Optimal User Weighting Fusion in DWT Domain On-Line Signature Verification

Isao Nakanishi[1], Hiroyuki Sakamoto[2], Yoshio Itoh[2], and Yutaka Fukui[2]

[1] Faculty of Regional Sciences, Tottori University, Japan
isao@rstu.jp
[2] Faculty of Engineering, Tottori University, Japan
{itoh,fukui}@ele.tottori-u.ac.jp

Abstract. DWT domain on-line signature verification method has bee proposed. Time-varying pen-position signal is decomposed into sub-band signals by using the DWT. Individual features are extracted as high frequency signals in sub-band. By using the extracted feature, verification is achieved at each sub-band and then total decision is done by combining such verification results. In this paper, we introduce a user weighting fusion into the total decision for improving verification performance. Through many verification experiments, it is confirmed that there is an optimal weight combination for each user and verifiaction rate can be improved when the optimal weight combination is applied. Such the optimal weight combination also becomes an individual feature which can not be known by others.

1 Introduction

Recently, multiple biometric systems have been attracted attentions to improve the performance of single biometric systems. Five scenarios of the multiple biometric system are considered in [1], that is, multi-sensor system, multi-modal system, multi-unit system, multi-impression system, and multi-matcher system. Among of them, the multi-matcher system which uses multiple representation and matching algorithm for the same input biometric signal is the most cost-effective way to improve the performance of the biometric system [1]. In addition, the multi-matcher system requires capturing biometrics only once.

We have proposed the on-line signature verification system in the Discrete Wavelet Transform (DWT) domain [2, 3]. This system utilized only pen-position parameter, that is, x and y coordinates since it was detectable even in portable devices such as the Personal Digital Assistants (PDA). Each time-varying signal of x and y coordinates was decomposed into sub-band signals by using the DWT. Verification was achieved by using the adaptive signal processing in each sub-band. Total decision for verification was done by averaging the verification results of several sub-bands in x and y coordinates. Verification rate was about 95%, which was improved by about 10% comparing with a time-domain verification system.

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Our proposed system is regarded as the multi-matcher system. In general, the multi-matcher system combines at most a few verification results [1]. On the other hand, the verification of our proposed system is achieved at several sub-bands in both x and y coordinates; therefore, there are much more verification results than general multi-matcher systems. This enables to adopt more unrestrained weighting of the verification results. If an optimal weighting for each user (signature) is applied in the total decision, the verification rate is expected to be improved. In this paper, we introduce a user weighting fusion into the total decision. Through many verification experiments, it is confirmed that there is an optimal weight combination for each signature and the verifiaction rate is improved when the optimal weight combination is applied. Moreover, the optimal weight combination also becomes an individual feature which can not be known by others.

2 On-Line Signature Verification in DWT Domain

2.1 On-Line Signature

The on-line signature is digitized with the electronic pen-tablet. Especially, we utilize only pen-position parameter since it is provided even 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 total number of sampled data. As the one-line signature is a dynamic biometrics, each writing time is different from the others. This results in the different number of sampled data even in genuine signatures. Moreover, different writing place and different size of signature cause variations in pen-position parameter. To reduce such variations, pen-position data are 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 a 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 described later.

However, such normalization makes the difference between a genuine signature and its forgery unclear. In addition, the on-line signature is relatively easy to forge if the written signature is known. Easiness of imitating pen-position data decreases the difference between the genuine signature and the forgery further. Figure 1 shows examples of the time-varying signal of x coordinate in a genuine signature and its forgery. The forgery data was obtained by tracing the

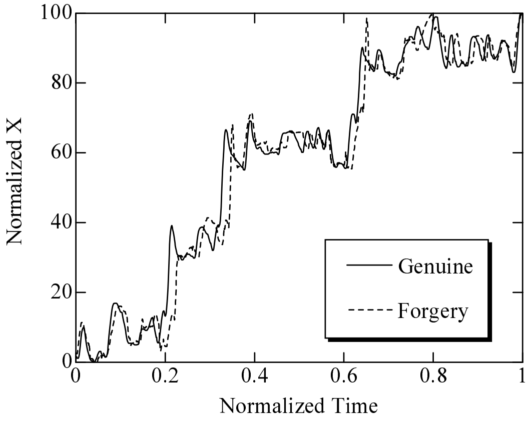

Fig. 1. Examples of the time-varying signal of x coordinate

genuine signature. It is clear that to distinguish between the genuine signature and the forgery is difficult by using the time-varying signal of the pen-position parameter.

2.2 Feature Extraction by Sub-band Decomposition

In order to enhance the difference between a genuine signature and its forgery, we have proposed to verify the on-line signature in DWT domain [2, 3]. In the following, $x(n)$ and $y(n)$ are represented as $v(n)$ for convenience. The DWT of the normalized pen-position $v(n)$ is defined as [4]

$$u_k(m) = \sum_n v(n)\overline{\Psi_{k,m}(n)} \tag{3}$$

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

Moreover, it is well known that the DWT corresponds to the octave-band filter bank. Figure 2 shows a parallel structure of the sub-band decomposition where M_d is a decomposition level and is set to guarantee the following relation

$$2^{M_d+1} \leq N_{tmp} < 2^{M_d+2} \tag{4}$$

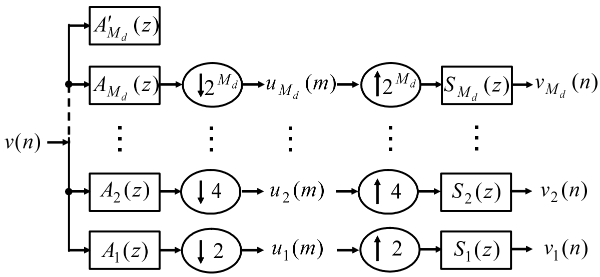

Fig. 2. Parallel structure of sub-band decomposition by DWT

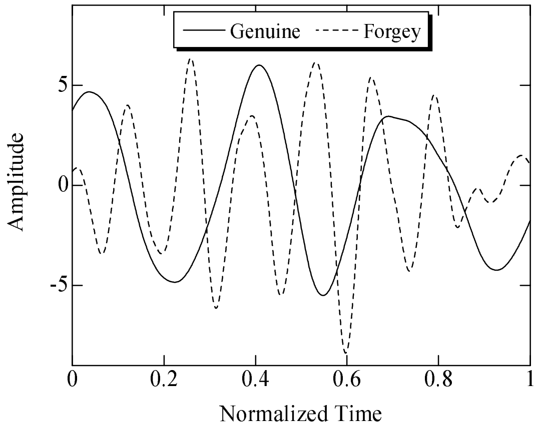

Fig. 3. Examples of *Detail*

N_{tmp} is the number of sampled data of pen-position template described later. Also, M_d has the upper limit: M_d^{max}. The synthesized signal $v_k(n)$ $(k = 1, 2, \cdots, M_d)$ is called *Detail*. The *Detail* is the signal in high frequency band and so it contains differences between signals. Therefore, we consider the *Detail* as an enhanced individual feature in pen-position.

Figure 3 shows examples of the *Detail* [2, 3]. We can confirm that the difference between a genuine signature and its forgery become remarkable by the sub-band decomposition even if the genuine signature is traced by the forger.

2.3 Verification System

Figure 4 shows a system overview. Pen-position, actually x and y coordinates are separately processed in verification block. Figure 5 describes the verification block. Firstly, the time-varying signal of x or y coordinate is decomposed into *Details* and then each *Detail* is verified with a corresponding template using the adaptive signal processing at each sub-band level.

Before verification, templates must be enrolled to be compared with input signatures. As the template, T genuine signatures which have equal number of

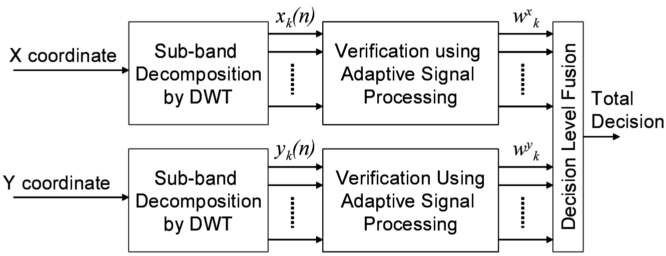

Fig. 4. System overview

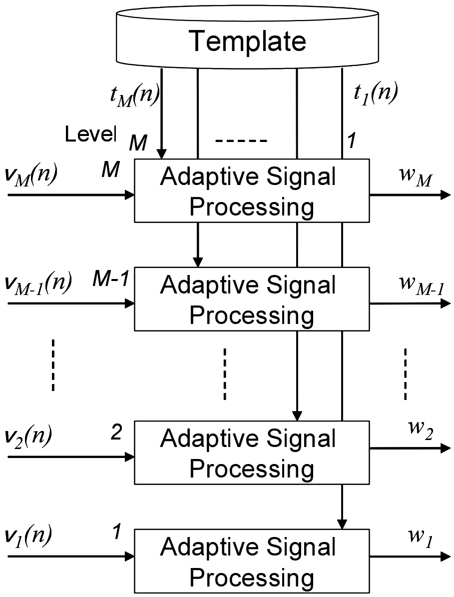

Fig. 5. Verification block

strokes are prepared and then their pen-position parameter is decomposed into sub-band signals by the DWT each other. Decomposition level is decided after examinations of those genuine signatures. Extracted *T Detail*s are averaged at the same level each other.

By the way, if the number of strokes in an input signature is different from that in a template, it is natural to consider the input signature as a forgery. However, not all genuine signatures have the same number of strokes. We adopt the dynamic programming (DP) matching method to identify the number of strokes in an input signature with that in a template. The procedure of the stroke matching is omitted for lack of space. It is described in detail in [2, 3].

2.4 Verification Using Adaptive Signal Processing

After enrollment of the template, verification is achieved by using the adaptive signal processing. The purpose of the adaptive signal processing is to reduce the error between the input signal and the desired signal sample by sample [5]. When an input signal is of a genuine signature, the error between the input and its template becomes small; therefore, adaptive weights are expected to converge close on 1. Inversely, if the input signature is a forgery, adaptive weights converge far from 1. In this way, the verification can be achieved by examining whether converged value is nearly 1 or not [2, 3].

As the adaptive algorithm, we use a new kind of steepest descent algorithm [5] defined as follows.

$$w_k(n+1) = w_k(n) + \mu E\left[e_k(n)v_k(n)\right] \tag{5}$$

$$e_k(n) = t_k(n) - w_k(n)v_k(n) \tag{6}$$

$$E\left[e_k(n)v_k(n)\right] = \frac{1}{N_{tmp}} \sum_{l=0}^{N_{tmp}-1} e_k(r-l)\ v_k(r-l) \tag{7}$$

$$\mu = \mu_0 / \left\{E\left[|v_k(n)|\right]\right\}^2 \tag{8}$$

$$E\left[|v_k(n)|\right] = \frac{1}{N_{in}} \sum_{l=0}^{N_{in}-1} v_k(n-l) \tag{9}$$

where N_{in} is the number of sampled data in an input *Detail*. N_{tmp} is the number of sampled data in a template. μ is a step size parameter which controls the convergence in the adaptive algorithm. The step size parameter is normalized by input power as shown in Eqs.(8) and (9), so that convergence is always guaranteed. μ_0 is a positive constant.

The verification is done in all sub-bands in parallel. After enough iterations for convergence, $w_k(n)$ is averaged in past N_{tmp} samples and then we obtain the converged value w_k.

Total verification score (TS) is obtained by combining converged values at several sub-band levels in x and y coordinates.

$$\mathrm{TS} = c_x \left(\sum_{p=0}^{L-1} f_p \cdot w^x_{M-p} \right) + c_y \left(\sum_{p=0}^{L-1} f_p \cdot w^y_{M-p} \right) \tag{10}$$
$$c_x + c_y = 1, \quad c_x > 0, c_y > 0, \quad \Sigma f_p = 1, \quad f_p > 0$$

where w^x_{M-p} and w^y_{M-p} respectively denote the converged values of x and y coordinates at level $M-p$. L is the number of used sub-band levels in decision fusion. c_x and c_y are the weights for x and y coordinates, respectively and f_p is the weight for sub-band.

In our conventional results, we set $c_x = c_y = 1/2$ and $f_p = 1/L$, that is, the total verification score was obtained by averaging all converged values. In that case, verification rate was about 95% [2, 3].

3 User Weighting Fusion

In our proposed system, total verification score is obtained by fusing $2 \times L$ converged values. In other words, it is possible to set the weights more unrestrained than the time-domain verification system which has only c_x and c_y.

There have been proposed many fusion methods such as the sum rule, the minimum score, the maximum score and so on [6]. In this paper, we introduce user weighting fusion into the total decision for verification. The total verification score is re-defined as

$$\mathrm{TS}^i = c^i_x \left(\sum_{p=0}^{L-1} f^i_p \cdot w^x_{M-p} \right) + c^i_y \left(\sum_{p=0}^{L-1} f^i_p \cdot w^y_{M-p} \right) \tag{11}$$
$$c^i_x + c^i_y = 1, \quad c^i_x > 0, c^i_y > 0, \quad \Sigma f^i_p = 1, \quad f^i_p > 0$$

where i $(i = 1, 2, \cdots, I)$ presents enrolled user (signature) identification number. In general verification systems, such a user identifier is used for one-to-one matching between an input and its template [7]. The user weighting fusion enables to set optimal weights for each user.

Next, in order to find such optimal weights, we carried out verification experiments in various weight combinations. In this experiment, we assumed the following severe situation. Before signing, the subjects were called upon to practice using the pen tablet for becoming skilled. This suppresses the variation of signature due to inexperienced pen-tablet. When the subjects signed genuine signatures, they were not able to refer to their already written signatures. This tends to increase the intra-class variation in signatures of one individual. On the other hand, assuming that the signature shape was easily imitated, forgers were permitted to trace the genuine signature by putting the paper to which the signature was written over the pen tablet.

On the above situation, we prepared an original database. Four subjects were requested to sign their own signatures and then we obtained 118 genuine signatures. The four subjects were labeled "a", "b", "c" and "d" in the following. Five genuine signatures for each subject were used to make a template and the remaining 98 genuine signatures were used for verification. Five subjects were required to counterfeit the genuine signature 10 times each, so that 200 forgeries were prepared in total.

Other conditions of simulation are summarized as follows.

- Scaling parameter: $\alpha_x = \alpha_y = 100$
- Wavelet function: Daubechies8
- Number of signatures for making a template: $T = 5$
- Upper limit decomposition level: $M^{max} = 8$
- Number of processed level: $L = 4$
- Step size constant: $\mu_0 = 0.0001$
- Number of iterations: 10^5

The weight for pen-position was changed from 0.0 to 1.0 every 0.1. Also, three combinations of weight for sub-band, (0.1, 0.2, 0.3, 0.4), (0.25, 0.25, 0.25, 0.25), (0.4, 0.3, 0.2, 0.1) were examined. Totally 33 weight combinations were evaluated. Verification performance was estimated by the Equal Error Rate (EER) where the False Rejection Rate (FRR) is equal to the False Acceptance Rate (FAR).

Results are shown in Table 1. When the case of $c_x = c_y = 0.5$ and $f_3 = f_2 = f_1 = f_0 = 0.25$ corresponds to the conventional setting. In that case, the total EER was 5% [2, 3].

Next, we defined an optimal combination as the weights which achieved the smallest EER and made it easier to set threshold value in total decision using the FAR and FRR curves. The optimal weight combinations are summarized in Table 2. Total EER was 4%. As a result, user optimal weighting improved the total EER by 1%.

It is interesting that each user (signature) has different optimal weight combination and the EER can be greatly decreased when the optimal weight is applied. Especially, the weight combination for user "b" is contrary to that for user "d".

Table 1. Weight combination vs. EER

Weights for pen-position		Weights for sub-band				EER(%)			
c_x	c_y	f_3	f_2	f_1	f_0	a	b	c	d
0.0	1.0	0.1	0.2	0.3	0.4	12.0	0.0	6.8	5.0
0.1	0.9	0.1	0.2	0.3	0.4	9.0	0.0	4.2	3.5
0.2	0.8	0.1	0.2	0.3	0.4	6.5	0.0	6.8	5.5
0.3	0.7	0.1	0.2	0.3	0.4	4.0	0.0	6.5	6.0
0.4	0.6	0.1	0.2	0.3	0.4	4.0	0.0	8.2	4.0
0.5	0.5	0.1	0.2	0.3	0.4	2.0	0.0	8.2	6.0
0.6	0.4	0.1	0.2	0.3	0.4	2.5	0.0	8.2	6.0
0.7	0.3	0.1	0.2	0.3	0.4	1.8	0.0	8.2	6.0
0.8	0.2	0.1	0.2	0.3	0.4	2.0	0.0	8.2	11.5
0.9	0.1	0.1	0.2	0.3	0.4	2.0	0.0	9.5	4.0
1.0	0.0	0.1	0.2	0.3	0.4	2.5	0.0	12.5	14.3
0.0	1.0	0.25	0.25	0.25	0.25	10.5	0.0	5.5	2.0
0.1	0.9	0.25	0.25	0.25	0.25	9.5	0.0	4.2	2.0
0.2	0.8	0.25	0.25	0.25	0.25	7.0	0.0	5.0	2.0
0.3	0.7	0.25	0.25	0.25	0.25	5.2	0.0	7.5	1.8
0.4	0.6	0.25	0.25	0.25	0.25	3.0	0.0	8.2	2.5
0.5	0.5	0.25	0.25	0.25	0.25	2.0	0.0	8.2	3.5
0.6	0.4	0.25	0.25	0.25	0.25	1.3	0.0	8.2	4.8
0.7	0.3	0.25	0.25	0.25	0.25	2.0	0.0	8.2	4.0
0.8	0.2	0.25	0.25	0.25	0.25	1.6	0.0	8.2	6.0
0.9	0.1	0.25	0.25	0.25	0.25	2.0	0.0	8.2	8.5
1.0	0.0	0.25	0.25	0.25	0.25	3.0	0.0	8.2	12.0
0.0	1.0	0.4	0.3	0.2	0.1	8.0	0.0	4.2	0.0
0.1	0.9	0.4	0.3	0.2	0.1	8.0	0.0	4.2	0.0
0.2	0.8	0.4	0.3	0.2	0.1	8.0	0.0	6.0	0.0
0.3	0.7	0.4	0.3	0.2	0.1	5.5	0.0	6.0	0.0
0.4	0.6	0.4	0.3	0.2	0.1	4.0	0.0	8.2	0.0
0.5	0.5	0.4	0.3	0.2	0.1	4.0	0.0	8.2	2.8
0.6	0.4	0.4	0.3	0.2	0.1	2.8	0.0	9.5	2.8
0.7	0.3	0.4	0.3	0.2	0.1	3.0	0.0	9.5	4.0
0.8	0.2	0.4	0.3	0.2	0.1	1.5	1.5	10.0	4.2
0.9	0.1	0.4	0.3	0.2	0.1	3.0	3.0	10.5	4.2
1.0	0.0	0.4	0.3	0.2	0.1	4.0	4.0	12.0	4.2

In the case of user "b", verification results at lower levels have more effect on verification performance than those at higher levels. Inversely, the verification results at higher levels play an important role in the total decision in user "d". These matters depend on the figure of signature and the user's habit in writing process. In other words, the optimal weight combination is also an individual feature which can not be known by others.

Table 2. Optimal user weighting

User	Weights for pen-position		Weights for sub-band				EER (%)
	c_x	c_y	f_3	f_2	f_1	f_0	
a	0.6	0.4	0.25	0.25	0.25	0.25	1.3
b	0.7	0.3	0.1	0.2	0.3	0.4	0.0
c	0.1	0.9	0.4	0.3	0.2	0.1	4.2
d	0.1	0.9	0.4	0.3	0.2	0.1	0.0

4 Conclusion

We introduced user weighting fusion into the total decision in the DWT domain on-line signature verification. Verification experiments showed that there was an optimal weight combination for each user and then verifiaction rate could be improved when the optimal weights were applied. In addition, the optimal weight combination is expected to be a new individual feature which can not be known by others. As amount of data of optimal weight combinations is quite small, they can be enrolled in the database as well as the template. It is easy to implement the proposed optimal fusion method in the on-line signature verification system.

In this evaluation, we used not only genuine signatures but also their forgeries. However, it may not be realistic for a real system. It must be studied to develop some statistical method for determining optimal weights by using only genuine signatures. Moreover, we will study to implement our on-line signature verification system in a portable device such as the PDA in the near future.

References

1. S. Prabhakar, A. K. Jain, "Decision-level Fusion in Fingerprint Verification," *Pattern Recognition*, vol.35, pp.861-874, 2002.
2. 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.
3. I. Nakanishi, N. Nishiguchi, Y. Itoh, and Y. Fukui, "On-line signature verification based on subband decomposition by DWT and adaptive signal processing," Electronics and Communications in Japan (Part III: Fundamental Electronics Science), vol.88, no.6, 2005.
4. G. Strang, T. Nguyen, Wavelet and Filter Banks, Wellesley-Cambridge Press, Massachusetts, 1997.
5. S. Haykin, Introduction to Adaptive Filters, Macmillan Publishing Company, New York, 1984.
6. M. Indovina, U. Uludag, R. Snelick, A. Mink, and A. Jain, "Multimodal Biometric Authentication Methods: A COTS Approach," *Proc. of Workshop on Multimodal User Authentication*, Santa Barbara, USA, pp.99-106, Dec. 2003.
7. A. K. Jain, F.D. Griess, and S.D. Connell, "On-Line Signature Verification," *Pattern Recognition*, vol.35, pp.2963-2972, 2002.