# Signature Verification System using Pen Pressure for Internet and E-Commerce Application

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## 1. Introduction

The need to ensure that only the right people have authorisation to high-security accesses has led to the development of systems for automatic personal verification. Fingerprints, palmprints, voice and handwriting have all been used to verify the declared identity of an individual. Among all, signature has a fundamental advantage in that it is the customary way of identifying an individual in daily operations such as automated banking transaction, electronic fund transfers, document analysis and access control [1, 3, 4]. A signature verification system must be able to detect forgeries and at the same time reduce rejection of genuine signatures. In this paper, an automated signature verification system based on the pressure exerted on the pen tip is presented. No digital pad or specific paper is needed in this proposed system as the instrumented pen was designed to function independently without any pad. As long as there is a surface to sign on, the pressure exerted on the pen tip can be measured. Our results show that it is possible to verify signatures and yield performance satisfactory especially in the case of point-of-sales (POS) applications such as credit card transaction. The technique used, which includes the instrumental pen, is very practical and reliable in Internet and E-commerce applications. Although work has been done to verify signatures using the pressure exerted on the pen tip, results obtained and the practicality of those methods are not convincing enough to be implemented.

## 2. Background

Research is very actively under way in the signature verification domain [2, 4, 5, 6, 7, 8]. In their in-depth article on this subject published in 1989, R. Plamondon and G. Lorette reflect this high level of activity in their description of the numerous verification methods available and by classifying the strengths and weaknesses of these techniques. A great deal has been done in the domain since this article was published. Researchers have applied new technologies, such as neural networks and parallel processing, to the problem of signature verification and they are continually introducing new ideas, concepts and algorithms [1, 6]. Signature verification is a real challenge for researchers because of the many difficulties that can arise during the process of creating such a system.

In this paper, we show that it is not sufficient to verify the validity of a signature only by comparing the physical image of it. Presentl**y,** in any point-of-sale (POS) application, either through Internet or credit card transaction, a signature, will be verify as genuine if the signature looks physically the same as the genuine signature being compared to. Though this problem is widely known, but with the presence of experience forgers, this problem is incredibly hard to solve.

## 3. Feature Extraction

The acquisition stage provides values of pressure exerted against a measure of time using an instrumented digital pen sensitive to pressure. A localized low pass Sum Filter of order 15 is applied to eliminate frequencies greater than 50 Hz (which could be considered as noise). Normalisation is then conducted to standardise the values of the pressure exerted between 0 and 1.

The feature extraction stage consists of 2 processes. A new technique of segmentation divides the time series data into specifically defined segments. Characteristic like the shape and curves of the graph, high and low points, stationery points and gradient of the graph are similar once normalisation has been done. The improved segmenting method is based on the algorithm to segment the time data graph into major curves. This is done by calculating the difference of pressure exerted between every 2 points. If the drop of pressure is more equal to 0.035, then a segmenting point is discovered.

The first step verifying a signature is done here. If the amount of segments produced by a test signature is very different from the genuine signature being compared to, the test signature is rejected. In the second process, we use time series modeling with autoregressive (AR) technique to calculate the AR coefficients from all the segments. Autoregressive (AR) models have proven to be superior to Fourier methods due to the ability of AR models to handle short segments of data while giving better frequency resolution and smoother power. In addition, AR methods need only one or more cycles of sinusoidal-type activity to be present in the segment to produce good spectral peaks and they also provide the ability to observe small shifts in peak frequencies, which are not easily observed with Fourier derived spectra. The AR model coefficients can be easily estimated by solving recursively using Levinson-Durbin or Burg method. These coefficients are then used to obtain the power spectral density (PSD) values to represent each segment. Combination of all the PSD values from all the segments represents the signature.

**4. Training of Neural Network**

The learning and verification stage is made up of a neural network topology known as multiplayer perceptron or MLP. MLP uses the back propagation algorithm to train the network. Training is equivalent to finding proper weights for all the connections such that a desired output is generated for a corresponding input. Using MLP in the context of a classifier requires all output nodes to be set to 0 except for the node that is marked to correspond to the class the input is from. That desired output is 1. In our study, the inputs are the PSD values obtained from the segmentation and spectral analysis stage.

**5. Experimental study**

An experimental study is performed to examine the proposed system. A database of 1000 signatures is used for training and testing. The signatures were collected under "normal" writing conditions from 20 writers. Each of them signed using an instrumented digital pen to obtain the pressure exerted on the pen tip while signing. No digital pad or specific paper is needed in this acquisition step as the instrumented pen functions independently without any pad. As long as there is a surface to sign on, the pressure exerted on the pen tip can be measured. However, in adapting the system to practical applications, each subject were asked to sign on ordinary multi purpose papers of weight 80 Gsm. Each subject produced his or her signatures regardless of the size of the signature within 25 seconds. The time period of 25 seconds is adjustable as the instrumented pen can be reprogram. However, we feel that 25 seconds is generally enough taking into consideration Japanese and Chinese signatures. A total amount of 6000 pressure values can be obtained within 25 seconds; therefore the sampling frequency of the pen is 240 Hz. Our research so far has obtained very satisfactory results with error rates of 2.13% in rejecting genuine signatures (type I error) and 3.40% in accepting forged signatures (type II error). This paper demonstrates how segmentation, spectral analysis and artificial neural network can be exploited to provide an optimised general-purpose system to verify genuine and forged signatures for applications in the Internet and E-commerce world.



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