Auto Correlation Verdict for Off-Line Signature Corroboration

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Abstract
In this paper, an off-line signature verification scheme based on Auto correlation and statistical parameters is proposed.
In this paper, we are following a signature basis. Furthermore, we are having a lot of feature model techniques. In this paper, we are implementing the best and reliable one. Further refinements could include finding and isolating the individual letters in a signature and comparing these, as well as the rotation of the signature. Simulationsshow that this scheme can detect the genuineness of the input signaturesfromour test database with an error rate as low as 4%.

Keywords
Corroboration, Verdict, Autocorrelation, Statistical Parameters

I. Introduction

Offline signature verification is now readily used in directly related applications like biometric identification. But now a days it is also applied to the field of image processing, especially relating to identification and comparison of images. The concept of offline signature is challenging because of very reasons. Firstly, there exists great variation between two signatures of the same person. They never start from the same position and neither do they terminate at same position. Also the angle of inclination of signatures, the relative spacing between letters of the signatures, height of letters all vary even for single person. Hence it becomes a challenging task to compare two signatures of the same person. In this project we are following a signature basis
The problem of signature identification basically means to decide whether or not a current test signature corresponds to a given reference signature. 'HUMANS' recognize each other according to their various characteristics for ages. We recognize others by their face when we meet them and by their voice as we speak to them. Identity verification (authentication) in computer systems has been traditionally based on something that one has (key, magnetic or chip card) or one knows (PIN, password). Things like keys or cards, however, tend to get stolen or lost and passwords are often forgotten or disclosed. To achieve more reliable verification or identification we should use something that really characterizes the given person. Biometrics offer automated methods of identity verification or identification on the principle of measurable physiological or behavioral characteristics such as a signature or a voice sample. These characteristics should not be duplicable, but it is unfortunately often possible to create a copy that is accepted by the biometric system as a true sample. Signature authentication technology uses the dynamic analysis of a signature to authenticate a person. The technology is based on measuring speed, pressure an dangle used by the person when a signature is produced. This technology uses the individual's handwritten signature as a basis for authentication of entities and data. An electronic drawing tablet and stylus are used to record the direction, speed and coordinates of a handwritten signature. There is no encryption or message confidentiality offered yet with signature dynamics, but more modern examples use one-way hash functions to encrypt the signature dynamics and data and append it to the document being signed. In one iteration, Created by Topaz Systems, the signature actually disappears from view if the document is tampered with after signature

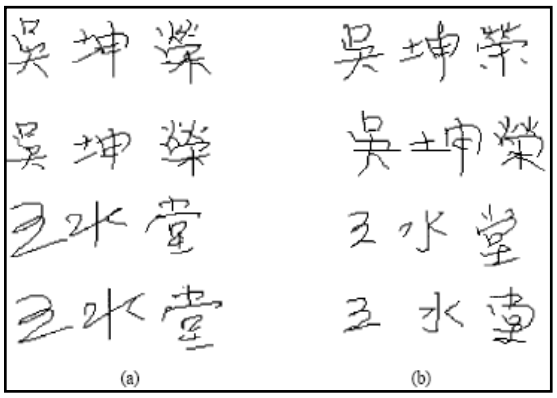


Fig. 1: The Example of (a). Genuine Signatures, (b). Forgeries

Fig.1, demonstrates examples of genuine signatures as well as forgeries inChinese. Visual examination is the most popular approach for signatureverification, yet there are occasions for the examiners to makemistakes or lower their thresholds of acceptance. For instance, ina commercial transaction, comparing the signature with a previouslywritten signature, such as the signature on the back of a credit card,is more or less a challenge to the clerks. As a result, large financiallosses may occur.

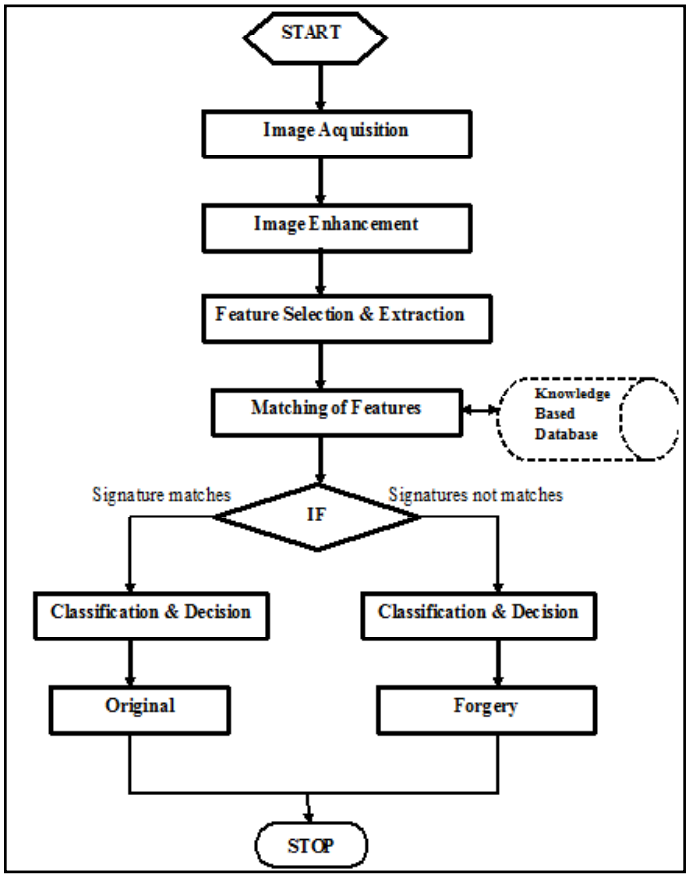


Fig. 2: Common Modules for Signature Corroboration System

It is clear that signature verification through visualexamination can only judge the authentication roughly. Human eyescan hardly analyze the detailed writing features.

Fig. 2 showsthecommon modules for off-line signatureverification in this the signature is taken in the image format as JPEG. Static features, such ascoordinates, mean , averages are usefulcharacteristics for off-linesignature verification. Other issues tobe considered in a verification system are distortion measurementscheme, learning scheme on the signatures, and the criteria for forgerydetermination.

II. Feature Extraction

Since we are interested in waves and they are all sins and cosines, the first thing we must do is subtract out the average value of our data from thedata record. If there are n time steps then:

$u(t_n)$ is the data we just digitized

$$\langle u \rangle \equiv \mu = \frac{1}{N}\sum_{n=1}^{n} u(t_n) \quad \text{average}$$

$$x(t_n) = u(t_n) - \mu \quad : \text{data with mean value removed}$$

The autocorrelation function tells us the time interval over which a correlation in the noise exists. If the noise is made entirely of waves, and the waves move through the plasma (or other medium) without decaying as they travel, the autocorrelation will be large for all time.

For digital data the autocorrelation is defined as :

If x is continuous

$$R_{xx}(\tau) = \underset{N\to\infty}{Lim}\frac{1}{N}\sum_{t=1}^{N} x(t)x(t+\tau)$$

IF x is digital and the data is taken at intervals rΔt(suppose t is .01 second then rΔt=0,.01,.02,.03 when r =0,1,2,3..)

$$R_{xx}(r\Delta t) = \frac{1}{N-r}\sum_{n=1}^{N-r} x(t)x(t+r\Delta t) \equiv \frac{1}{N-r}\sum_{n=1}^{N-r} x_n x_{n+1}$$

III. Performance Evaluation

The below fig. 3 shows that the signature with which we have to compare is converted into signal first

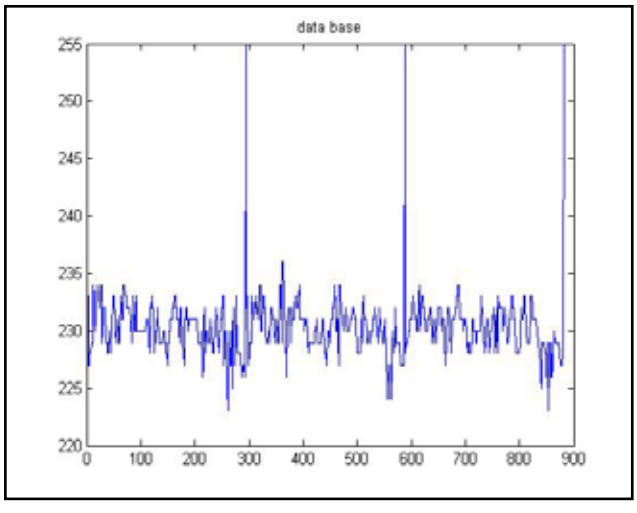


Fig. 3: Database Represented in Image

Here the signature 1 is converted into signal and the fig4 is shown below

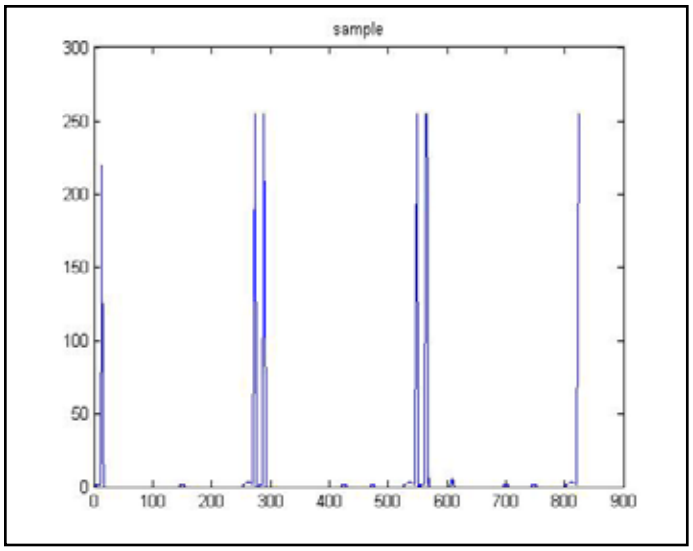


Fig. 4: Sample Image

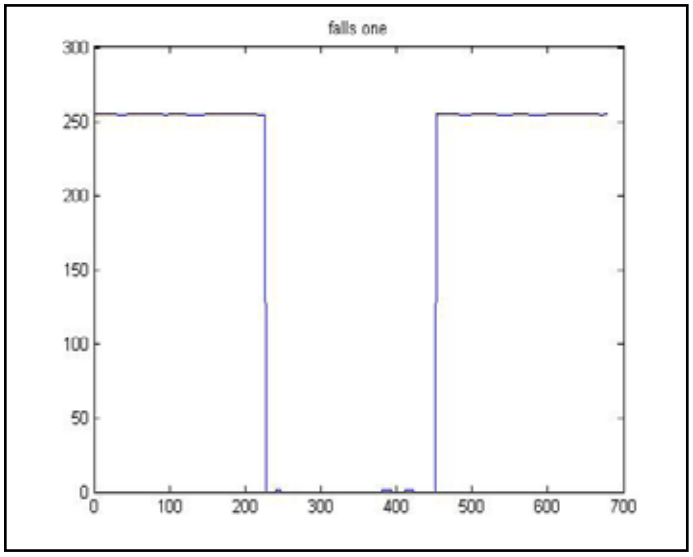


Fig. 5: False Image

Here the signature 2 is converted into signal and the fig. 5 is shown above.

Now Auto correlation is done to data base image and data base and it is shown in fig. 6 below.

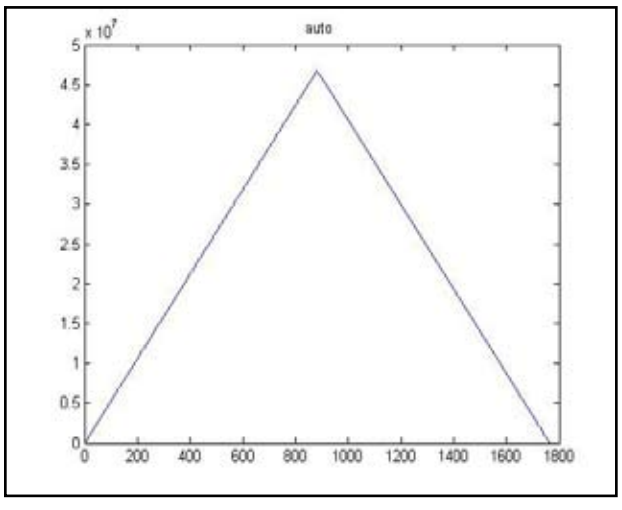


Fig. 6: Auto Correlation on Two Same Signals

Now Auto correlation is done to data base image and sample and it is shown in fig. 7 below.

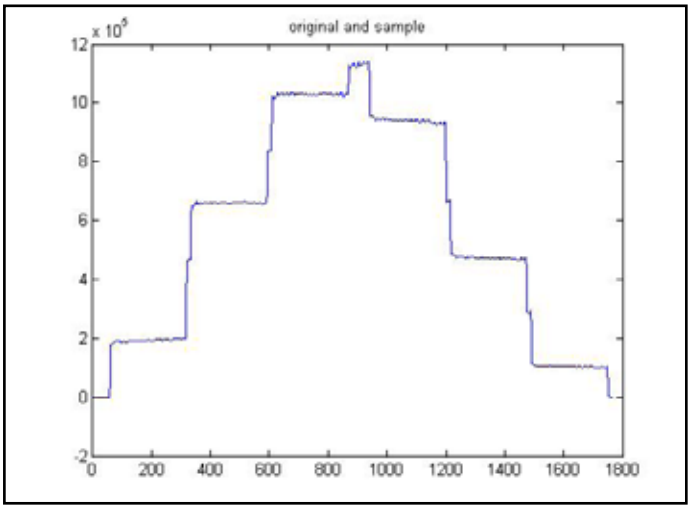


Fig. 7: Image of Original and Sample

Now Auto correlation is done to data base image and false and it is shown in fig. 8 below.
Original and false image is represented by using auto correlation function i.e the plot for original and false image is shown in fig. 8.



Fig. 8: Image of Original and False

Now Auto correlation is done to auto and original sample and it is shown in fig. 9 below.

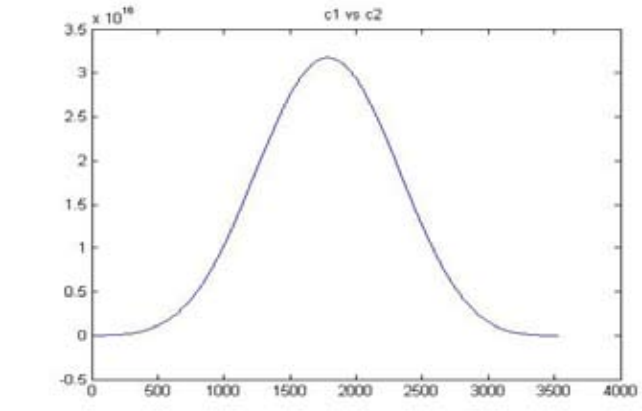


Fig. 9: Auto Correlation on Two Signals

Now Auto correlation is done to auto and original false and it is shown in fig. 10 below.

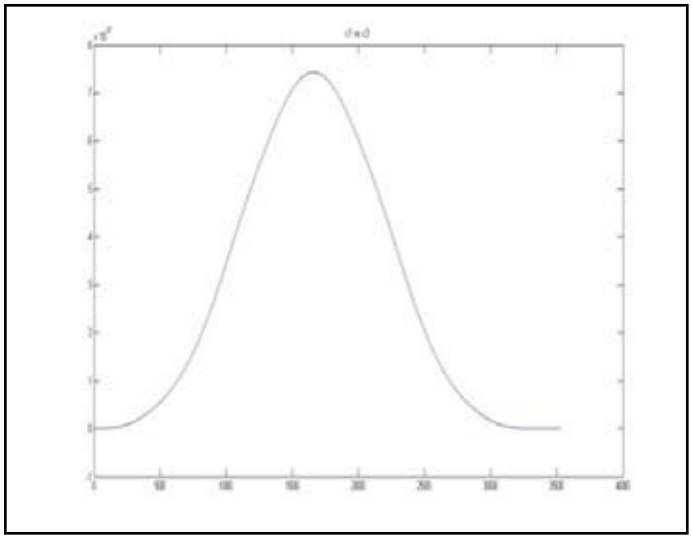


Fig. 10: Auto Correlation on Different Signals

At the last the cross correlation matrix coefficients are generated. Then by using statistical parameter as average, the average of the matrix is calculated . This value is taken for final comparision with the threshold values range.

IV. Conclusion

In this paper the combination of correlation and statistical parameters are used to determine whether the input signature is a genuine one or not. The result of verification is "signature is identified" when the statistical parameter value is in the threshold range, while it is "signature is not identified" when the parameter value is not in the threshold range.

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