.67	1.67
2003	Dynamic Program Matching (ZE-NIAN LI, et al.,2003)	1.8	2.5
2003	Variable length segmentation / HMM (Shafiei, et al., 2003)	12	4
2003	Local Shape/HMM : DB1 (Zhengliang Lou, et al., 2003)	6.67	0
	DB2	9.94	0.5
	DB3	11.3	2
2004	Dynamic features / BPNN	1.8	2
2007	Local and global feature simple AND Gate fusion	5.3	0
2008	Multiple classifiers and multiple fusion techniques (Hamam, 2008)	2.5	0

The previous studies have used Artificial Intelligence (AI) methods to verify the signature (Khairulmizam, et al,.2008) . These include the use of neural network, fuzzy logic and fuzzy neural in verifying handwritten signatures. The common weaknesses of the previous techniques used are always the emergence of the rate of errors: False Rejection Rate (FRR), and False Acceptation Rate (FAR).

Fuzzy logic has emerged as one of the most successful AI technologies in recent years. It is a tool that can be used for controlling complex industrial processes, as well as for household and entertainment electronics, and diagnostic systems (Heikki Koivo , 1999).

Conventional fuzzy is used since it has two inputs and one output. In signature verification, the fuzzy system has four inputs that should be calculated on its average and decides the status of the signature (Hamam, 2008). Since it is rather difficult to derive the fuzzy inference rules with more than two input parameters (Figure 1.2) at one time using conventional fuzzy reasoning method, most of the researchers created several rule-based blocks where each block was able to handle only two input parameters each time. In these study, we are not focused on the complex of the weights structure.

There is another technical can take multi parameters at one time which is called as Fuzzy Ordinal Structure Model (Figure 1.3). The inference engine is capable of considering all the input parameters at one time. It has an advantage over the conventional fuzzy algorithm by overcoming the difficulty of handling multi-dimensional space rules into single space structure. The ordinal structure model of fuzzy reasoning has an advantage of approach of setting the rules with multiple inputs and outputs. This is achieved by giving an associated weight to each rule in the process. However finding the best weight for each rule is a large and complex search problem.

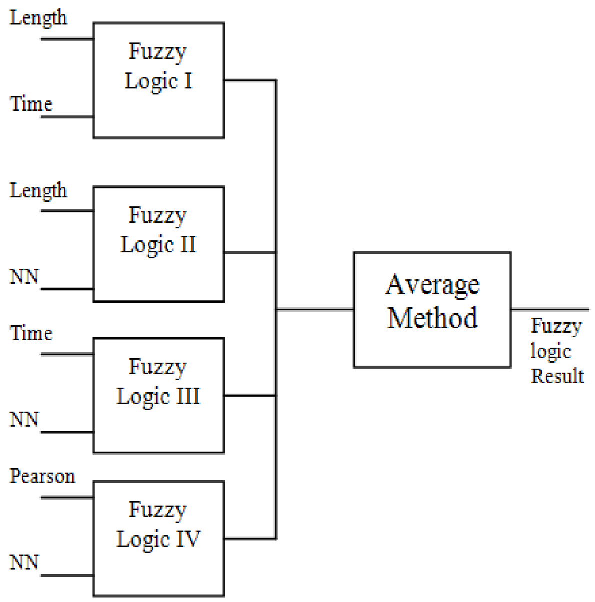

Figure 1.2 Conventional Fuzzy System

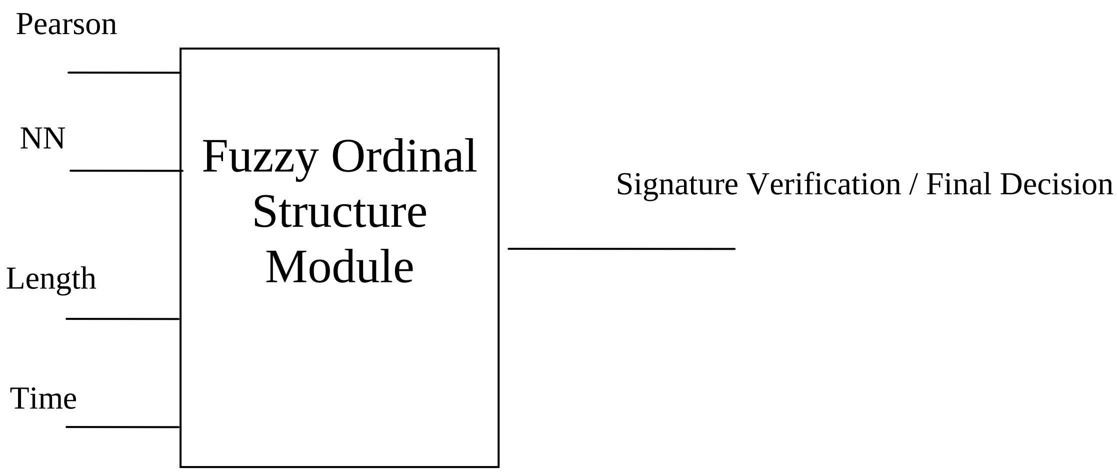

Figure 1.3: Ordinal Structure Module of Fuzzy

1.3 Problem Statement

From the previous studies on signature verification systems (Hamam Mokayed. el at,. 2008) , we notice that all of the above techniques have faced many challenges. The first challenge is the value of the rejection of an authentic signature which is referred to as Type I error or commonly called as FRR (False Rejection Rate). The second challenge is the value of the acceptance for forgeries as being authentic; this type of error is referred to as Type II error or commonly referred as FAR (False Acceptance Rate). In this study, we enhance the study of (Hamam Mokayed. el at,. 2008) to reduce the error rate.

Hence, the research question of the study can be derived as:
Could Ordinal Structure Module Fuzzy with multiple fusion techniques enhance the signature of the verification system?

1.4 Objectives

The objectives of this project can be summarized as follows:

1- To develop different fusion techniques in the signature verification.
2- To reduce the value of FAR (*False Acceptance Rate)*, FRR *(False Rejection Rate)* in the signature verification.
3- To design an Ordinal Fuzzy Logic (OFL) for signature verification decision Module.
4- To verify the effectiveness of Ordinal Fuzzy Logic on signature verification

1.5 Project Scope

The scope of the study is given as follows:

1. The study uses WACOM tablet to collect signatures.
2. Programming in .Net is developed using C# and Visual basic
3. The comparisons are conducted between ordinal fuzzy logic and conventional fuzzy logic.

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