9

DWT Domain On-Line Signature Verification

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1. Introduction

Biometrics attracts attention since person authentication becomes very important in networked society. As the biometrics, the fingerprint, iris, face, ear, vein, gate, voice and signature are well known and are used in various applications (Jain et al., 1999; James et al., 2005). Especially, assuming mobile access using a portable terminal such as a personal digital assistant (PDA), a camera, microphone, and pen-tablet are normally equipped; therefore, authentication using the face, voice and/or signature can be realized with no additional sensor.

Fig. 1. A PDA with a pen-tablet

On the other hand, the safety of biometric data is discussed actively. Every human being has limited biometrics, for example, only ten fingerprints and one face. If the biometric data are leaked out and it is known whose they are, they are never used for authentication again.
To deal with this problem, cancelable biometric techniques have been proposed, which use not biometric data directly but one-to-one transformed data from the biometric data. However, such a technique is unnecessary if the biometrics itself is cancelable.
Among various biometric modalities, only the signature is cancelable from a viewpoint of spoofing. Even if a signature shape is known by others, it is possible to cope with the problem by changing the shape. Especially, in on-line signatures, the habit during writing is biometrics and it is not remained in the signature shape; therefore, to imitate it is quite difficult even if the signature shape is copied. As a result, the on-line signature verification is actively researched

(Dimauro et al., 2004; Fierrez & Ortega-Garcia, 2007; Jain et al., 2002; Plamondon & Srihari, 2000). However, the verification performance tends to be degraded since the on-line signature is a dynamic trait.

We have proposed a new on-line signature verification method in which a pen-position parameter is decomposed into sub-band signals using the discrete wavelet transform (DWT) and total decision is done by fusing verification results in sub-bands (Nakanishi et al., 2003; 2004; 2005). The reason why we use only the pen-position parameter is that detecting functions of other parameters such as pen-pressure, pen-altitude, and/or pen-direction are not equipped in the PDA.

However, since the signature shape is visible, it is relatively easy to forge the pen-position parameter by tracing genuine signatures by others. In the proposed method, individual features of a signature are enhanced and extracted in the sub-band signals, so that such well-forged signatures can be distinguished from genuine ones. Additionally, in the verification process of the proposed method, dynamic programming (DP) matching is adopted to make it possible to verify two data series with different number of sampled points. The purpose of the DP matching is to find the best combination between such two data series. Concretely, a DP distance is calculated in every possible combination of the two data series and as a result the combination which has the smallest DP distance is regarded as the best.

But there are problems in use of the DP matching. The DP distance is obtained as dissimilarity; therefore, signatures with large DP distances are rejected even if they are of genuine. For instance, in a pen-tablet system, a pen-up while writing causes large differences in coordinate values of pen-position and so increases false rejection. On the other hand, signatures with small DP distances are accepted even if they are forgery. The DP matching forces to match two signatures even if either is forgery. It increases false acceptance.

Consequently, we propose simply-partitioned DP matching. Two data series compared are divided into several partitions and the DP distance is calculated every partition. The DP distance is initialized at the start of a next partition, so that it reduces excessively large DP distances, that is, the false rejection. On the other hand, limitation of combination in matching is effective for rejecting forgeries; therefore, it reduces the false acceptance.

There is another important problem when we use the DP matching. The DP distance is proportional to the number of signature's sampled data, that is, signature complexity (shape), so that if it is used as a criterion in verification, each signature (user) has a different optimal threshold. But, it is general to use a single threshold commonly in an authentication system. If the common threshold is used for all signatures, it results in degradation of verification performance. Therefore, we have studied threshold equalization in the on-line signature verification (Nakanishi et al., 2008). We propose new equalizing methods based on linear and nonlinear approximation between the number of sampled data and optimal thresholds.

2. DWT domain on-line signature verification

In this section, we briefly explain the proposed on-line signature verification in the DWT domain.

2.1 System overview

A signal flow diagram is shown in Fig. 2. An on-line signature is captured as x and y coordinate (pen-position) data in a digital pen-tablet system and their sampled data are

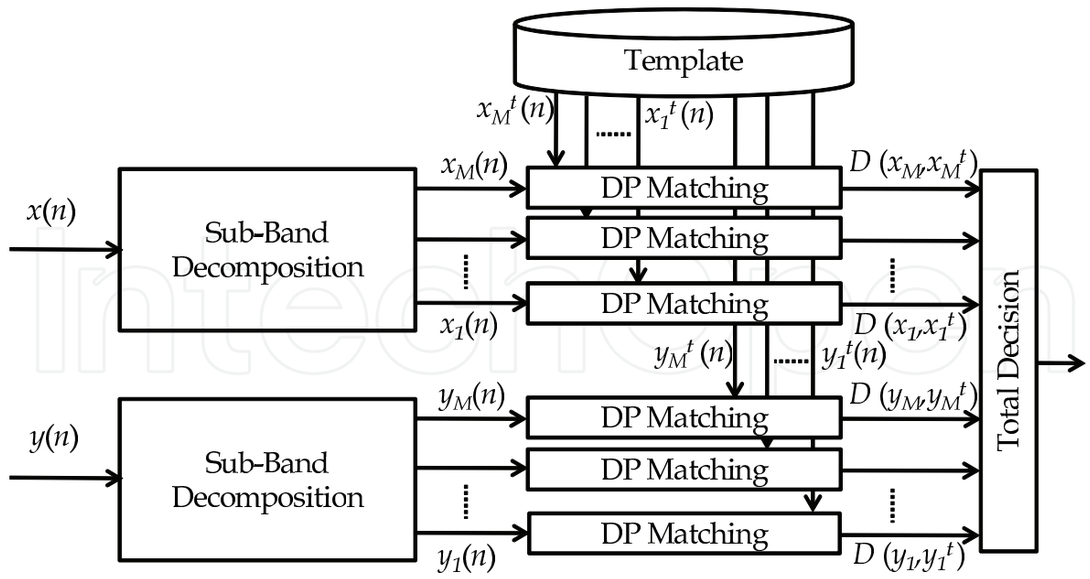


Fig. 2. DWT domain on-line signature verification

given by $x(n)$ and $y(n)$ where $n = 0, 1, \cdots, S_n - 1$ and S_n is the number of sampled data. They are respectively normalized in both time and amplitude domains and then decomposed into sub-band signals using sub-band filters by the DWT (Nakanishi et al., 2003; 2004; 2005). In advance of verification, sub-band signals are enrolled as a template for each user. Templates are generated by ensemble-averaging several genuine signatures. Please refer to Ref. (Nakanishi et al., 2003) for the details. At the verification stage, each decomposed signal is compared with its template based on the DP matching and a DP distance is obtained at each decomposed level. Final score is calculated by combing the DP distances at appropriate sub-bands in both coordinates. Total decision is done by comparing the final score with a threshold and it is verified whether the signature data are of genuine or not.

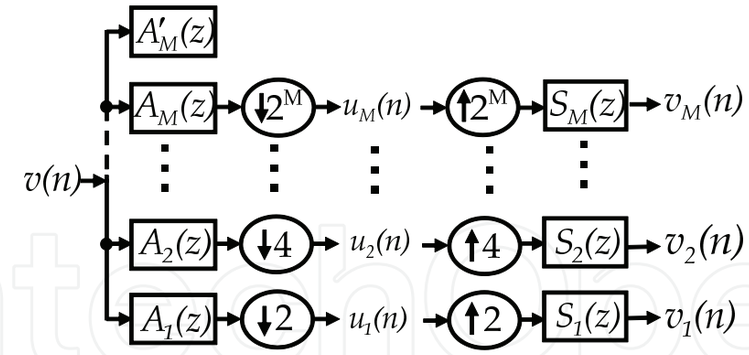
2.2 Feature extraction by DWT

In the following, the $x(n)$ and $y(n)$ are represented as $v(n)$ together for convenience. The DWT of the pen-position data: $v(n)$ is defined as

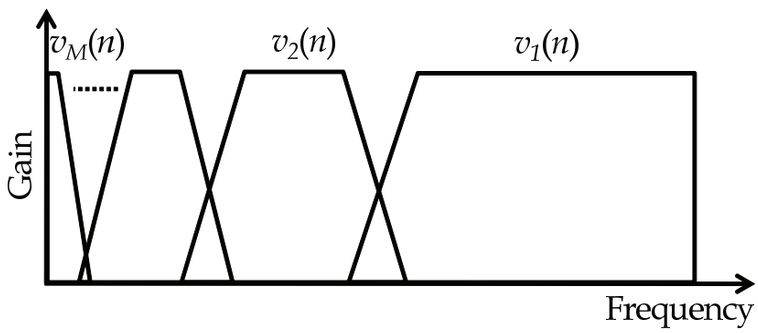
$$u_k(n) = \sum_m v(m)\overline{\Psi_{k,n}(m)} \tag{1}$$

where $\Psi_{k,n}(m)$ is a wavelet function and $\bar{\cdot}$ denotes the conjugate. k is a frequency (level) index. It is well known that the DWT corresponds to an octave-band filter bank (Strang & Nguyen, 1997) of which parallel structure and frequency characteristics are shown in Fig. 3, where $(\downarrow 2^k)$ and $(\uparrow 2^k)$ are down-sampling and up-sampling, respectively. M is the maximum level of the sub-band, that is, the decomposition level. $A_k(z)$ and $S_k(z)$ $(k = 1, \cdots, M)$ are analysis filters and synthesis ones, respectively.

The synthesized signal: $v_k(n)$ in each sub-band is the signal in higher frequency band and called *Detail* which corresponds to the difference between signals. Therefore, we adopt the *Detail* as an enhanced individual feature which can be extracted with no specialized function: pen-pressure, pen-altitude, and/or pen-direction which are not equipped in the PDA.



(a) Parallel structure



(b) Frequency characteristics

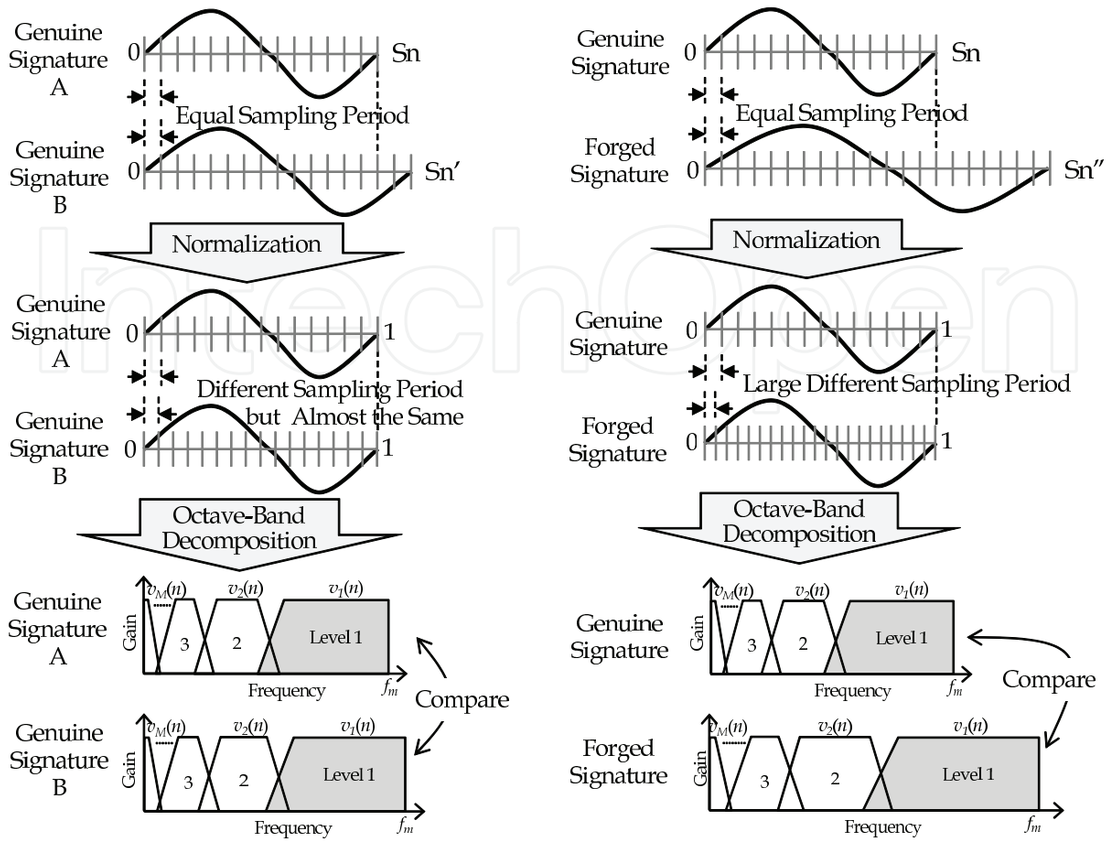
Fig. 3. Sub-band decomposition by DWT

Let us get another perspective on the effect of the sub-band decomposition using Fig. 4. Each signature is digitized at equal (common) sampling period using a pen-tablet system. In the proposed system, writing time of all signatures is normalized in order to suppress intra-class variation. Concretely, the sampling period of each signature is divided by the number of sampled data and so becomes real-valued.

Even genuine signatures have different number of sampled data; therefore, all signatures have different normalized sampling periods, that is, different sampling frequencies.

In general, variation of writing time in the genuine signatures is small, so that their sampling periods (frequencies) are comparable as shown in Fig. 4 (a). On the other hand, in the case of forged signatures, the variation of writing time is relatively large since it is not easy for forgers to imitate writing speed and rhythm of genuine signatures. Thus, sampling periods (frequencies) of the forged signatures become greatly different from those of the genuine signatures as in Fig. 4 (b).

The maximum frequency: f_m of the octave-band filter bank is determined by the sampling frequency based on the “sampling theory". If the sampling frequencies are greatly different, each octave band (decomposition level) includes greatly different frequency elements as illustrated in (b). In other words, even if levels compared are the same, frequency elements included in one level are different from the other, so that the differences between genuine signatures and forged ones are accentuated.



(a) Comparison of genuine signatures

(b) Comparison of a genuine signature with its forgery

Fig. 4. Effect of sub-band decomposition

The advantage was confirmed comparing with a time-domain method (Nakanishi et al., 2005). Of course, if forgers imitate writing speed and rhythm of genuine signatures, it is impossible for the proposed method to distinguish forged signatures from genuine ones.

2.3 Verification by DP matching

Since on-line signatures have large intra-class variation, one-to-one matching cannot be applied in verification. In order to deal with the problem, the verification was performed every stroke (intra-stroke or inter-stroke) in the conventional system (Nakanishi et al., 2003; 2004; 2005; 2008). However, a part of signature databases eliminates the data in inter-strokes and so we could not apply the conventional system to such a database.

Therefore, we introduce DP matching into the verification process. The DP matching is effective in finding the best combination between two data series even if they have different number as illustrated in Fig. 5.

Letting the two data series be $a(i)$ $(i = 0, 1, \cdots, I-1)$ and $b(j)$ $(j = 0, 1, \cdots, J-1)$, the local distance at kth is defined as

$$d(k) = |a(i)_k - b(j)_k| \quad (k = 0, 1, \cdots, K-1) \tag{2}$$

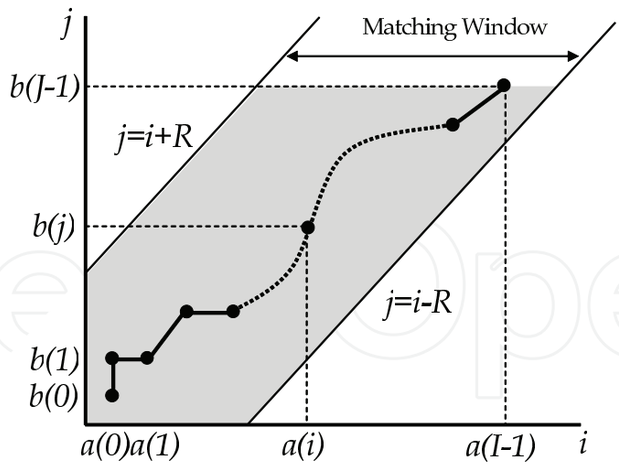


Fig. 5. DP matching

where instead of i and j, k is used as another time index since these data are permitted to be referred redundantly.
By accumulating the local distances in one possible combination between the two series, a DP distance is given by

$$D(a,b) = \sum_{k=0}^{K-1} w(k)d(k) \tag{3}$$

where $w(k)$ is a weighting factor. After calculating the DP distance in all possible combinations, we can find the best combination by searching the combination with the smallest DP distance.
Moreover, since the DP distance depends on the number of sampled data, the normalized DP distance is used in general.

$$nD(a,b) = D(a,b) / \sum_{k=0}^{K-1} w(k) \tag{4}$$

Assuming the weight is symmetric: (1-2-1) and the initial value is zero,

$$\sum_{k=0}^{K-1} w(k) = I + J. \tag{5}$$

In the proposed method, the DP distance is obtained at each sub-band level. Let the DP distance at lth level be $D(v,v^t)_l$ where v is sampled data series of a signature for verification and v^t is that of a template, the normalized DP distance is given by

$$nD(v,v^t)_l = D(v,v^t)_l / (V_n + T_n) \tag{6}$$

where V_n is the number of sampled data in the verification signature and T_n is that of the template.

A total distance (TD) is obtained by accumulating the normalized DP distances in sub-bands.

$$TD = c_x \cdot \frac{1}{L} \sum_{l=M-L+1}^{M} nD(x, x^t)_l + c_y \cdot \frac{1}{L} \sum_{l=M-L+1}^{M} nD(y, y^t)_l \tag{7}$$

where c_x and c_y are weights for combining the DP distances in x and y coordinates and $c_x + c_y = 1, c_x > 0, c_y > 0$. L is the number of levels used in the total decision.

2.4 Verification experiments

In order to confirm verification performance of the proposed system, we carried out experiments in the following conditions. The wavelet function was Daubechies8. The maximum level of the sub-band: M was 8 and the number of levels used in the total decision: L was 4. The combination weights were $c_x = c_y = 0.5$, which mean to take the average. For generating templates, data of five genuine signatures were ensemble-averaged.

We used a part of the on-line signature database: SVC2004 in which the data in inter-strokes were eliminated. The number of subjects was 40 and 17 subjects signed their names in Chinese characters and the rest in alphabetical ones. For collecting skilled forgeries, imposters could see how genuine signatures were being written. The total number of signatures was 1600. Please refer to Ref. (SVC2004, 2004) for more information.

The verification performance was evaluated by using an equal error rate (EER) where a false rejection rate (FRR) was equal to a false acceptance rate (FAR). The EER of the proposed system was 20.0 %. For reference, the EER of the conventional system was 28.3 %, so that it is confirmed that introducing the DP matching is effective for not only applying to the standard database but also improving verification performance.

On the other hand, assuming to use individually-optimal thresholds for all subjects, we averaged EERs of all subjects and then so obtained EER of 15.3 %. This is a rough evaluation but suggests that if a single common threshold is optimal for all subjects, the verification performance could be improved further. This issue is examined in Sect. 4.

3. Simply partitioned DP matching

There is another issue to be overcome in order to improve the verification performance. For instance, in a pen-tablet system, when the pen tip is released from the surface of the tablet, it is not guaranteed to get precise coordinate values of pen-position. It sometimes brings large differences from template data and then leads to a large DP distance. The signature with such a large DP distance is rejected even if it is genuine. This increases false rejection.

Conversely, signatures with small DP distances are accepted even if they are forgery. In particular, skilled forgeries (well-forged signatures) could make the DP distance smaller. The DP matching forces to match two signatures even if either is forged one. This increases false acceptance.

Consequently, we propose simply-partitioned DP (spDP) matching. The concept is illustrated in Fig. 6, where the number of partitions is four. Both data series: $a(i)$ and $b(j)$ are divided into several partitions of the same integer number and a sub DP distance is calculated every partition. If the division leaves remainders, they are singly distributed to partitions. The sub DP distances are initialized at the start of next partitions and a total DP distance is obtained by summing the sub DP distances in all partitions.

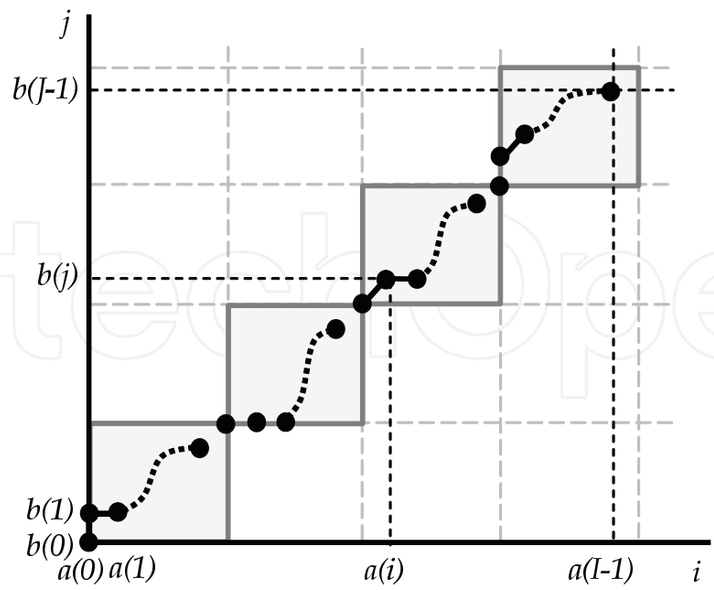


Fig. 6. Simply-partitioned DP matching (Q=4)

Assuming that genuine signatures have equivalent rhythms in writing, even if their data are partitioned, rhythms in corresponding partitions compared are still equivalent. Therefore, when a verification signature is genuine, appropriate matching pairs tend to exist in diagonal direction in Fig. 6. As a result, the spDP matching has no ill effect for false rejection.
Furthermore, even if excessively a large sub DP distance is caused by the irregular pen-up mentioned above in a partition, it is initialized at the start of the next partition, so that the spDP matching prevents the total DP distance from becoming excessively large and has an effect on reducing false rejection.
On the other hand, it is difficult for forgers to copy rhythms in writing of genuine signatures, so that the rhythm in each partition of forged signatures becomes different from that of genuine ones. Resultingly, matching pairs between the genuine signature and its forged one are not in the diagonal direction and so are excluded even if they have small DP distances. The spDP matching is also effective in reducing false acceptance.
Such a concept that inappropriate pairs are excluded by partitioning the DP distance has been already proposed (Sano et al., 2007; Yoshimura & Yoshimura, 1998) but they assume to write Chinese (Kanji) characters in standard style and the partitioning is done every character or stroke. Therefore, they could not be directly applied to the case of a cursive style (connected characters). Of course, they need additional processing for character or stroke detection.
Let the number of partitions and the sub DP distance be Q and $D(v, v^t)^q$, respectively, the normalized DP distance at the sub-band level: l is obtained by summing sub DP distances in all partitions.

$$nD(v, v^t)_l = \left(\sum_{q=1}^{Q} D(v, v^t)^q \right) / (V_n + T_n) \tag{8}$$

A total distance (TD) is given by Eq. (7).

By the way, the matching window is generally adopted in the DP matching as shown in Fig. 5 in order to reduce calculation amount by excluding unlikely pairs. Comparing between Figs. 5 and 6, it is clear that the spDP matching is more effective for excluding inappropriate pairs than the matching window.

3.1 Evaluation of spDP matching

We evaluated verification performance using the spDP matching. Conditions are similar with those in Sect. 2.4. EERs in various numbers of partitions are summarized in Table 1 where the case of 0 partitions corresponds to the conventional normalized DP matching.

Number of Partitions	0	2	3	4	5	6
EER (%)	20.0	17.8	16.4	16.6	17.0	16.4

Table 1. EERs in various numbers of partitions

From these results, it is confirmed that the spDP matching decreased the EER by 2-3%. In the following, we set the number of partitions at 4.

4. Threshold equalizing

There is an important issue to be overcome as mentioned in Sect. 2.4 in order to improve verification performance. In not only on-line signature verification but also all biometric authentication systems, final scores are compared with a threshold which is preliminary determined. In addition, the threshold should be common to all users. Therefore, when the final score (the DP distance) of each user is greatly different from those of others, the verification performance tends to be degraded by using the common threshold.
In general, the normalized DP distance given by Eq. (4) is used for dealing with this problem. However, the normalization also makes the DP distances of forged signatures small and thereby might increases false acceptance.
We have studied to equalize the threshold instead of using the normalization (Nakanishi et al., 2008). A total distance (TD) is rewritten as

$$TD = c_x \cdot \frac{1}{L} \sum_{l=M-L+1}^{M} D(x, x^t)_l + c_y \cdot \frac{1}{L} \sum_{l=M-L+1}^{M} D(y, y^t)_l \tag{9}$$

where please be aware that unnormalized DP distance $D(v, v^t)_l$ is used.
Generally, complex signatures have large number of sampled data since they consume relatively long time for writing. The larger the number of sampled data of a signature becomes, the larger intra-class variation becomes and as a result, it makes a DP distance large. Final decision is achieved by comparing the DP distance with a threshold; therefore, to make the DP distance inversely proportional to the number of sampled data suppresses the variation range of the DP distance and then it leads to equalization of thresholds.
Based on this concept, the conventional equalization is defined as

$$TD_{eq}^{p} = \frac{\gamma}{T_n^p} TD^p \tag{10}$$

where p is user number and TD^p, TD_{eq}^{p} and T_n^p are the total distance, the equalized total (final) distance and the number of sampled data of the template of the user, respectively. γ is a

constant for adjusting the final distance to an appropriate value. When the number of sampled data in a signature is too small, the final distance of the signature is enlarged. Conversely, large number of sampled data in a signature reduces the final distance. The effect of the threshold equalizing was already confirmed (Nakanishi et al., 2008).

4.1 New threshold equalizing methods

Figure 7 shows the relation between the number of sampled data in signatures (templates) and their optimal thresholds (total DP distances) using the spDP matching ($Q = 4$) in SVC2004, where the thresholds which bring EERs are regarded as optimal.

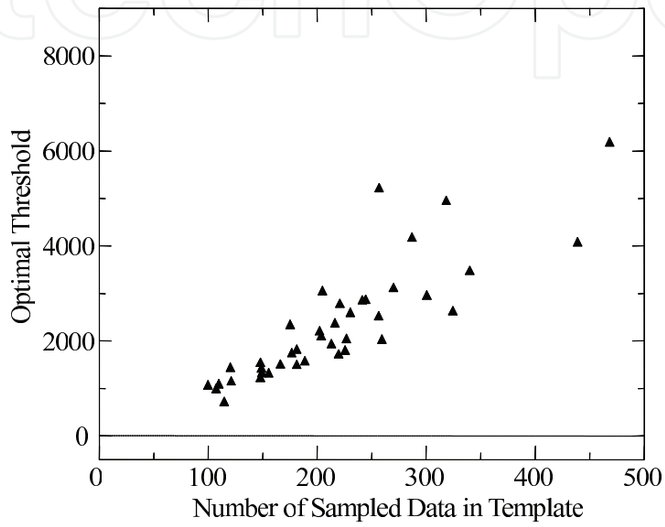


Fig. 7. Relation between the number of sampled data and optimal thresholds

The optimal thresholds are widely distributed; therefore, it is easy to guess that common use of a single threshold is not good for verification performance. In addition, the relation between the number of sampled data and the optimal threshold is not simple differently from that assumed in the conventional equalization.

4.1.1 Equalization using linear approximation

Assuming that the relation between the number of sampled data and the optimal threshold is approximated by a linear function, the total DP distance is equalized as

$$TD^p_{eq} = \frac{\gamma}{\alpha \cdot T^p_n + \beta} TD^p \tag{11}$$

where γ is the adjustment constant as well as the conventional method. α and β are the gradient and intercept of the linear function.

4.1.2 Equalization using nonlinear approximation

On the other hand, the relation between the number of sampled data and the optimal threshold could be fitted by a nonlinear function. The total DP distance is adjusted by using an exponential function as

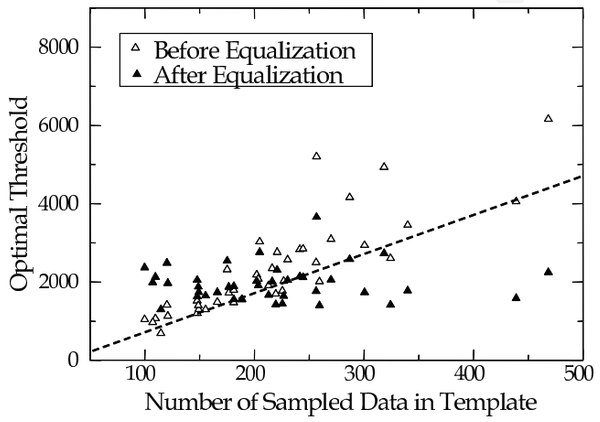
$$TD^p_{eq} = \frac{\gamma}{\exp(\alpha \cdot T^p_n + \beta)} TD^p \tag{12}$$

where α and β are constants for fitting the nonlinear function to the relation between the number of sampled data and the optimal threshold.

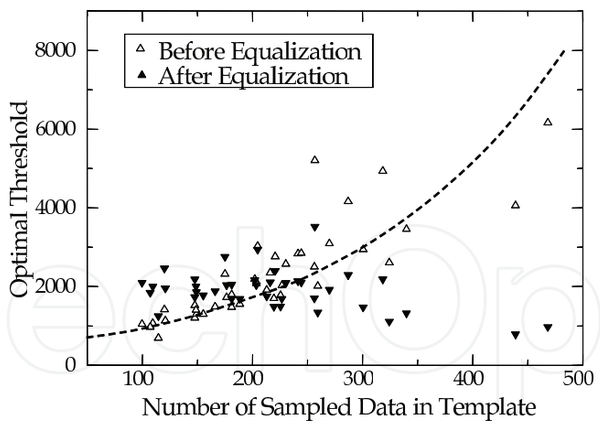
4.2 Evaluation of threshold equalizing

In order to verify effectiveness of the threshold equalizing methods, we evaluated verification performance using the SVC2004, again. Conditions are the same as those in Sect. 2.4. The number of partitions in DP matching was 4.

The distribution of optimal thresholds after equalization is compared with that before equalization in Fig. 8 where the uncolored triangles are before equalization and the black ones are after equalization. The broken lines indicate approximation functions where $\alpha = 10$ and $\beta = -293$ in the linear case and $\alpha = 0.0069$ and $\beta = 3.3$ in the nonlinear case.



(a) Linear case



(b) Nonlinear case

Fig. 8. Distribution of optimal thresholds before and after equalization in the linear and nonlinear approximation cases

From a viewpoint of their universality, it is better to determine them using a training data set, which is independent of a test data set. However, the proposed equalizing methods are based on rough approximation of the relation between the number of sampled data and the optimal threshold in the SVC2004. If the relation in the training data set is equivalent with that in the

test data set, the proposed methods does not depend on the data used. The approximation depends on not training data sets but databases. The larger the number of data becomes, the more universal the constants. In both cases, γ was set to a value which adjusts the thresholds to around 2000.
It is confirmed that the optimal thresholds, that is, the DP distances were adjusted to around 2000 and the variation range of the DP distances was narrowed.
For achieving quantitative evaluation, we analyzed statistical variance of optimal threshold values before and after the equalization. The variance before the equalization was 0.27 but after the equalization it was reduced to 0.05 in the linear case and 0.07 in the nonlinear case.

Method	EER(%)	Variance
Unnormalized DP	25.4	0.54
Normalized DP	20.0	0.17
4-partitioned DP	16.6	0.05
Conventional equalization	19.9	0.24
Linear equalization	19.0	0.22
Nonlinear equalization	19.5	0.23
4-partitioned DP + Linear equalization	14.6	0.05
4-partitioned DP + Nonlinear equalization	14.9	0.07

Table 2. EERs and variances in various methods

Finally, EERs and variances in various methods are summarized in Table 2. Comparing the EER and variance in the 4-partitioned DP matching to those in the normalized DP one, it is confirmed that the proposed spDP matching is more effective in improving verification performance than the general-used DP matching. Similarly, the proposed new threshold equalization methods are confirmed to be more efficient than the normalized DP matching and the conventional method. Moreover, combining the spDP matching with the new threshold equalization is much more effective. Especially, the smallest EER of 14.6% and variance of 0.05 were obtained when the threshold equalization using the linear approximation was applied. As confirmed in Fig. 8 (b), the adjustment in the nonlinear case might be excessive when the number of sampled data was large. It is a future problem to adopt other functions for approximating the relation between the number of sampled data and the optimal threshold.
On the other hand, the EER of about 15% may not be absolutely superior to those of other on-line signature verification methods. However, it is possible to introduce the spDP matching and/or the threshold equalizing into the methods based on the DP matching and it might also improve their performance.

5. Conclusions

We have studied on-line signature verification in the DWT domain. In order to improve the verification performance, we introduced spDP matching and threshold equalizing into the verification process.
In the spDP matching, two data series compared were divided into partitions, a sub DP distance was calculated every partition, and then a total DP distance was obtained by summing the sub DP distances. The sub DP distances were initialized at the start of next partitions; therefore, accumulative distances were also initialized and the total DP distance

was prevented from becoming excessively large. It was effective in reducing false rejection. Also, the spDP matching reduced false acceptance since limitation of combination in matching excluded inappropriate matching pairs.

In the threshold equalizing, by approximating the relation between the number of sampled data in a signature and its optimal threshold by linear or nonlinear functions, the variation range of optimal thresholds of all signatures were suppressed and as a result, it prevented the verification performance from being degraded by using a single common threshold for all signatures.

In experiments using a part of the signature database: SVC2004, it was confirmed that each proposed method was efficient in improving the verification performance. Moreover, combining the spDP matching with the threshold equalizing was more effective and reduced the error rate by about 5% comparing with the general-used DP matching.

We have an issue that there might be more effective approximate functions for threshold equalization. Also, we evaluated signature's complexity by using the number of sampled data but it is expected to use sub-band signals for evaluating the complexity.

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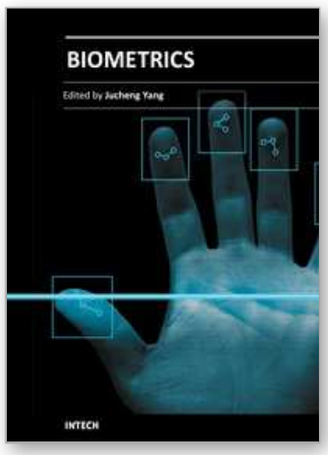

Biometrics

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Biometrics uses methods for unique recognition of humans based upon one or more intrinsic physical or behavioral traits. In computer science, particularly, biometrics is used as a form of identity access management and access control. It is also used to identify individuals in groups that are under surveillance. The book consists of 13 chapters, each focusing on a certain aspect of the problem. The book chapters are divided into three sections: physical biometrics, behavioral biometrics and medical biometrics. The key objective of the book is to provide comprehensive reference and text on human authentication and people identity verification from both physiological, behavioural and other points of view. It aims to publish new insights into current innovations in computer systems and technology for biometrics development and its applications. The book was reviewed by the editor Dr. Jucheng Yang, and many of the guest editors, such as Dr. Girija Chetty, Dr. Norman Poh, Dr. Loris Nanni, Dr. Jianjiang Feng, Dr. Dongsun Park, Dr. Sook Yoon and so on, who also made a significant contribution to the book.

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