DWT Domain On-line Signature Verification Using Pen-movement Vector

Isao Nakanishi

Faculty of Regional Sciences, Tottori University
4-101 Koyama-minami, Tottori, 680-8551 Japan

Hiroyuki Sakamoto, Naoto Nishiguchi, Yoshio Itoh and Yutaka Fukui

Faculty of Engineering, Tottori University
4-101 Koyama-minami, Tottori, 680-8552 Japan

Abstract— **We examine a pen-movement vector parameter to reduce the computational complexity in the on-line signature verification method based on Discrete Wavelet Transform (DWT) and adaptive signal processing. The pen-movement vector is a time-varying signal which is derived from pen-position parameters and is decomposed into sub-band signals by using the DWT. Individual features are extracted as high frequency components in sub-bands. Verification is achieved in each sub-band by using the adaptive signal processing. Total decision for verification is done by combining multiple verification results. Experimental results show that the verification rate using the pen-movement vector parameter is equivalent to that of our conventional method which utilizes the pen-position parameter although computational complexity is reduced to half of that of the conventional method.**

I. Introduction

As information services over internet such as the Electronic Commerce (EC) and the electronic data interchange widely come to be used, the biometrics for user authentication has attracted attention [1]. On-line signature verification system classifies the signature by time-varying parameters such as pen-position, pen-pressure, pen-inclination and so on [2]-[4]. In addition, the on-line signature verification is suitable for the user authentication in computer network services because the electronic pen-tablet which is used to digitize the on-line signature is prepared as a standard input device of the computer.

We have proposed the on-line signature verification method based on DWT and adaptive signal processing [5]-[7]. Verification rate was about 95% which was improved by about 10% comparing with a time-domain verification method. Moreover, such verification rate was achieved by using only a pen-position parameter, which is at least detectable even in portable devices such as the Personal Digital Assistants (PDA). However, the computational complexity of our conventional method is large since a pen-position parameter consists of x and y coordinates which require two sets of sub-band decomposition by the DWT and the adaptive signal processing.

In this paper, we adopt a pen-movement vector as an on-line signature parameter. The pen-movement vector is derived from x and y coordinates, so that computational complexity is reduced to half of that of our conventional method. The time-varying signal of pen-movement vector is decomposed into sub-band signals by using DWT [8]. Individual features are extracted as high frequency components in sub-bands. Verification is achieved by using adaptive signal processing in each sub-band. In the adaptive signal processing, an adaptive weight is updated to reduce an error between an input signal and a desired one [9]. If the input signal is close to the desired one, the error becomes small and then the adaptive weight is sure to converge on one. Therefore, when both the input and desired time-varying signals are of genuine signatures, the adaptive weight is expected to converge on one. By using the convergence of the adaptive weight, we can verify whether a verification signature is genuine or forged. Total decision for verification is done by combining several verification results in sub-bands. Finally, we carry out a computer simulation to confirm the performance of the verification method using pen-movement vector.

II. Feature Extraction in Pen-Movement Vector

On-line signature is digitized with the electronic pen-tablet. In this paper, we identify the signature by using only pen-position parameter since it is at least provided in such as the PDA for handwriting or pointing. Actually, the pen-position parameter consists of discrete time-varying signals of x and y coordinates which are $x^*(n')$ and $y^*(n')$, respectively. $n'(= 0, 1, \cdots, N_{max} - 1)$ is a sampled time index. N_{max} is the number of sampled data. As the one-line signature is a dynamic biometrics, each writing time is different from the others. This results in different number of sampled data even in genuine signatures. Moreover, different writing place and different size of signature cause parameter variations. To reduce such variations, the pen-position parameter is normalized in general. The normalized pen-position parameter is defined as

$$x(n) = \frac{x^*(n) - x_{min}}{x_{max} - x_{min}} \cdot \alpha_x, \tag{1}$$

$$y(n) = \frac{y^*(n) - y_{min}}{y_{max} - y_{min}} \cdot \alpha_y \tag{2}$$

where $n(= 0 \sim 1)$ is the normalized sampled time index given by $n = n'/(N_{max} - 1)$. x_{max} and y_{max} are maximum and minimum values of $x^*(n)$ and $y^*(n)$, respectively. α_x and α_y are scaling factors for avoiding underflow calculation in sub-band decomposition.

Next, we define pen-movement vector parameter $v(n)$ as

$$v(n) = d(n)\ \theta(n) \tag{3}$$

where $d(n)$ and $\theta(n)$ are pen-movement distance and pen-movement angle, respectively. These are derived from pen-position as shown in Fig.1 and they are formulated as

$$d(n) = \sqrt{\Delta x(n)^2 + \Delta y(n)^2}\ /\ s \tag{4}$$

$$\theta(n) = \begin{cases} \tan^{-1} \frac{\Delta y(n)}{\Delta x(n)}, & \Delta x(n) > 0 \\ \tan^{-1} sgn(\Delta y(n)) \cdot \frac{\pi}{2}, & \Delta x(n) = 0 \\ \tan^{-1} \frac{\Delta y(n)}{\Delta x(n)} + \pi, & \Delta x(n) < 0, \Delta y(n) \geq 0 \\ \tan^{-1} \frac{\Delta y(n)}{\Delta x(n)} - \pi, & \Delta x(n) < 0, \Delta y(n) < 0 \end{cases} \tag{5}$$

where

$$\Delta x(n) = x(n) - x(n-s),\ \Delta y(n) = y(n) - y(n-s) \tag{6}$$

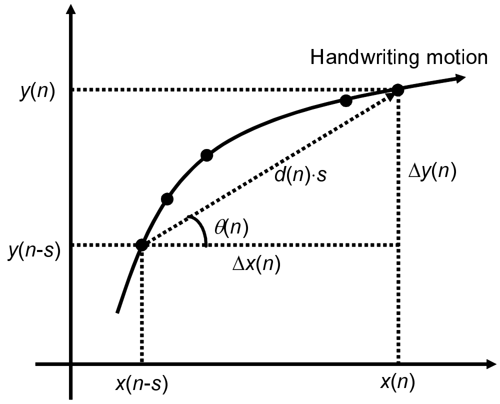


Fig. 1. Pen-movement distance $d(n)$ and pen-movement angle $\theta(n)$.

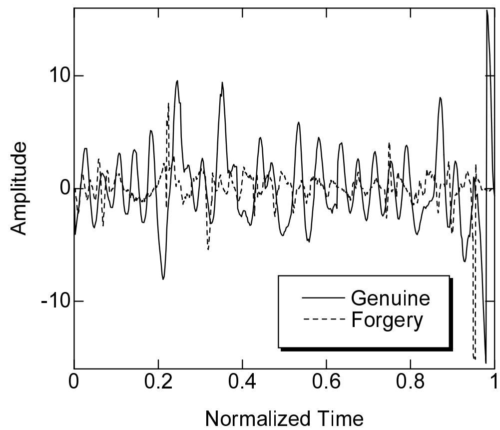


Fig. 2. Examples of time-varying pen-movement vector.

and s presents amount of time shift. Fig.2 shows examples of time-varying pen-movement vector.

The DWT of the pen-movement vector $v(n)$ is defined as

$$u_k(m) = \sum_n v(n)\overline{\Psi_{k,m}(n)} \tag{7}$$

where $\Psi_{k,m}(n)$ is the wavelet function. k is a frequency (level) index. $\bar{\cdot}$ denotes the conjugate.

On the other hand, it is well known that DWT corresponds to octave band filter bank [8]. Fig.3 shows the parallel structure of the DWT. (↓2) and (↑2) denote the down-sampling and the up-sampling, respectively. $A_k(z)$ and $S_k(z)$ where $k = 1, \cdots, Md$ are synthesis filters and analysis filters, respectively. Synthesized signal $v_k(n)$ in each sub-band is called *Detail*. The *Detail* is high frequency signal, so that it contains the difference between signals. Therefore, we consider the *Detail* as an enhanced feature of the pen-movement vector. Fig.4 shows examples of the *Detail* of the pen-movement vector. Daubechies8 filter was used as the wavelet function. It is clear that the difference between a genuine signature and a forgery becomes more remarkable by sub-band decomposition.

III. Signature Verification Using Pen-movement Vector

The procedure of the proposed signature verification method is described in Fig.5 which is similar with that in our conventional method [5]-[7]. Before verification, templates must be prepared. T genuine signatures which have equal number of strokes are decomposed into sub-band signals by DWT each

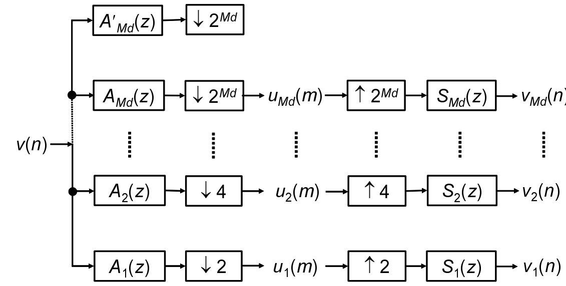
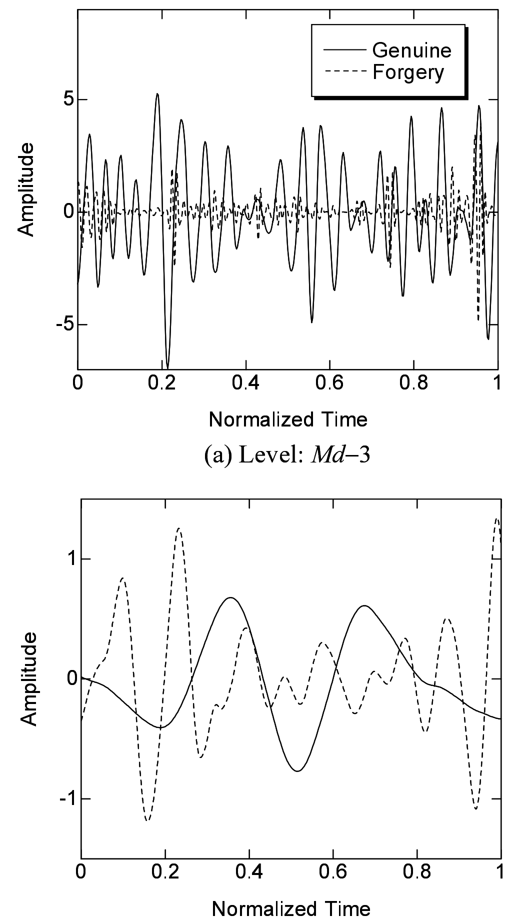


Fig. 3. Parallel structure of sub-band decomposition by DWT.



(a) Level: *Md*–3

(b) Level: *Md*

Fig. 4. Examples of *Detail* of pen-movement vector.

other. Decomposition level is decided after preliminary examinations of those signatures. Next, we ensemble-average extracted T *Detail*s at the same level. However, each number of sampled data is generally different from the others even in genuine signatures. It is difficult to average *Detail*s which have different number of sampled data. To solve this problem, T *Detail*s are averaged every intra-stroke and inter-stroke (intra/inter-stroke). Concretely, the number of data in each intra/inter-stroke in a template is determined by averaging the number of data in T intra/inter-strokes. Then, comparing the normalized sampling period in the template with those in the T intra/inter-strokes, the nearest T *Detail* data are selected and then averaged. As a result, we obtain the template data in each intra/inter-stroke. Such template data are generated in all intra/inter-strokes at all level and then they are enrolled in database.

In verification phase, the verification signature is also decom-

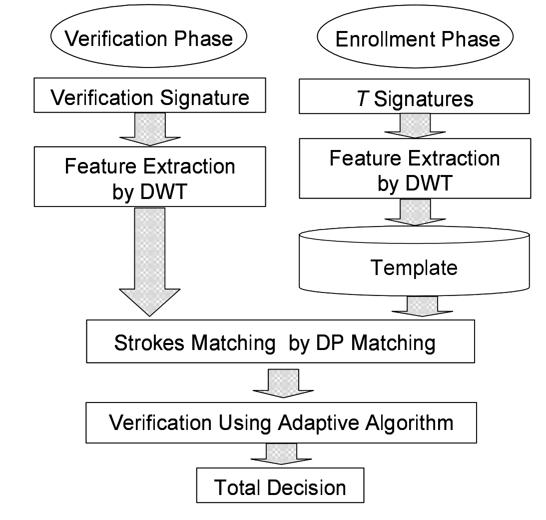


Fig. 5. Procedure of proposed signature verification method.

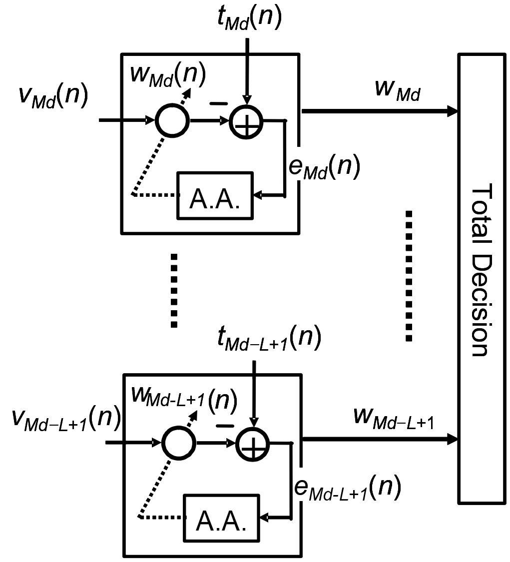


Fig. 6. Verification based on adaptive signal processing.

posed into *Detail*s. The decomposition level Md for the verification signature is determined by $2^{Md+1} \leq N_t < 2^{Md+2}$ where N_t is total number of corresponding template; however, the maximum value of Md is limited to Md_{max}.

By the way, if the number of strokes in a verification signature is different from that in a template, it is natural to consider the verification signature as forged. However, not all genuine signatures have the same number of strokes. In fact, we confirmed that there was the stroke difference within ± 2 even in genuine signatures in some preliminary experiments. Immediately rejection of the verification signature with different number of strokes causes degradation of verification performance. For such a reason, we accept the verification signature with the stroke difference within ± 2. However, our proposed verification method is done every intra/inter-stroke and so the number of strokes in a verification signature should be equal to that in a template. Therefore, the Dynamic Programming (DP) matching method is adopted to identify the number of strokes in a verification signature with that of a template. The procedure of the stroke matching is omitted for duplication of presentation. It is described in detail in [5]-[7].

After the stroke matching, verification is processed by using adaptive signal processing. The block diagram of proposed verification method is shown in Fig.6. The *Detail*s at only $k = Md, \cdots, Md - L + 1$ are used in this method. L is the number of processed levels. The *Detail*s at lower levels correspond to higher frequency elements, so that their variation is too large. They are not suitable for verification. An input signal $v_k(n)$ is a *Detail* at kth level of a verification signature. A desired signal $t_k(n)$ is a *Detail* of a template. $w_k(n)$ is an adaptive weight and updated based on the adaptive algorithm (A.A.) to reduce an error signal $e_k(n)$. As the adaptive algorithm, we use a new steepest descent algorithm defined as follows [6], [7].

$$w_k(n+1) = w_k(n) + \mu\ E\left[e_k(n)\ v_k(n)\right] \tag{8}$$

$$e_k(n) = t_k(n) - w_k(n)\ v_k(n) \tag{9}$$

$$E\left[e_k(n)\ v_k(n)\right] = \frac{1}{N_t}\sum_{l=0}^{N_t-1} e_k(n-l)\ v_k(n-l) \tag{10}$$

$$\mu = \mu_0 / \left\{E\left[|v_k(n)|\right]\right\}^2 \tag{11}$$

$$E\left[|v_k(n)|\right] = \frac{1}{N_i}\sum_{l=0}^{N_i-1} |v_k(n-l)| \tag{12}$$

where N_i is the number of sampled data in a *Detail* of a verification signature. μ is step size parameter which controls convergence of the adaptive algorithm. The step size parameter is normalized by *Detail* power as shown in (11) and (12), so that the convergence is always guaranteed.

When an input signal is of a genuine signature, the error between the input and the template becomes small; therefore, an adaptive weight converges close on one. Inversely, if the input signal is of a forgery, the weight converges far from one. In this way, verification can be achieved by examining whether converged value is nearly one or not. The adaptive signal processing for verification is done in parallel at $k = Md, \cdots, Md - L + 1$ levels. After enough iterations for convergence, w_k is obtained by averaging $w_k(n)$ in past N_i samples.

Total decision of verification is achieved by combining several verification results. In this paper, we give total convergence value TC by averaging L converged values of adaptive weight w_k.

$$\mathrm{TC} = \frac{1}{L}\sum_{k=Md-L+1}^{Md} w_k \tag{13}$$

TC is compared with threshold value. If the TC of a verification signature is larger than the threshold, the signature is decided to be genuine.

IV. Experimental Results

We prepared original signature data by using an interactive pen display device which made it possible to move the pen directly on the LCD monitor instead of the pen-tablet separated from the CRT monitor. Although it had the advantage of natural hand-eye coordination, all subjects were called upon to practice using the interactive pen display device for becoming skilled before experiments. Four subjects were requested to sign their own signatures 30 times each. When the subjects signed genuine signatures, they were not able to refer their already written signatures. After excluding unusable signatures which have only one sample data in intra/inter strokes which causes zero division in making of template *Detail*, we obtained 118 genuine signatures. Moreover, $T = 5$ genuine signatures for each subject were used to make template and the remaining

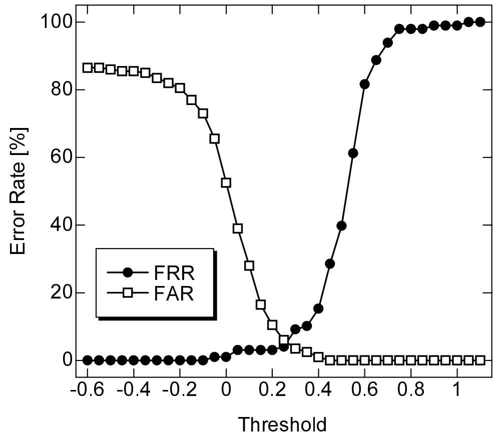


Fig. 7. Verification results.

98 genuine signatures were used for verification. On the other hand, five subjects were required to counterfeit genuine signature 10 times each, so that 200 forgeries were prepared in total. The forgers were permitted to trace genuine signatures. In order to obtain fully convergence of adaptive weight, the number of iterations was set to 100 thousands. Other fixed values used in the experiment are as follows.

- Scaling parameter: $\alpha_x = \alpha_y = 100$
- Time shit in pen-movement vector: $s = 8$
- Wavelet function: Daubechies8
- Maximum decomposition level: $Md_{max} = 8$
- Number of genuine signatures for template: $T = 5$
- $\mu_0 = 0.0001$
- Number of processed levels: $L = 4$

Fig. 7 shows False Rejection Rate (FRR) and False Acceptance Rate (FAR) versus threshold value. In general, verification performance is estimated by Equal Error Rate (EER) where the FRR and the FAR are the same. The EER was about 5% when the threshold value was about 0.25. This rate is equivalent to that by our conventional method [6], [7], while computational complexity is reduced to half of that of our conventional method.

V. Conclusion

We examined the performance of the on-line signature verification method based on DWT and adaptive signal processing using pen-movement vector. The pen-movement vector was easily derived from x and y coordinates which had been used in our conventional method. Therefore, the computational complexity could be reduced to half of that of our conventional method. In experimental results, verification rate was about 95% which was equivalent to that by our conventional method. We confirmed that equivalent verification rate was achieved in spite of a half computational complexity.

In this paper, converged values of adaptive weights are simply averaged to obtain total convergence value. To adjust weighting of the converged value should be introduced for improving verification performance. For reducing FRR, it is also studied in future to cope with variation in genuine signatures.

References

[1] A. Jain, R. Bolle and S. Pankanti, BIOMETRICS Personal Identification in Networked Society, Kluwer Academic Publishers, Massachusetts, 1999.

[2] Y. Sato and K. Kogure, ”Online signature verification based on shape, motion, and writing pressure,” *Proc. of 6th International Conference on Pattern Recognition*, pp.823-826, 1982.

[3] M. Yoshimura, Y. Kato, S. Matsuda, and I. Yoshimura, ”On-line signature verification incorporating the direction of pen movement,” IEICE Trans., vol.E74, no.7, pp.2083-2092, July 1991.

[4] Y. Komiya, T. Ohishi and T. Matsumoto, ”A pen input on-line signature verifier integrating position, pressure and inclination trajectories,” IEICE Trans. Inf. & Syst., vol.E84-D, no.7, pp.833-838, July 2001.

[5] I. Nakanishi, N. Nishiguchi, Y. Itoh, and Y. Fukui, ”On-line signature verification method utilizing feature extraction based on DWT,” *Proc. of 2003 IEEE International Symposium on Circuits and Systems (ISCAS2003)*, Bangkok, Thailand, vol.IV, pp.73-76, May 2003.

[6] I. Nakanishi, N. Nishiguchi, Y. Itoh, and Y. Fukui, ”On-line signature verification method based on DWT and adaptive algorithm,” *Proc. of 2003 International Symposium on Intelligent Signal Processing and Communication Systems (ISPACS2003)*, Awaji Island, Japan, pp.553-556, Dec. 2003.

[7] I. Nakanishi, N. Nishiguchi, Y. Itoh, and Y. Fukui, ”On-line signature verification method based on discrete wavelet transform and adaptive signal processing,” *Proc. of Workshop on Multimodal User Authentication*, Santa Barbara, USA, pp.207-214, Dec. 2003.

[8] G. Strang, T. Nguyen, Wavelet and Filter Banks, Wellesley-Cambridge Press, Massachusetts, 1997.

[9] S. Haykin, Introduction to Adaptive Filters, Macmillan Publishing Company, New York, 1984.