On-line signature writer identification

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This paper presents a set of descriptors for On-line signature writer identification. These descriptors are intended to be used in e-business and e-government to detect signature forgery where it is hard to identify the writer across the Internet. Some descriptors represent global signature features, while the rest are dynamic signature features derived from the pen's linear speed. The forms of forged and the genuine signatures used in this work look identical. Cepstral descriptors showed a higher rejection rate of (98%) for all forged signatures, and 100% acceptance of any genuine signature. Linear Predictive descriptors derived from de-noised signature data delivered significant results with a rejection rate of (95%).

يقدم هذا البحث مجموعة من الصفات للتثبت من هوية الموقع عند التوقيع المباشر. هذه الصفات يمكن إستخدامها لاكتشاف الإحتيال والتزوير في أعمال التجارة الإلكترونية والحكومة الإلكترونية والبنوك الإلكترونية. وتنقسم هذه الصفات إلى صفات شمولية، تصف الخصائص العامة للتوقيع، وصفات ديناميكية مستخلصة من السرعة الخطية للقلم تحدد هوية الموقع وشكل التوقيع. التوقيعات الإصلية و التوقيعات المقلدة التي شملتها الدراسة تبدو مطابقة بالعين المجردة. صفات السبسترال أعطت معدل رفض عالى يصل إلى ٩٨% من إجمالى التوقيعات المقلدة، وقبول لجميع التوقيعات الأصلية. كذلك صفات التنبؤ الخطي المستخلصة من بيانات التوقيع بعد إزالة التشويش أعطت نتائج جيدة حيث رفضت ٩٥% من التوقيعات المقلدة وقبلت كل التوقيعات الأصلية.

Keywords: On-line signature writer identification, On-line signature verification, Cepstral descriptors, Linear predictive coding, Biometric identification.

1. Introduction

The advent in e-commerce, e-business, e-banking and, in general, web services necessitates the use of a robust, acceptable, collectable, and circumventable biometric technology for personal identification. According to Jain et al. [1], face, facial thermogram and signature are the most acceptable and collectable biometric techniques. Face biometric shows medium performance whilst the facial thermogram and signature show lower performance.

Signature verification has been an interesting research topic in Forensic Sciences since the beginning of the 20th century. Although, these researches are based on human signature verification rather than automated signature verification, they have reported very important notes. Osborn [2] reported that the process of forging a signature involves two processes; signature imitation by copying the features of the imitated signature and hiding writer's personal writing characteristics. If the writing is free and rapid, it will certainly show many of the characteristics of the natural writing of the writer no matter what disguise may have been employed. Hilton [3] stated that the signature has at least three attributes; form, movement, and variation.

The inadequacy of signature for personal identification stems from the signature matching methods. These methods rely on the signature form, and neglect the biometric features of the writer [4-8]. Biometric features are produced by the movement of the pen on the paper. The pen movement is produced by muscles of fingers, hand, wrist, and; for some writers; the arm. These muscles are controlled by brain impulses without any particular attention to detail [3]. Thus, this movement is the most important part of a signature, and can only be captured using graphic tablet and stylus.

The objective of this work is to determine the most appropriate descriptors for writer identification, given that the forged signature and genuine signature look identical. Linear predictive coding, linear spectrum frequencies, discrete wavelet transform, and Cepstral descriptors are tested for writer identification.

Although all of them showed some acceptable results, the significant results are produced by Cepstral Descriptors and Linear Prediction Coding.

The signature verification system, as shown in fig. 1, consists of a graphic tablet that samples the user signature data and delivers it to the host computer. The computer receives the data and reformats it to a readable form. The data is then filtered, and normalized to remove noise, translation and rotation information. Different features may be extracted from this data, depending on the criteria adopted for verification. Verification is performed by matching the stored descriptors with the input descriptors using the Least Mean Square Error (LMSE) criteria to decide either to accept or reject the signature. If accepted the user is granted access to the system.

The following sections elaborate the presented work. section II describes the preprocessing of the raw signature data. section III explains the Cepstrum Descriptors. section IV explains the linear predictive coding, and section V demonstrates the experimental results. section VI is the conclusion.

2. Signature preprocessing

Signatures are captured using an A5 graphic tablet called "Wacom Graphire". The tablet resolution is 40 pixels/mm (1015 pixel/inch). It samples the pen information at 100 samples/second. The tablet's pen is pressure sensitive (512 Pressure Levels). The sampling process is activated as soon as the pen enters the proximity above the tablet active area (≈ 5mm). Signature capturing software starts recording the pen movement when pen tip, and continues recording as long as the pen is moving. If the pen stops, the recording is paused until it moves again. Pen removal will pause the recording which will be resumed when pen tip pressure reaches the pre-defined threshold, and a delimiter code is inserted in the data stream. Signature data (S) consists of four vectors; two vectors for the (x, y) coordinates of the pen, one vector for pen-tip pressure (p) and one vector for sample's time in milliseconds (t).

$$S(t) = [x(t), y(t), p(t)]^T, \ t = 0, \ t_1, t_2, \ldots, t_n . \tag{1}$$

Signature data in its raw form is not convenient for further processing. This data is preprocessed for axis displacement, size normalization and noise, and jitter removal. Different data is derived from the raw data such as the derivative of both x and y, pen linear speed $\upsilon(t)$, and orientation $\sin\theta(t)$, and finally the smoothed pressure $\overline{p}(t)$. Fig. 2 shows the derived data.

$$x_i{}'(t) = \frac{x_i(t) - x_{i-1}(t)}{X}, \qquad y_i{}'(t) = \frac{y_i(t) - y_{i-1}(t)}{Y}, \tag{2}$$

$$\upsilon(t) = r_i{}'(t) = \sqrt{x_i'^2(t) + y_i'^2(t)}, \tag{3}$$

$$\sin\theta_i(t) = \frac{y_i'(t)}{r_i'(t)}, \tag{4}$$

$$\overline{p}(t) = \frac{p_i(t) + p_{i-1}(t)}{2}. \tag{5}$$

$$\hat{S} = [x'(t), y'(t), r'(t), \sin\theta, \overline{p}(t)]^T, \quad t = 0, \ldots, t_n . \tag{6}$$

Where X is the signature's width and Y is the signature's height.

The pen linear speed $\upsilon(t)$ is the most important data, as it combines the features of $x'(t)$ and $y'(t)$. The movement orientation $\sin\theta(t)$ has abrupt changes, which is natural for human writing. Movement orientation does not play a significant role in writer identification, therefore it is neglected. The normalized pressure may reflect the writer emotion. Unfortunately, out of the collected signatures, forty eight percent of the writers are pressing the pen to saturation making pressure data insignificant for any further processing. Consequently, all the features in the next stage are derived from the linear speed $\upsilon(t)$.

3. Cepstral descriptors

Cepstrum analysis is a nonlinear signal processing technique with a variety of applications in areas such as speech and image processing. The complex cepstrum for a sequence υ is calculated by finding the complex natural logarithm of the Fourier transform of υ, then the inverse Fourier transform of the resulting sequence [9].

$$V(k) = \sum_{n=1}^{N} \upsilon(n).e^{-j\frac{2\pi(n-1)(k-1)}{N}} . \quad (7)$$

$$C_{complex}(n) = \frac{1}{2\pi} \int_{-\pi}^{\pi} \log[V.(e^{i\omega})].e^{i\omega n}\, d\omega . \quad (8)$$

The real cepstrum of a signal υ, sometimes called simply the cepstrum, is calculated by determining the natural logarithm of magnitude of the Fourier transform of υ, then obtaining the inverse Fourier transform of the resulting sequence.

$$C_{real}(n) = \frac{1}{2\pi} \int_{-\pi}^{\pi} \log|V.(e^{i\omega})|.e^{i\omega n}\, d\omega . \quad (9)$$

The cepstrum can be seen as information about rate of change in the different spectrum bands. It was originally invented for characterizing the seismic echoes resulting from earthquakes and bomb explosions. It has also been used to analyze radar signal returns.

The linear speed $\upsilon(t)$ signal may be considered as the pen movement signal (low frequency spectrum), and different types of noise (high frequency spectrum). In the cepstrum graph, the pen movement signal will appear as steep slant at the beginning of the plot. The noise part is usually truncated. Thus, only ten cepstrum coefficients are used. fig. 3 shows the cepstral descriptors of a signature segment.

4. Linear predictive coding

Linear Predictive Coding (LPC) is a tool used mostly in audio signal processing and speech processing for representing the spectral envelope of a digital signal of speech in compressed form, using the information of a linear predictive model. It is a powerful speech analysis technique and a very valuable method for encoding good quality speech at a low bit rate and provides extremely accurate estimates of speech parameters [10].

Linear predictive coding has been rarely used for signature verification [6]. Although there may not be a clear analogy between the signature linear speed $\upsilon(t)$ and the speech signal, LPC is expected to produce good descriptors for the signature. Similar to cepstrum analysis, the linear speed will be considered as pen movement speed and multiple noises. LPC is required to model the pen movement speed only.

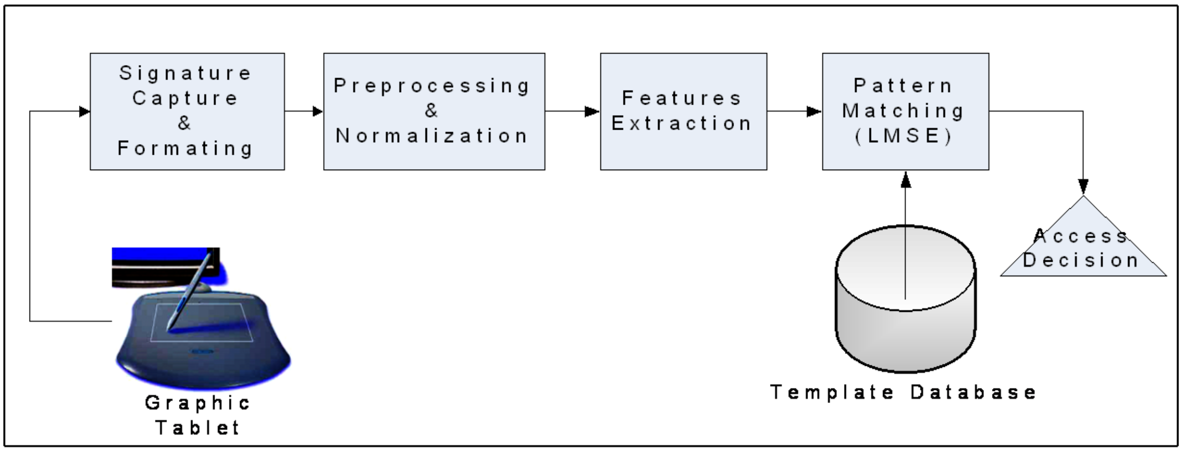
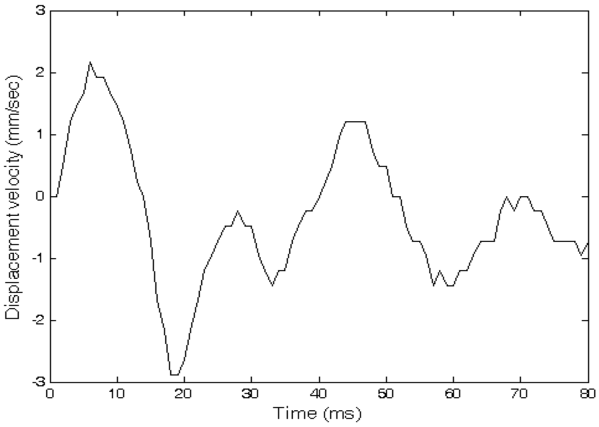
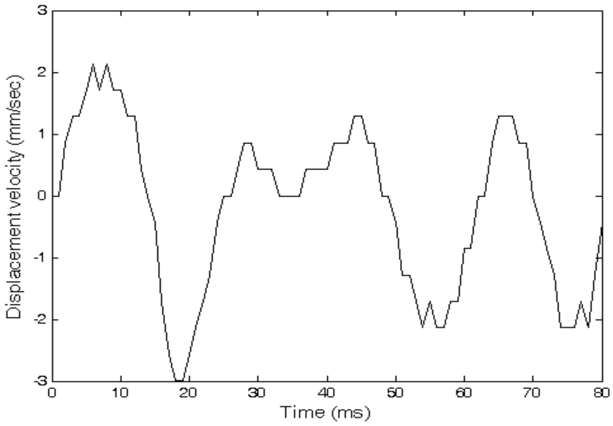


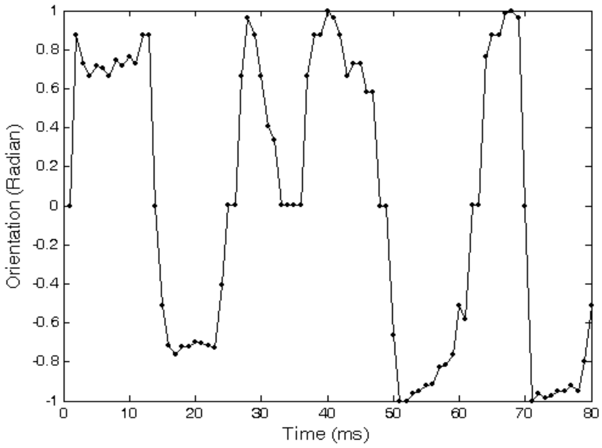
Fig. 1. On-line signature verification.



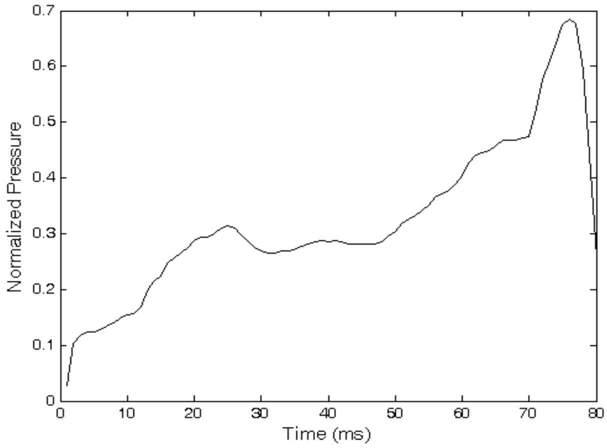
a- Displacement speed *x'(t)* in X direction.



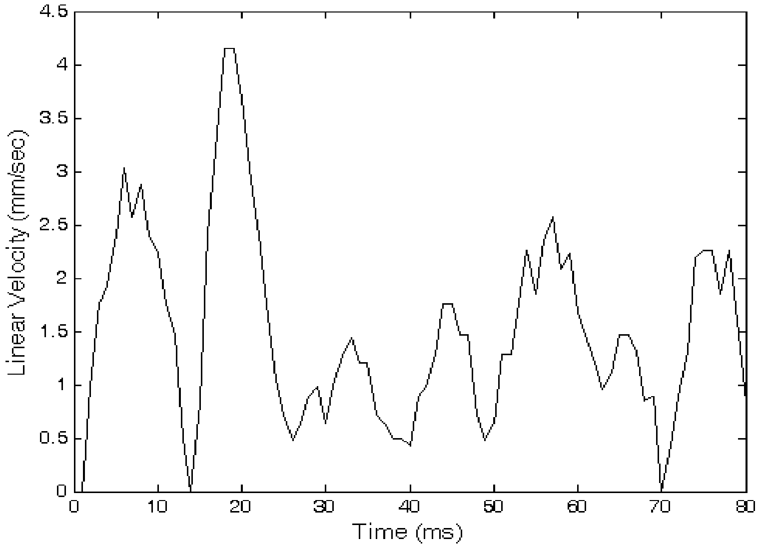
b-) Displacement speed *y'(t)* in Y direction.



c- Movement orientation sin *θ(t)*.



d- Normalized pressure *p(t)*



e- Linear speed *υ(t)*.

Fig. 2. Data derived from signature.

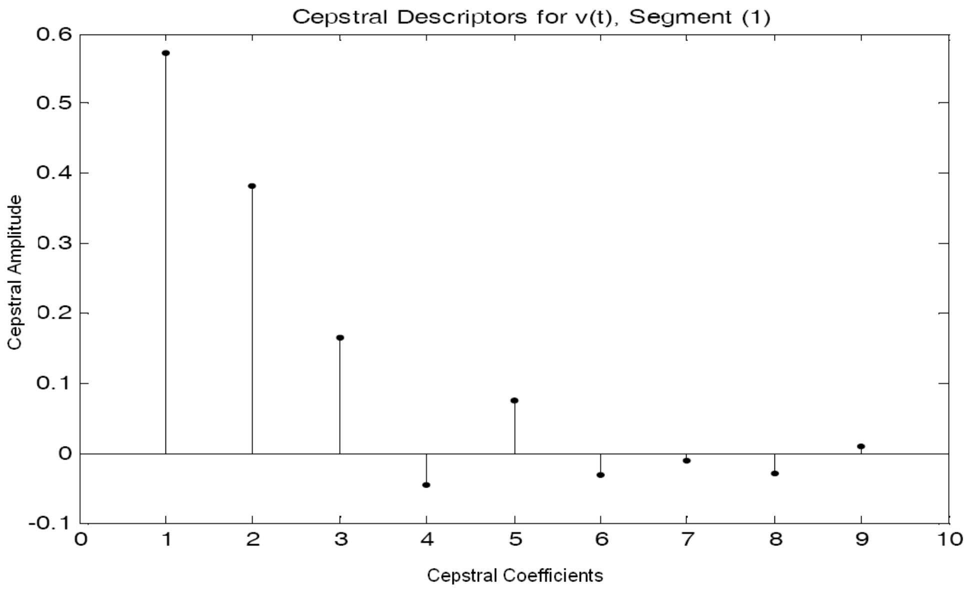


Fig. 3. The relevant cepstral descriptors for a signature segment.

Linear prediction modeling assumes that each output sample of a signal, $\upsilon(i)$, is a linear combination of the past n outputs and that the coefficients are constant from sample to sample:

$$\hat{\upsilon}(n) = -\sum_{i=1}^{p} a_i \upsilon(n-i)\,, \tag{10}$$

where $\hat{\upsilon}(n)$ is the predicted signal value, $\upsilon(n-i)$ the previous observed values, and a_i the predictor coefficients. The error generated by this estimate is

$$e(n) = \upsilon(n) - \hat{\upsilon}(n)\,, \tag{11}$$

where $\upsilon(n)$ is the true signal value.

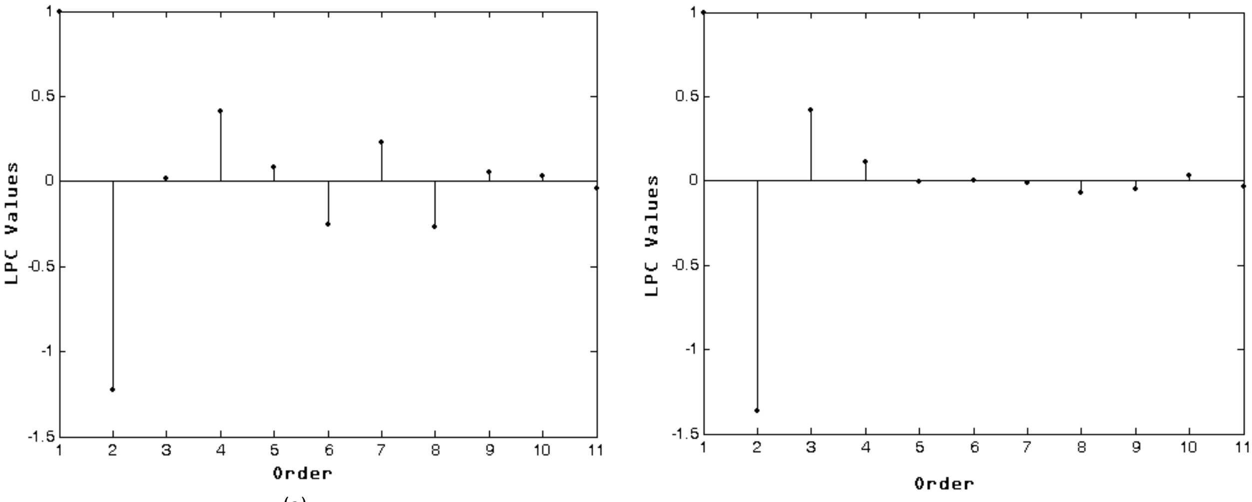
Unfortunately, the linear predictive coefficients derived directly from the linear speed were insignificant. The insignificance is caused by the proximity of noise frequency spectrum to the frequency spectrum of the movement speed. Therefore, LPC technique is unable to split them.

The Stationary Wavelet Transform (SWT) [12] is employed to de-noise the linear speed $\upsilon(t)$. The SWT algorithm is very simple and is close to the discrete wavelet transform one. More precisely, for level 1, all the ε-decimated DWT (only two at this level) for a given signal can be obtained by convolving the signal with the appropriate filters as in the DWT case but without down sampling [13]. Then the approximation and detail coefficients at level 1 are both of size N, which is the signal length.

The linear predictive coding is then applied on approximation coefficients obtained from the SWT. Fig. 4 shows the LPC coefficients produced for a signature signal [14].

5. Experimental results

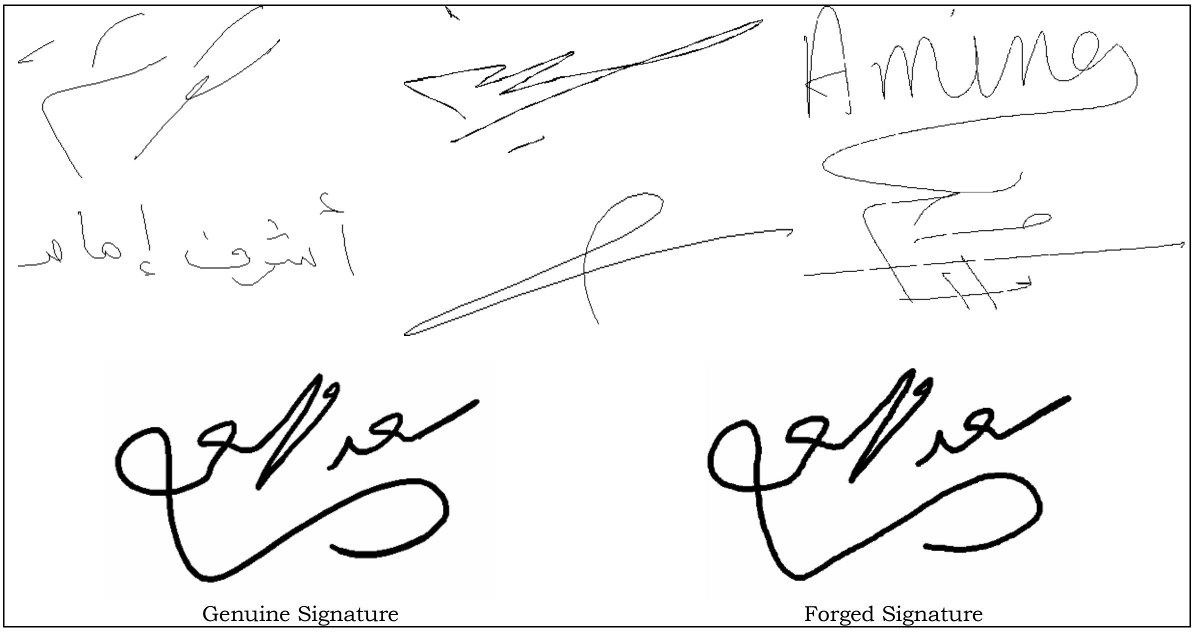
The proposed descriptors are implemented and evaluated with 750 signatures from 35 different writers. The first dataset contains 250 genuine signatures from 25 writers. Each writer is given enough time to get familiar with the tablet and the capture software before writing his/her ten signatures taken collected in one session. The second dataset contains 500 forged signatures from 10 imitators. None of these imitators are professional. Each one is trained to imitate one genuine signature flawlessly. Afterward each imitator makes 50 forged identical signatures collected in five different sessions. Fig. 5 shows seven genuine signatures and one forged signature.



(a) (b)

a- LPC applied to Linear Speed $v(t)$ b- LPC applied to approximation coefficients of SWT

Fig. 4. Linear predictive coefficients.



Genuine Signature Forged Signature

Fig. 5. Sample signatures.

For each signature, the system stores a single set of global descriptors and ten dynamic descriptor sets for each signature's segment. The signature aspect ratio, number of segments, and the end-point location of each segment are the global descriptors. Dynamic descriptors must contain shape information as well as writer specific information. Two feature extraction techniques are candidate for this task: Cepstral descriptors and LPC applied on SWT coefficients.

5.1. Global descriptors

Global Descriptors matching consists of three tests:
(a) Number of segments must be an exact match.
(b) Aspect ratio value must be within 10% of the template aspect ratio.
(c) Endpoints relative locations must be similar and within 10% tolerance. Endpoints locations are sensitive to the writing order of signature segments.

Throughout the experiments, the global descriptors of 4% of the forged signatures did not match the global descriptors of their corresponding genuine signatures. The mismatch is due to either difference in number of segments or out of order writing of the segments. Aspect ratio value did not cause any rejection.

From the experiment, it is observed that a forged signature dataset is larger by a factor of three to six than a corresponding genuine signature dataset. On the other hand, the changes in size among genuine signatures for the same writer are between 10% and 15%.

5.2. Dynamic descriptors

After the Signature has succeeded the global descriptors matching, it is subjected to shape analysis and writer identification. The input signature is matched to ten stored genuine signature. The matching is performed as segment to segment matching. The failure in matching of any segment will cause signature rejection.

Two types of descriptors are tested for writer identification. The first type is the Cepstral coefficients. Fig. 6 shows the distribution of Cepstral coefficients. The first five coefficients which represent the movement speed are sufficient for signature matching. Fig. 7 shows example of cepstral coefficients of a genuine descriptors versus cepstral coefficients of forged signature. From the experiments, the cepstral descriptors are more likely describing the writer, as 98% of the forged signatures are rejected and all genuine signatures are accepted.

The second type of descriptor is the Linear Predictive Coding. Fig. 8 shows the distribution of linear predictive descriptors. From the experiments, the Linear Predictive Descriptors yield a remarkable significance after removing the noise from the input signal using the SWT. Fig. 9 shows the LPC descriptors for two segments of a genuine signature versus the same LPC descriptors for two segments of a corresponding forged signature.

The LPC descriptors has rejected 95% of all forged signatures and accepted all genuine signatures.

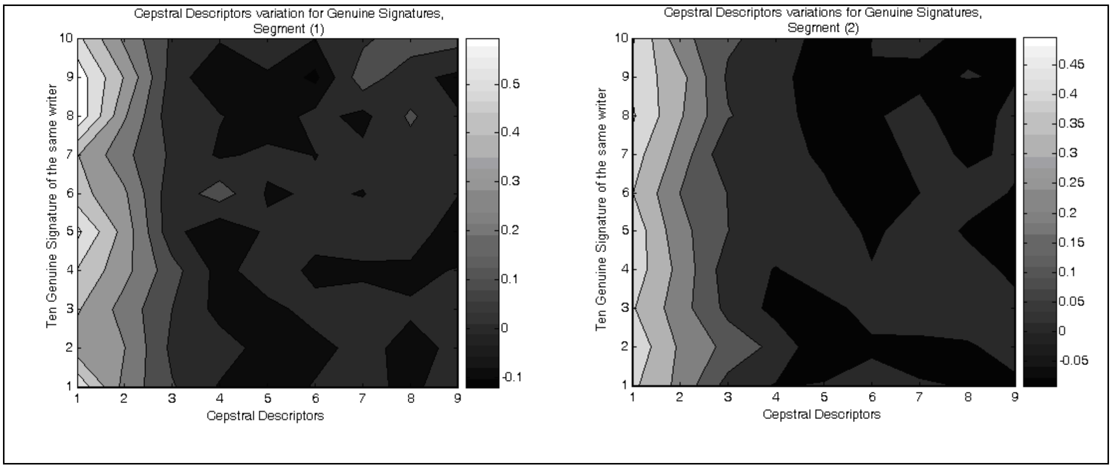


Fig. 6. Cepstral descriptors variations for genuine signatures.

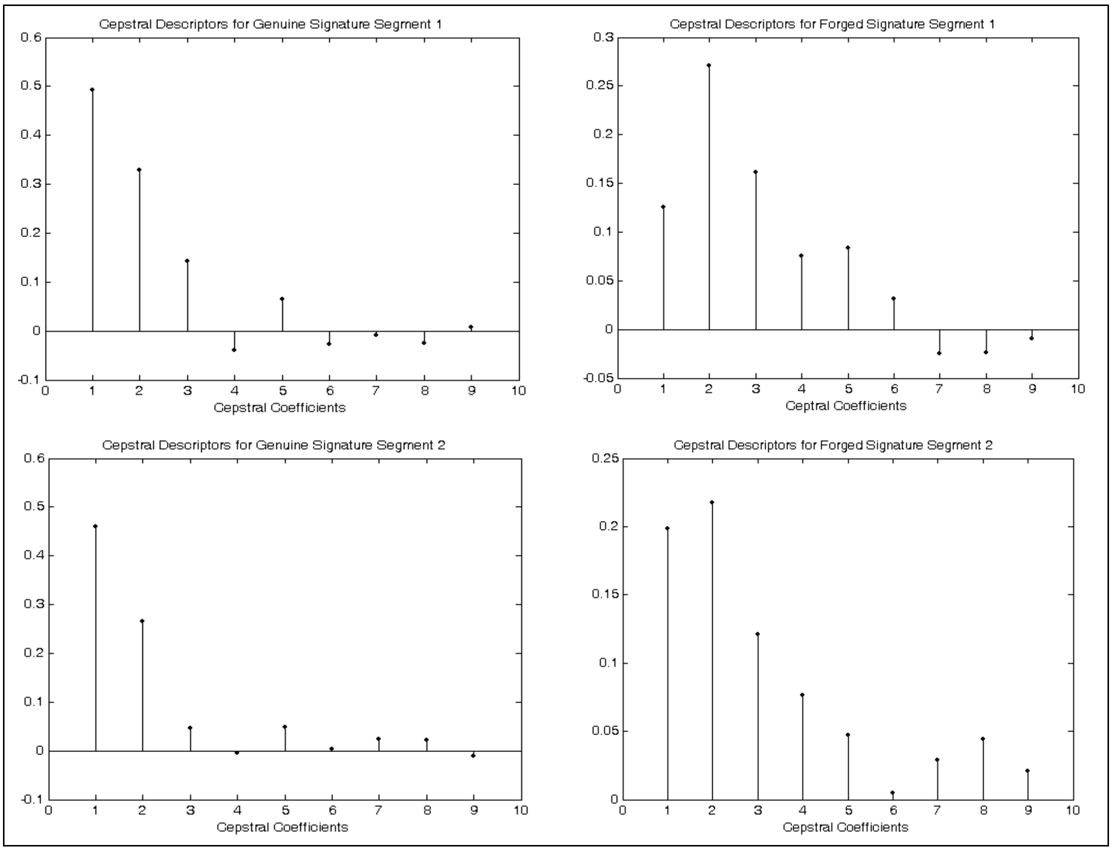


Fig. 7. Cepstral coefficients for genuine and forged signatures.

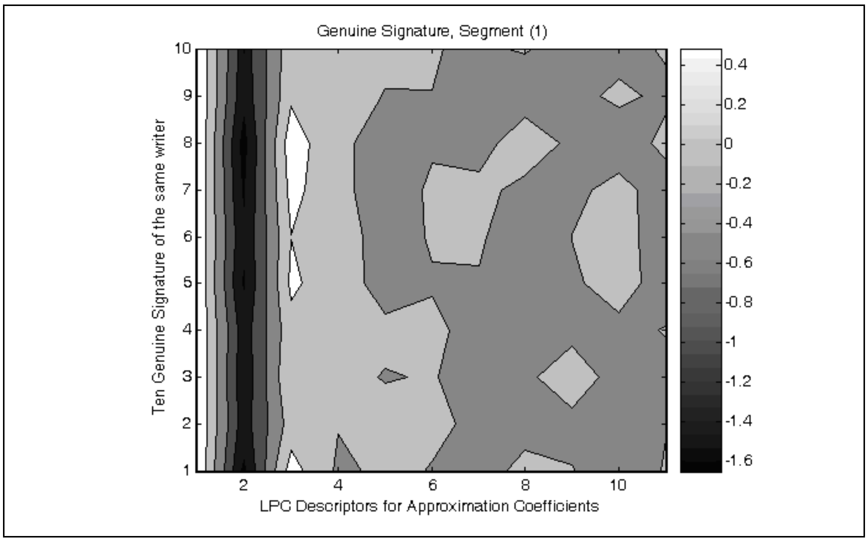


Fig. 8. LPC Descriptors variations for genuine signatures.

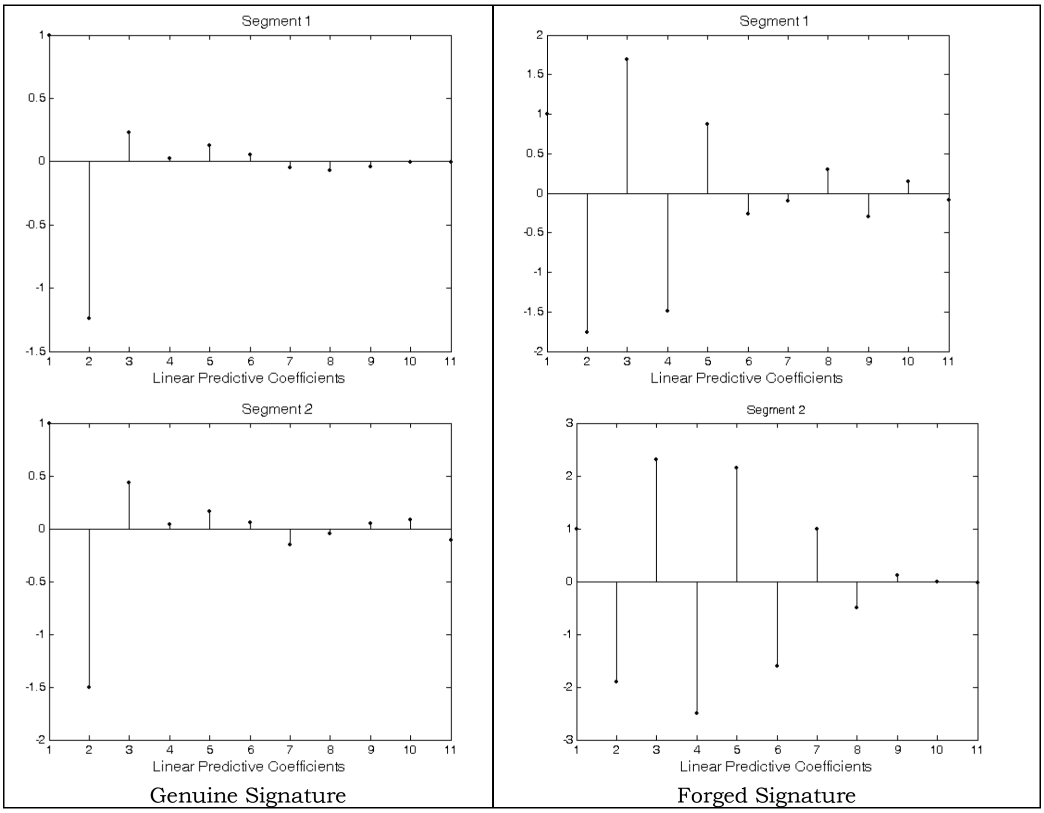


Fig. 9. LPC for genuine and forged signature.

6. Conclusions

In this paper, two feature extraction techniques are investigated for dynamic signature verification. Cepstrum analysis is a spectrum analysis technique, while linear predictive coding is a parametric modeling technique, but both have a common concept. They consider the input signal as a combination of high frequency noise source and a transfer function that shapes the generated high frequency noise. This concept is justified for voice and speech signal processing. In this work, it is assumed that the pen linear speed is a combination of two signals, the pen movement speed and different types of noise; such as the quantization noise, the human hand vibration, the friction of the pen again the writing surface, …, etc.. Cepstrum analysis delivered a significant discrimination between genuine and forged signature. It rejected about 98% of all forged signature. Linear Predictive coding failed to discriminate between genuine and forged signatures. This failure is due to the small frequency gap between noise frequencies and the pen movement speed frequencies. Unlike Linear Predictive Coding, Cepstrum succeeded to split the movement speed from the noise in a single step.

To test this hypothesis, the stationary wavelet transform is applied to the input signature data in order to remove the noise. The approximation coefficients of the stationary wavelet transform is the de-noised signature data. Linear Predictive descriptors derived from the de-noised signature data delivered significant results. The Linear Predictive Coding is able to discriminate between genuine and forged signatures with a rejection rate of 95% of all the forged signatures.

The computational complexity of the Cepstral technique is in the order of $O(n^3)$. The computational complexity of LPC algorithm plus the wavelet de-noising algorithm is in the order of $O(n^4)$. Using a Pentium D Dual Core computer at 3.4GHz, the calculation of the

Cepstral descriptors and LPC descriptors for fifty signatures required less than 3 seconds. A hardware implementation of these processes is advised to perform the authentication at real-time.

From this work, it can be concluded that most of the feature extraction techniques working on speech signal envelop can be applied to signature data after the removal of the noise signal. Moreover, signature verification is still a promising biometric measure for use in electronic transactions and more research works are needed to improve writer identification techniques.

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