MVA2002 IAPR Workshop on Machine Vision Applications, Dec. 11-13, 2002, Nara-ken New Public Hall, Nara, Japan

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A method of writer verification without keyword registration using feature sequences extracted from on-line handwritten sentences

Hiroshi Kameya* Shunji Mori* Ryuichi Oka*
Graduate School of Computer Science and Engineering
University of Aizu

Abstract

The paper proposes a method of writer verification based on a spotting method called CDP (Continuous Dynamic Programming). The method has more advantageous aspects over conventional methods; 1) no keyword registration in advance except that a user writes a sentence-like sequential pattern of stroke, 2) acceptance of any segment of the above pattern as an input for writer verification. The used and evaluated features of sequence pattern are five kinds, that is, x, y, pressure, azimuth and altitude extracted from on-line writing sentences on a tablet. The paper shows several experiments to investigate those of performance of the method, the best selection of feature combination and determination of essential parameters to realize a verification system, which hits almost 100% correct rate of writer verification.

1 Introduction

Person verification is highly required as cellar phone and broadband network are commonly used.

In real life, we can verify a person by seal impression, face, signature, voice and fingerprint. Verification based on biometrical measurement is called as biometrical verification. Writer verification is variously studied with improvement of electronic device [1][2][3]. For example, Zimmermann et al. researched verification method using their electric pen[4]. Jin et al. reported verification experiment using their developed pen, which can measure writing pressure, writing velocity and grasp pressure[5]. Kikuchi et al. constructed verification experiments with their developed speedy and high sensitive pen system for writing pressure[6]. Yamanaka et al. experimented signature verification with combination pen slant information and conventional information such as location and pressure[7]. Ando et al. conducted verification experiment with writer's own features extracted from handwriting by GA[8]. Komiya et al. proposed an algorithm for pen-input online signature verification incorporating pen-position, pen-pressure and pen-inclinations trajectories[9].

Signature verification is popular because signature is supposed to be stable identification feature because we get accustomed to writing our name. However, signature is not always stable. Our past research shows that there is considerable variance in subjects' signatures[10]. Verification method, which is with various patterns more than signature, is required.

This paper proposes a new verification method with CDP[11](Continuous Dynamic Programming) for long pattern. There are a few merits against conventional signature verification. 1) Writing pattern is not limited in content, length, font, language and so on. 2) Keyword for verification doesn't have to be registered beforehand. 3) A part of registered pattern as an input pattern can be verified.

We test out the proposed method by some experiments with data set of Japanese sentences and English sentences. The best verification rate achieves 100% when the feature for verification is suitably selected and threshold is tuned to each individual.

*Address: Tsuruga, Ikki-machi, Aizu-Wakamatsu City Fukushima, 965-8580 Japan. E-mail: d8021102@u-aizu.ac.jp, s-mori@u-aizu.ac.jp, oka@u-aizu.ac.jp

2 Concept of the Proposed Method

The proposed method makes users can verify themselves by inputting keyword pattern. Once they register a sentence-like sequential pattern, they can have many acceptable patterns. If the sentence-like pattern is enough long, the number of the acceptable patterns achieves infinity. Therefore, the proposed method is convenient for them who would like to be verified.

Figure 1 shows the concept of the proposed method. The top row in the figure means the reference pattern. The second row shows the feature, which is the writing pressure in this case, of the reference pattern. The proposed method can verify a person by many acceptable patterns instead of one signature pattern. We don't have to register many keywords as reference pattern. We just have to register sentence-like long pattern as a reference pattern. The reference pattern shows the identification model of a person, which is transformed into feature vector sequence by feature extraction algorithms. The reference pattern is independent from both its contents and language. The proposed method uses many patterns as acceptable input patterns. The number of possible acceptable patterns is

$$M = \sum_{k=k_0}^{N} (N-k+1), \tag{1}$$

where N means the frame number of the reference pattern and the k_0 means the minimum frame number of the acceptable pattern. For example, when $N = 100$ and $k_0 = 5$, the acceptable patterns are 4656 patterns. Therefore, the longer the reference pattern is, the more the acceptable pattern increases.

Distance between an input pattern and the reference pattern is evaluated by CDP. CDP is well-known

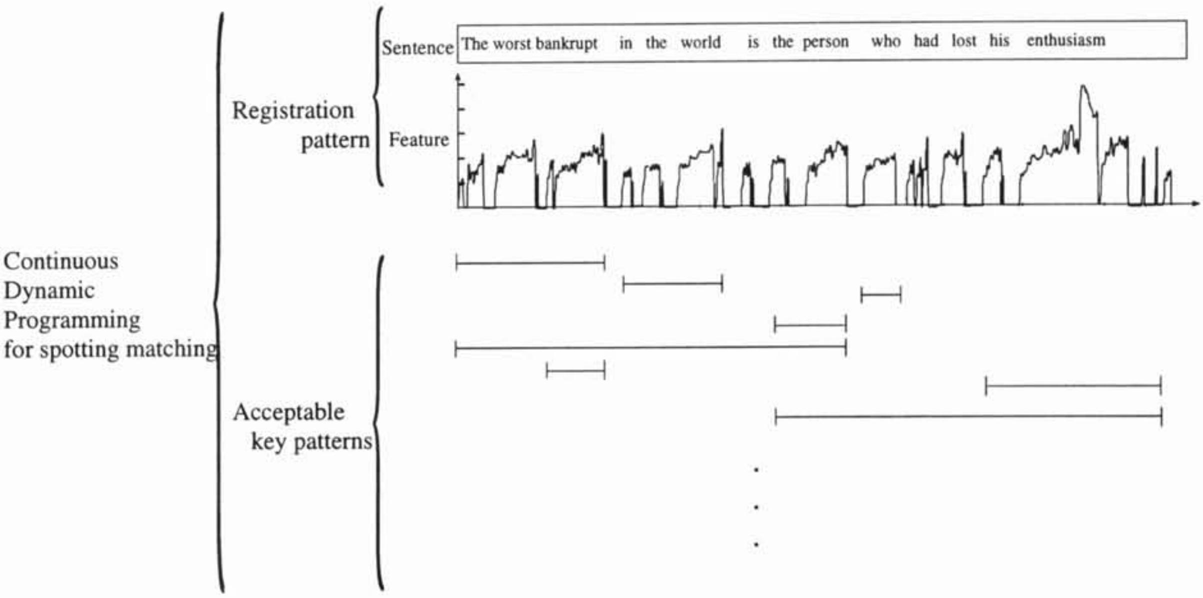


Figure 1: Concept of the proposed method for writer verification without keyword registration.

spotting method, which can simultaneously extract the important part from all input pattern and recognize it. The CDP value is outputted at each frame. A local dip in CDP output stream appears only when the end of the input pattern reaches the one of the acceptable pattern. If the minimum value in the local dip is less than threshold, the input pattern is verified as genuine pattern.

3 Feature for Verification

The raw data available from our tablet (WACOM intuos2 i-920) consists of five time series data.

1. Pen location $x(t_i)$.
2. Pen location $y(t_i)$.
3. Pen pressure $p(t_i)$.
4. Pen azimuth $az(t_i)$.
5. Pen altitude $al(t_i)$.

Here, t_i is the i-th time in time series. $az(t_i)$ and $al(t_i)$ specify the rotation of the pen with respect to the tablet as shown in Fig.2. $az(t_i)$ is the clockwise rotation of the pen about the z-axis though a full circular range. $al(t_i)$ is the angle with the x-y plane through semicircular range.

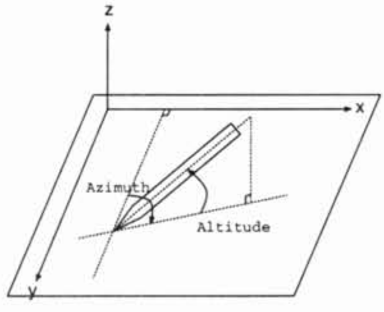


Figure 2: Data from tablet.

The pen location data is varied by the change of the start point in writing. Therefore, we use the differential data to eliminate the variation instead of the raw location data.

$$\Delta x_i = x(t_i) - x(t_{i-1}), \tag{2}$$

$$\Delta y_i = y(t_i) - y(t_{i-1}). \tag{3}$$

These differential data are normalized that the mean is zero and the standard deviation is one.

$$\Delta x_i^* = \frac{\Delta x_i - \mu_{\Delta x}}{\sigma_{\Delta x}}, \tag{4}$$

$$\Delta y_i^* = \frac{\Delta y_i - \mu_{\Delta y}}{\sigma_{\Delta y}}. \tag{5}$$

The writing pressure data is normalized so as to range from zero to one in the following equation.

$$p^*(t_i) = \frac{p(t_i) - \min_{t_i} p}{\max_{t_i} p - \min_{t_i} p} \tag{6}$$

We use the raw rotation data without normalization. Because these information are based on difference in physical structure of hand which grasps a pen.

As a result, our feature for verification consists of the following data.

$$\Delta x_i^*,\ \Delta y_i^*,\ p^*(t_i),\ az(t_i),\ al(t_i) \tag{7}$$

4 The Proposed Method

4.1 Continuous Dynamic Programming

A test pattern with T frames is represented by

$$Z = \{\mathbf{z}_\tau | 1 \leq \tau \leq T\}. \tag{8}$$

The feature vector z_τ is

$$\mathbf{z}_\tau = (z_\tau(1),\ z_\tau(2),\ \cdots,\ z_\tau(N)), \tag{9}$$

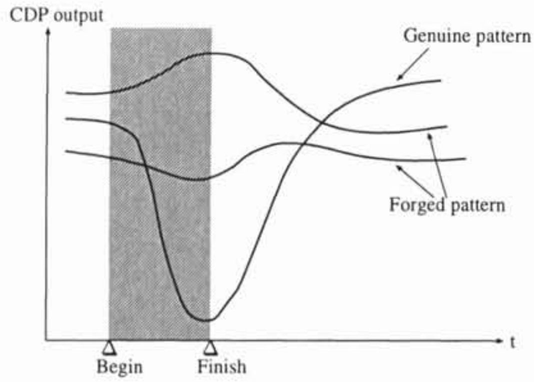


Figure 3: Output peculiarity of CDP.

where the dimension is N. Also, a feature vector u_t $(0 \leq t < \infty)$ is given from a reference pattern. Then, the local distance $d(t, \tau)$ between u_t and z_τ is defined by

$$d(t,\tau) = \sqrt{\sum_{k=1}^{N} (u_t(k) - z_\tau(k))^2}. \tag{10}$$

Here, t means the time axis of the reference pattern and τ means the axis of the test pattern and the reference pattern. When the accumulative distance $S(t, \tau)$ at (t, τ) is computed by the following step.
Initial Condition:

$$S(-1,\tau) = S(0,\tau) = \infty \tag{11}$$

Iteration ($t = 1, 2, \cdots$):
For $\tau = 1$

$$S(t,1) = 3 \cdot d(t,1) \tag{12}$$

For $\tau = 2$

$$S(t,2) = \min \left\{ \begin{array}{l} S(t-2,1) + 2 \cdot d(t-1,2) + d(t,2) \\ S(t-1,1) + 3 \cdot d(t,2) \\ S(t,1) + 3 \cdot d(t,2)) \end{array} \right. \tag{13}$$

For $3 \leq \tau \leq T$

$$S(t,\tau) = \min \left\{ \begin{array}{l} S(t-2,\tau-1) + 2 \cdot d(t-1,\tau) + d(t,\tau) \\ S(t-1,\tau-1) + 3 \cdot d(t,\tau) \\ S(t-1,\tau-2) + 3 \cdot d(t,\tau-1) + 3 \cdot d(t,\tau) \end{array} \right. \tag{14}$$

Assume that $\tau = T$, $S(t, T)$ shows the accumulative distance when the section of the test pattern between $\tau = 1$ and $\tau = T$ is optimally matched with the reference pattern. The CDP output is defined by the accumulative distance, which is normalized by the length of the test pattern.

$$A(t) = \frac{1}{3 \cdot T} S(t,T). \tag{15}$$

Therefore, $A(t)$ is not affected by the frame number of the test pattern.

If a forger gives a test pattern, the CDP output is shown like Fig.3. The only CDP output with genuine pattern shows a dip around the terminative time of the verification key pattern from the reference pattern.

Table 1: Experimental data in our research.

Data	Content
Eng01	The man who makes no mistakes do not usually make anything.
Eng02	The worst bankrupt in the world is the person who had lost his enthusiasm.
Jpn01	会津大学コンピュータ理工学部 (Aizu daigaku konpyu-ta rikougakubu 画像処理学講座 gazou shorigaku kouza)
Jpn02	朝あけて船より鳴れる (asa akete hune yori nareru ふとぶえのこだまは流しなみよろう山 hutobue no kodama ha nagasi namiyorou yama)
Jpn03	海ならずたたへる水の底までも (umi narazu tataheru mizu no soko mademo 清き心は月ぞ照らさむ kiyoki kokoro ha tuki zo terasamu)

5 Experiments

We conducted verification experiments to elucidate the effectiveness of our method. This section shows the detail of our experiments.

5.1 Experimental Data

The experimental data, which consisted of the genuine pattern and forged pattern, was taken from eleven individuals. The experimental patterns are shown in table 1. Five individuals writes the two genuine pattern for reference and test, and imitates other's pattern as forged pattern. The other seven individuals write forged patterns for the five individuals. Moreover, the test patterns are those, which are extracted from the experimental patterns using writing pressure information.

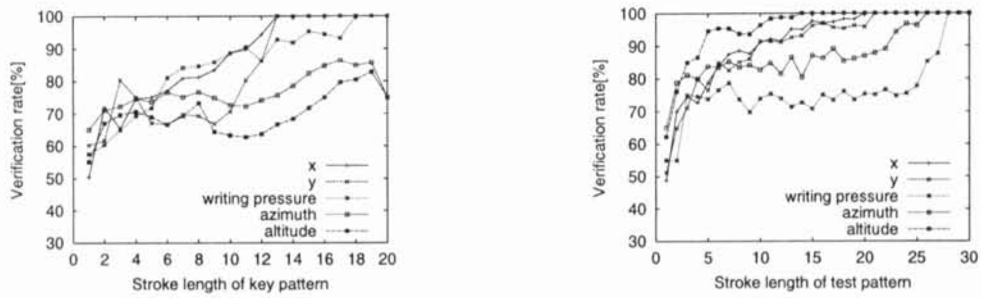
We assume that the pen tip doesn't touch the tablet when the writing pressure is less than 8. We define stroke as the sequence of data when the pen tip touch the tablet.

5.2 Experiment 1

We carry out experiments to investigate which feature is the best for verification. Figure 4 shows the verification rate with English sentences. Both graphs reveal that the verification rate is getting better as the length of test pattern is increasing. The verification rates by x, y and writing pressure information with Eng01 are more than 90% when the length of test pattern is up to 13 strokes. The test patterns of Eng02 are verified at more than 90% by x, y and altitude information. Writing pressure information is very effective in Eng02. But it isn't in Eng01. These results summarize that x and y information is important feature for verification.

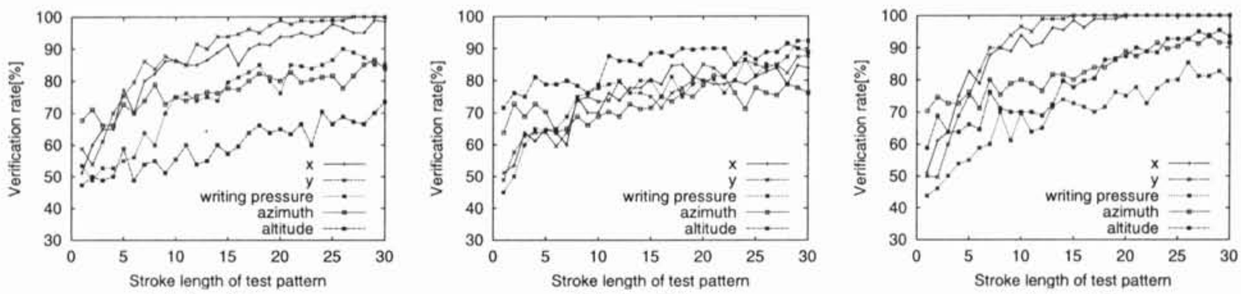
5.3 Experiment 2

The verification rates in Jpn01, Jpn02 and Jpn03 show in Fig.5(a)(b)(c). These results also reveal that x and y information are useful feature for verification.



(a) Eng01 (b) Eng02

Figure 4: Verification rate in (a)Eng01 and (b)Eng02.



(a) Jpn01 (b) Jpn02 (c) Jpn03

Figure 5: Verification rate in (a)Jpn01, (b)Jpn02 and (c)Jpn03.

Moreover, these disclose that the traditional writing pressure information isn't always effective.

The result shows that the relation between pattern and effective feature information is not clear.

5.4 Experiment 3

We do experiments to examine whether the verification performance by more than two features information is better than by one feature. We use the following combination(x and y, x and writing pressure, y and writing pressure, x and altitude, y and altitude, writing pressure and altitude) because x and y information are almost good performance for verification; writing pressure information is traditional; altitude is most effective in Eng02 and Jpn02 in experiment 1 and 2.

The integrated feature vector $\mathbf{z}_\tau$ is defined by

$$\mathbf{z}_\tau = (\alpha \cdot a, (1-\alpha) \cdot b), \tag{16}$$

where $\alpha \in [0.1, 0.9]$ means the coefficient of integration, and a and b represent the feature information such as x, y and so on. Moreover, we define local difference as

$$d(t,\tau) = 1.0 - \frac{\mathbf{u_t} \cdot \mathbf{z}_\tau}{||\mathbf{u_t}|| \, ||\mathbf{z}_\tau||} \tag{17}$$

instead of Eq.9.

In this experiment, the length of test pattern is set to five strokes. Because the above-mentioned result shows the tendency, which the verification rate is getting better as the length of test pattern, is increasing. When the length is up to 20 strokes, the verification is almost perfect. Therefore, we conduct experiments with short test pattern. The verification rates with Eng01 and Eng02 are shown in Fig.6(a) and (b). The verification with writing pressure and altitude is best in Eng01. Moreover, the integrated feature, which includes altitude information, is effective for verification. Also, the verification rates by the feature information related altitude are more than 90% in Eng02.

Figure 7(a)(b)(c) shows the experimental result in Jpn01, Jpn02 and Jpn03. The verification rates with altitude information are better more than with other features. However, the performance with writing pressure information is bad. This shows that the altitude is important feature in verification.

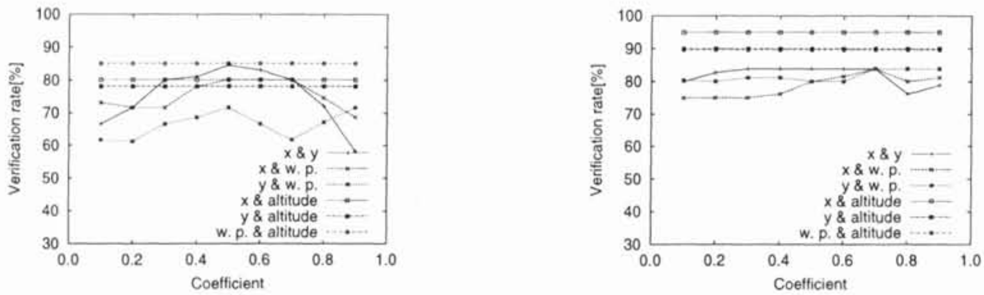
The verification by x and y information is unstable when the coefficient of integration is changing. However, when the coefficient is 0.5 so that the weights against the two features are same, the verification rate is good.

5.5 Experiment 4

The proposed method can accept many patterns as test pattern only with registering sentence-like long pattern. To confirm the flexibility, we investigate the relation between the minimum frame number k_0 in Eq.1 and the verification rate. The experimental condition is same as Experiment 3. However, the coefficient for feature integration is 0.5. Figure 8 illustrates the verification rate in Eng02 when the minimum frame number k_0 is changing from one to thirty. The verification rate amount to about 100% at $k_0 = 5$. Then, the possible acceptable pattern is 351 patterns though the reference pattern consists of 30 strokes.

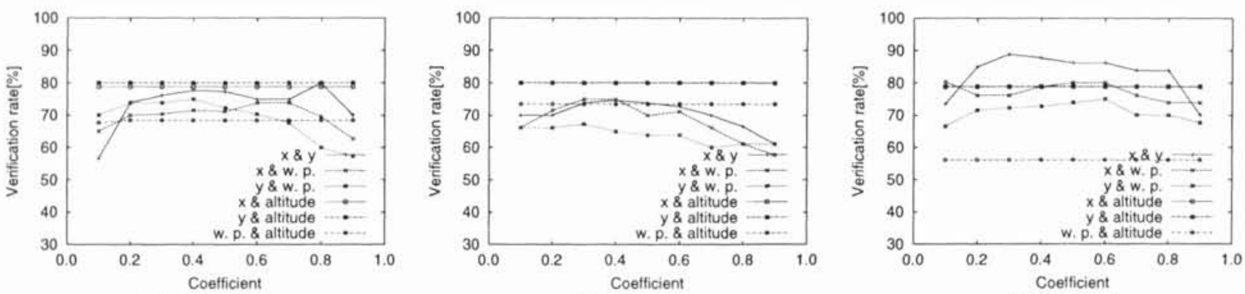
6 Conclusion

We have presented extensive experimental results on writer verification using feature sequenced of on-line handwritten sentence. In spite of no keyword registration, we found that many test patterns are correctly verified. We show that the verification rate improved by the integrated feature such as x and altitude, and y and altitude more than by the single information.



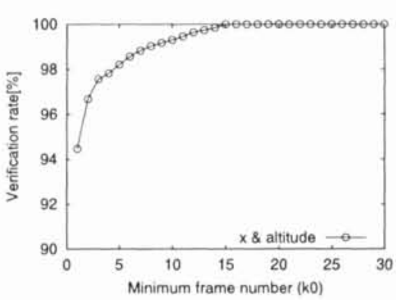
(a) Eng01 (b) Eng02

Figure 6: Verification rate in (a)Eng01 and (b)Eng02. The "w.p." in figure means writing pressure.



(a) Jpn01 (b) Jpn02 (c) Jpn03

Figure 7: Verification rate in (a)Jpn01, (b)Jpn02 and (c)Jpn03. The "w.p." in figure means writing pressure.



Eng02

Figure 8: Verification rate in Eng02 when the minimum frame number k_0 is changing.

In most of applications, the pattern for verification is usually varying in length, language, kind and content. We would like to investigate a more advanced method for further applications.

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