On-line Signature Verification Method Using Adaptive Algorithm in Wavelet Transform Domain

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Abstract: In this paper, a new signature verification method is proposed. In the proposed method, on-line signature features are decomposed into multi-level signals by using the discrete wavelet transform, and then they are verified using the adaptive algorithm in time-frequency domain. Through computer simulations, the effectiveness of the proposed method is examined.

1. Introduction

Recently the network banking service, the electronic commerce, the electronic money, the database access service, and the information service over the internet have become popular. In such applications, it is significant to give security for the secret information on the network. The user verification is one of the essential technologies to achieve high security in those services. As the user verification methods, the biometrics such as the fingerprint and the retina have been utilized, and they require particular detective equipments. Therefore, they are inferior in portability. The on-line signature verification which utilizes the difference of personal dynamic features such as the velocity, the acceleration, the pen-pressure, the pen-inclination and the trajectory profiles brings high security by simple operation in the PDA (personal digital assistants) system with the pen input method [1]-[4].

In this paper, a new signature verification method is proposed. In the proposed method, on-line feature parameters are decomposed into some wavelet components by multiple resolution analysis based on the discrete wavelet transform, and then they are verified using the adaptive algorithm in time-frequency domain. Each level verification is done by the converged value of the adaptive coefficient.

2. Analysis of On-line Signature

2.1 Extraction of Signature Parameters

We digitize on-line signatures with a pen-tablet as shown in Fig.1 and extract the time-variant parameters such as x and y components concerning the pen-position, the pen-pressure P and the pen-altitude φ. Each parameter has the different sampled data since the spent time for writing is generally different, even if the same person writes the same signature. In this paper, such writing time is normalized to reduce the personal fluctuation. Moreover, the pen-position data is normalized to decrease the personal fluctuation.

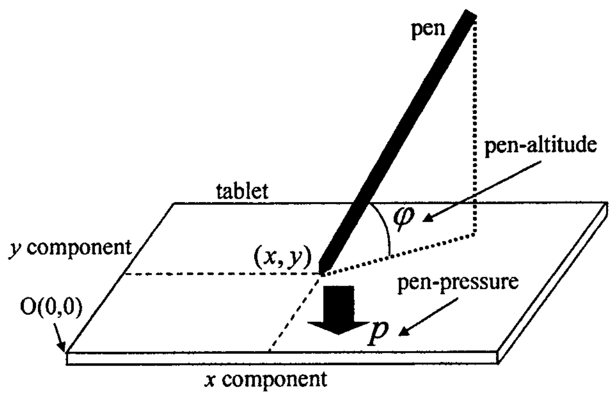


Fig.1 On-line signature parameters

Therefore, we define the normalized pen-position as

$$x^{*}(t)=\frac{x(t)-x_{\min}}{x_{\max}-x_{\min}}\cdot\alpha_x \quad \left(x_{\min}\le x(t)\le x_{\max}\right) \tag{1}$$

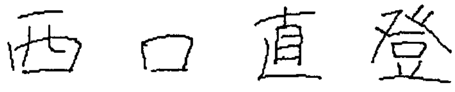
$$y^{*}(t)=\frac{y(t)-y_{\min}}{y_{\max}-y_{\min}}\cdot\alpha_y \quad \left(y_{\min}\le y(t)\le y_{\max}\right) \tag{2}$$

where $x(t)$ and $y(t)$ are the original pen-posotion data. α_x and α_y are coefficients for scaling each parameter, and these are 100 in this paper. Indices $_{\max}$ and $_{\min}$ correspond to each maximum and minimum values, respectively.

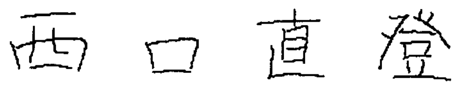
2.2 Signature Data

Before signing, the writer is required to do some practices so as to get accustomed to using the pen-tablet. Also, when the writers sign the genuine signatures, they are not able to refer the original ones. On the other hand, for its forgery, the forgers are made to admit signing over referring character shapes of genuine signatures. The examples of the signatures (genuine signature and its forgery) are shown in Fig.2. And their on-line parameters about x and y components concerning the pen-position, the pen-pressure and the pen-altitude are shown in Fig.3 and Fig.4.

It is clear that x and y components concerning the pen-position of the forgery are similar to those of its genuine signature in the time-domain signal.



(a) genuine signature



(b) forgery

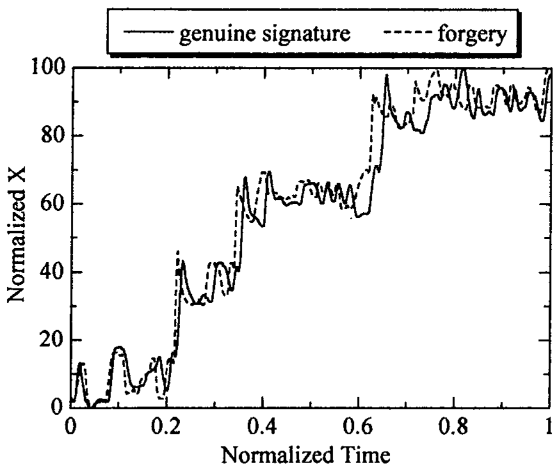
Fig.2 Examples of the signature

That is to say, it is difficult to discriminate signatures in the time-domain signal, especially for x component. Also, the pen-position data is easy to forge since it remains in the written signature. Inversely, it is obvious that the pen-pressure and pen-altitude data have personal features, so that it is easy to discriminate writers. Also, these parameters are not visible features; therefore, their imitation is impossible even if the writing motion is watched. As a result, these on-line parameters are convenient for signature verification. However, particular equipments are required to detect them, so that they are inferior in portability. In this paper, we try to make it easy to discriminate signatures by using the pen-position data which requires no additional equipment.

2.3 Time-frequency Analysis

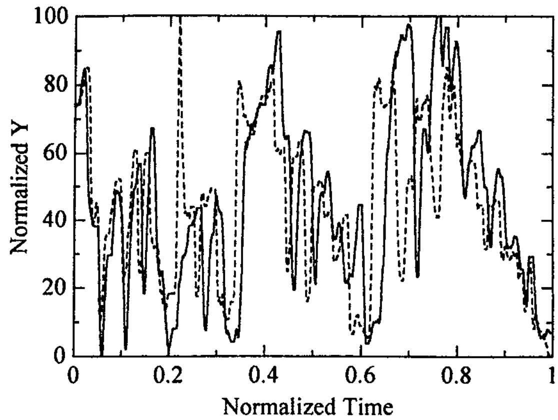
We analyze on-line parameters concerning the pen-position as the time-frequency signals using the multiple resolution analysis based on the discrete wavelet transform (DWT).

As the mother wavelet, the Daubechies' wavelet (N=8) is employed, and the maximum level is 10. Time-frequency signals at level 5 and 8 for x component signals in time domain of Fig.3 are shown in Fig.5.

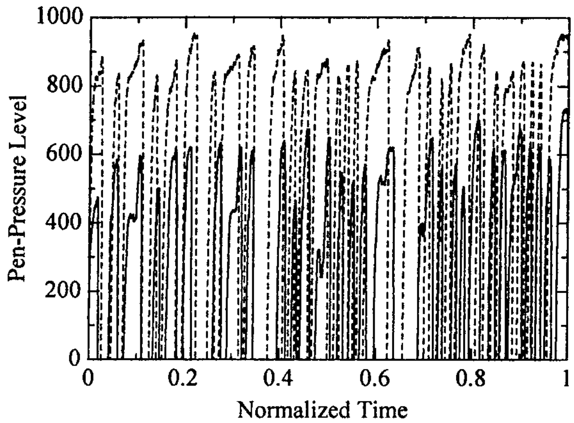


pen-position (x component)

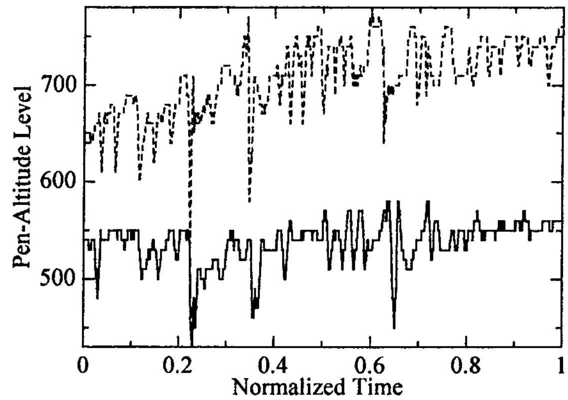
Fig.3 On-line parameters (1)



(a) pen-position (y component)



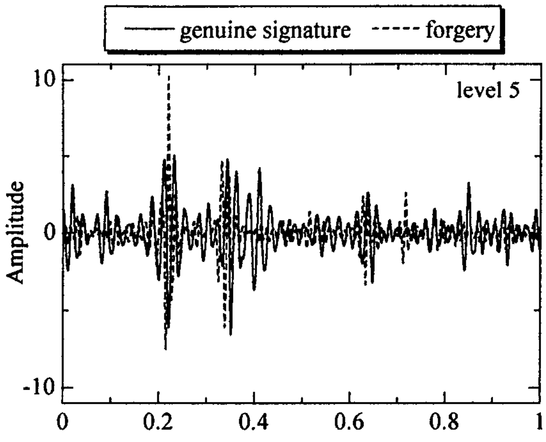
(b) pen-pressure



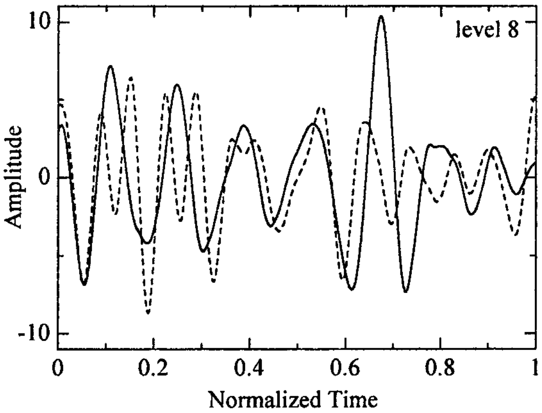
(c) pen-altitude

Fig.4 On-line parameters (2)

These results show that the time-frequency analysis makes it easy to discriminate between the genuine signature and its forgery while it was difficult in time domain. By using the time-frequency analysis, we require no particular functions such as pen-pressure and pen-inclination with the pen-tablet. Moreover, by considering all level results, we can obtain higher accuracy of verification than that in each level for increasing the comparative objects.



(a) wavelet components at level 5



(b) wavelet components at level 8

Fig.5 Results of multiple resolution analysis based on DWT

3. Signature Verification System

In this section, a signature verification method using adaptive algorithm is proposed. A block diagram of the proposed signature verification system is illustrated in Fig.6. The sign data concerning the pen-position is decomposed into multi-level signals by using the DWT. Next, the extraction of feature for matching and the adaptive processing are carried out at each level. Each verification is done by the converged value of the adaptive weight. The total verification is achieved by considering all level results.

3.1 Feature Extraction from Wavelet Component

Through the preparatory experiments, we found that only utilizing the intra-stroke of wavelet component was suitable for the matching. The inter-stroke was greatly influenced by the personal fluctuation, so that it was unsuitable for the personal verification. The intra-stroke and inter-stroke are pen tip movements from pen-down to pen-up and from pen-up to pen-down, respectively. Individual intra-stroke is redefined as a stroke.

In this paper, to extract the intra-stroke, we utilized the pen-pressure data. However, the intra-stroke can be extracted by using whether the pen tip is on the tablet or not instead of the pen-pressure data. In such a case, no particular equipment is necessary.

For the correct matching of data, the number of the extracted data must be equal to that of the registered reference data. Therefore, both the number of data are normalized every stroke. Concretely, the large number of data is reduced equal to the less one.

3.2 Adaptive Process for Signature Verification

An adaptive process for signature verification at level j is shown in Fig.7, where $x_j(n)$ is the wavelet component extracted feature and $e_j(n)$ is the error signal at level j. $d_j(n)$ is the wavelet component extracted feature for the reference signal at level j and is an averaged value of the past five signals of the genuine signature. The coefficient $w_j(n)$ is adaptively updated based on the LMS (least-mean-square) algorithm given by[5]

$$w_j(n) = w_j(n) + \mu_j e_j(n) x_j(n) \tag{3}$$

$$e_j(n) = d_j(n) - w_j(n) x_j(n) \tag{4}$$

where μ_j is the step size parameter. Ideally, the adaptive coefficient converges on 1 if the input signal $x_j(n)$ is of the genuine signature. Otherwise, it converges on the smaller value than 1.

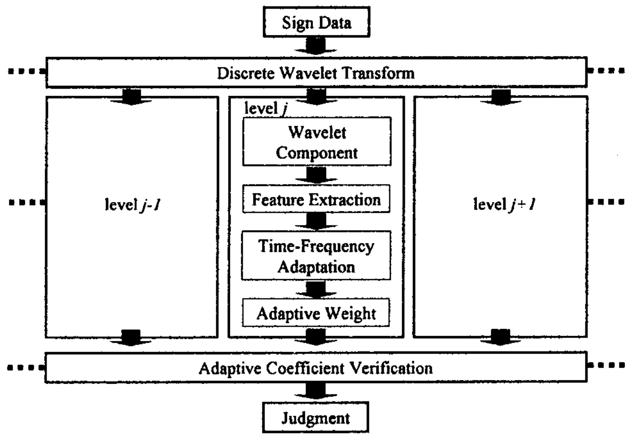


Fig.6 Block diagram of the proposed signature verification system

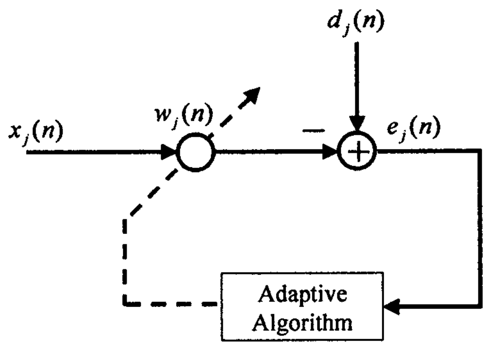


Fig.7 Adaptive process for signature verification

The signature verification is achieved by whether the converged value of the adaptive coefficient is nearly 1 or not.

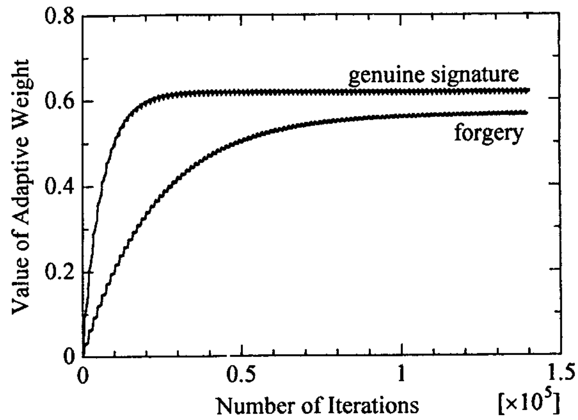
4. Simulation Results

The levels of wavelet components used for the matching were from 5 to 8. The wavelet components at level 1 to 4 have large personal fluctuations since they correspond to small fluctuations of pen movements. And those signals at level 9 to 10 don't include obvious difference of features, because the signals of these levels reflect the shape of characters. The step size parameters are shown in Table 1.

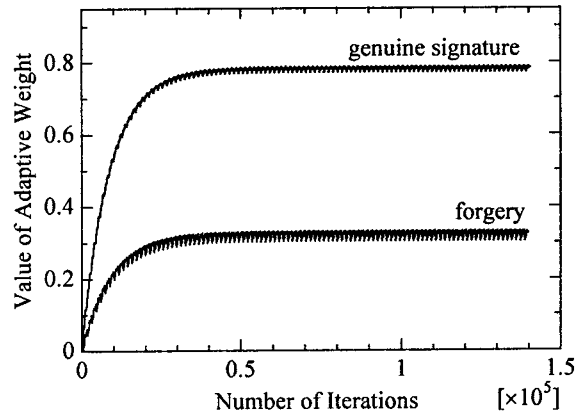
Table 1 Step size parameters

level	x component
5	0.0001
6	0.00003
7	0.00001
8	0.00001

Fig.8 shows the convergence characteristics of the adaptive coefficient $w_j(n)$ in x component at level 5 and 8. When the input signal was of the genuine signature, the adaptive coefficient converged on 1 closer than that of the forgery. At level 5, the fully converged value in the genuine signature had a little difference from that in the forgery, so that it may be difficult to set the threshold. If the number of iterations is set small, such a difference becomes obvious and then we can discriminate them. Considering some level results is also effective to cope with such a problem. Consequently, it was confirmed that the proposed method enabled to distinguish the genuine signature from the forgery.



(a) level 5



(b) level 8

Fig.8 Convergence characteristics of adaptive coefficient

5. Conclusion

We presented a new on-line signature verification method using adaptive algorithm in wavelet transform domain. In the proposed method, on-line signature features are decomposed into multi-level signals by using the DWT, and then, the signature was verified by using converged value of the adaptive coefficient. Consequently, it was possible to discriminate whether the writer was the genuine or not. However, the proposed method requires a setting of the threshold value to determine that the signature is of the genuine or not. Setting of the threshold to the optimum is studied further. Also next studies are signature verification method considering multi-level results and introduction of the nonlinear process like the neural network which is superior in the pattern recognition.

References

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