Text-indicated Writer Verification Using Hidden Markov Models

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Abstract

We propose an HMM-based text-indicated writer verification method, which is based on a challenge and response type of authentication process. In this method, a different text including ordinary characters is used on every occasion of verification. This text can be selected automatically by the verification system so as to reflect a specific writer's personal features. The specific writer is accepted only when the same text as indicated by the verification system is inputted, and the system can verify the writer's personal features from the inputted text. Moreover, the characters used in the verification process can be different from those in the enrollment process. This method makes it more difficult to get away with forged handwriting than the previous methods using only signatures. In the proposed method, the characteristics of the indicated text and each writer's personal features are both represented by using Hidden Markov Models.

1. Introduction

In this paper, we focus on an identity verification scheme based on on-line handwriting information. Most of the recent research focus on signature verification, especially in the field of on-line writer verification[1,2,3]. However, signature verification has the serious problem of forged handwriting, because the same signature is used in both the enrollment process and verification process. To deal with this problem of forged handwriting, we introduced a text-indicated writer verification method, which is based on a challenge and response type of authentication process[4]. In the proposed method, a writer is accepted only when the same text as indicated by the verification system is inputted, and also the system can verify the writer's personal features from the inputted text. A different text is selected automatically as the indicated text on every occasion of verification by the system so as to reflect the writer's personal features. Moreover, the indicated text includes ordinary characters and the characters used in the verification process can be different from those in the enrollment process. These characteristics make it more difficult to get away with forged handwriting than the previous methods using only signatures. However, in the proposed method, there is a problem that various recognition techniques are introduced to realize the text-indicated writer verification. For example, VQ (Vector Quantization)[5] is used for classifying the shapes of handwritten characters, and DP (Dynamic Programming) matching for comparing the indicated text with the inputted text, and LVQ (Learning Vector Quantization)[6] for extracting personal features. This complicatedness makes it difficult to evaluate the overall reliability of the proposed method.

To overcome the above problem, we propose an HMM-based text-indicated writer verification method. In the proposed method, most of the recognition tasks are integrated by using the Hidden Markov Models and both the shapes of handwritten characters and each writer's handwritten features are represented more concisely than the previous method.

2. Text-indicated writer verification

The proposed writer verification method is based on a challenge and response type of authentication process. We call it a text-indicated writer verification method[4] (see Fig.1). In the method, writer verification is carried out as follows:

(1) A writer sends his ID(i) to the verification system.
(2) The system generates a random number RAND and text T_x by using text generation function $\boldsymbol{T}$ with parameters RAND and ID(i). The generated text is selected so as to reflect the feature of writer i. Next, the system indicates generated text T_x to the writer.
(3) The writer inputs his handwritten version of indicated text T_x. We have defined K_i as the feature parameter representing the unique features of writer i, and $\boldsymbol{f}$ as the function giving the personal features of his handwriting. T'_x, the text inputted by writer i, is given

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as follows: $T'_x = \boldsymbol{f}(K_i, T_x)$.

(4) The system recognizes characters of text T'_x and judges whether T_x and T'_x are the same. If they are, the writer verification process (5) is executed. Otherwise, the verification process terminates and rejects the writer as not being the specified writer.

(5) Function $\boldsymbol{g}$ discriminates the writer by referring to the handwriting information of the inputted text. The system judges whether the values of $\boldsymbol{g}(T'_x)$ and ID(i) are the same. If so, the claimed writer is accepted. Otherwise, the claimed writer is rejected.

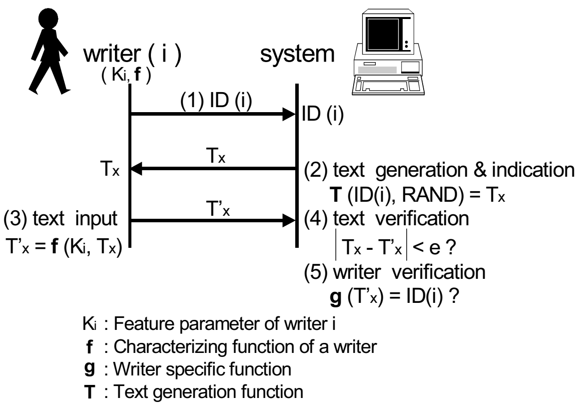

Figure 1. Text-indicated writer verification

3. Enrollment and verification process

In this section, we have described the enrollment and verification processes of the HMM-based text-indicated writer verification method. In the following subsections, we will explain the enrollment and verification process (see Fig.2).

3.1 Enrollment process

3.1.1 Preprocess

Handwriting information is taken from a tablet and a set of feature vectors is produced. First, one stroke (i.e., when a pen is in contact with the tablet) is extracted from handwritten data after eliminating duplicate points where there is no hand movement. The stroke has a sequence of two-dimensional pen-position data in the form of (x_i, y_i), which denotes a sequence of sampled points on the tablet. Second, a set of pen-position data is resampled to form N kinds of two-dimensional mean vectors (feature vectors), which represent the approximate direction of the pen movement within a stroke.

3.1.2 Categorization

The feature vectors are classified into M kinds of categories by referring to category HMMs. The category HMM is a kind of continuous HMM, where the emission probability of a feature vector in a state of the HMM is modeled with a mixture of Gaussians. The category HMMs represent the shapes of handwritten strokes and are produced by using another set of feature vectors as follows. First, the feature vectors are classified into M kinds of categories by referring to templates using vector quantization method. In the proposed method, these templates are prepared in advance by applying the LBG algorithm[5] to another set of feature vectors. Next, category HMMs are produced using the Baum-Welch algorithm[7], where one category corresponds to one category HMM and the classified feature vectors are used as initial values of parameters for each category HMM.

3.1.3 HMM training

A set of writer HMMs is produced by using the classified feature vectors during the Baum-Welch HMM training. The writer HMMs represent each writer's personal features in handwriting. In the proposed method, each category HMM is used as the initial model of the corresponding writer HMM to be trained.

3.2 Verification process

3.2.1 Text verification

A decision is made whether the writer has inputted the same handwritten characters as the system requested by performing character recognition of the inputted text. It should be noted that the same feature vectors are used in this text verification process as in the writer verification process. When the inputted text is different from the indicated text, the writer will be rejected. The inputted text is compared with the indicated text by each character as follows. First, category HMMs are concatenated according to the writing order information regarding a character in the indicated text. For example, when a character consists of those strokes which correspond to category 1,2, and 5 according to the writing order, No.1, No.2, and No.5 of the category HMMs are selected and concatenated. Here, the writing order is examined in advance for each character in the indicated text. Next, the likelihood for the concatenated category HMMs for the given character (inputted character) is calculated. When the calculated value is larger than the preset threshold value, it is decided that the indicated character was correctly inputted by the writer. The same process is repeated for all characters in the indicated text and the final decision is made whether the inputted text is the same as the indicated text.

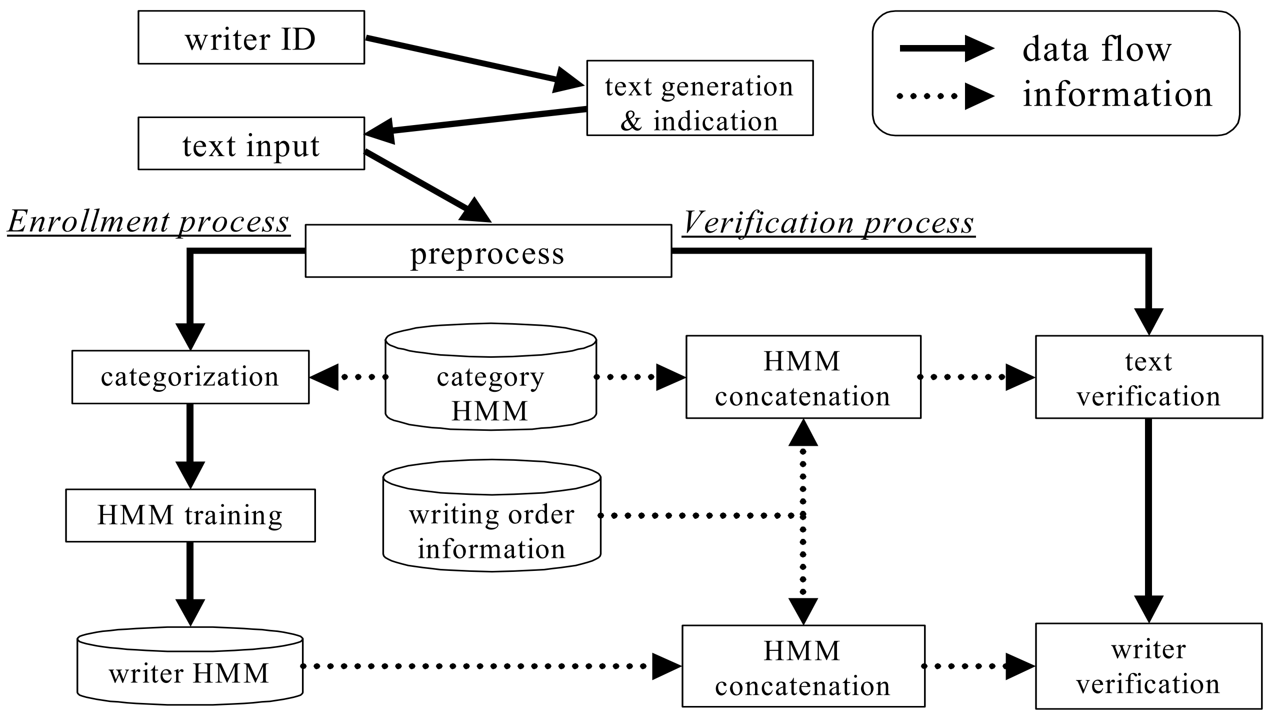

Figure 2. Enrollment and verification process of HMM-based text-indicated writer verification

3.2.2 Writer verification

The writer is verified based on the inputted text. The writer verification process is similar to the preceding text verification process. First, writer HMMs are concatenated according to the writing order information regarding a character in the inputted text. In this process, writing order is obtained by giving a sequence of feature vectors formed from the inputted character to the category HMMs. Next, the likelihood for the concatenated writer HMMs for the given character (inputted character) is calculated. When the calculated value is larger than the preset threshold value, the writer is accepted. The same process is repeated for all characters in the inputted text and the final decision is made whether the writer is accepted or not.

4. Reliability test

In this section, the reliability of the proposed method is shown with simulation results.

4.1 Data description

In the proposed method, it is important to ascertain how efficiently each category can represent many handwriting characteristics without missing any personal features. We use a set of *Kanji* characters (Chinese-Japanese characters) as the text in the reliability test, because the writers are accustomed to using *Kanji* characters in their daily life. In the reliability test, we used two kinds of text. One is the text for making category HMMs, and the other for writer HMMs. In this paper, the former is called the 'codebook text' and the latter the 'experimental text'. A codebook text consists of 400 characters which were selected from the top part of the frequency list of *Kanji* characters used in a major Japanese newspaper[8]. Each of the 20 writers wrote 20 different characters to compile the codebook text. On the other hand, 13 writers wrote 22 characters which represent part of a Japanese address, and repeated this writing process seven times to compile the experimental text. Namely, the experimental text consists of 154 characters. We selected 77 characters from the experimental text and used them as training data. On the other hand, the remaining 77 characters were used as test data (see Table 1). It should be noted that the training data are different from the test data. Here, all handwritten data were gathered using a standard digitizing tablet with a spatial resolution of 1000 points/in and a sampling rate of 205 samples/s.

Table 1. Text for the reliability test

Training data	早稲田大学理工学部電子	X (7 times)
Test data	情報通信学科小松研究室	X (7 times)

4.2 Parameter description

Parameters for the reliability test are shown in Table 2. These parameters were chosen, based on the results of a preparatory experiment, so as to achieve stable extraction of personal features.

Table 2. Parameters for the reliability test

Type of HMM	Left-to-right
Type of pdf	Gaussian mixtures
Number of states (N)	4
Number of mixtures	4
Number of categories (M)	16

4.3 Experimental results

Table 3 shows the EER (Equal Error Rate) for text verification and writer verification. For text verification, FRR (False Rejection Rate) is defined as the error rate in which the system cannot recognize characters inputted by a writer, otherwise FAR (False Acceptance Rate) is defined as the error rate in which the system recognizes characters inputted by a writer as different ones. From the simulation results, we could obtain an EER of 28% in which the verification threshold was set to the intersecting point of the curve FRR and FAR. These results show that character recognition can be performed by using the category HMMs. For writer verification, on the other hand, FRR is the rate of incorrectly rejecting a genuine writer, and FAR is the rate of accepting a wrong writer. In the reliability test, any writer wrote three different characters which were selected from the test data. The recognition system automatically selected the characters which contained a specific writer's features. The test results are shown in Table 3 with the label named 'with text indication'. Also, the results from a writer writing the whole characters of the test data, are shown with the label named 'without text indication'. Comparing the results referred to as 'with text indication' and 'without text indication', the former results are superior to the latter. These results suggest that the method of selecting and indicating characters which contain personal features is effective.

Table 3. Experimental results

	Equal Error Rate (%)
Text verification	28
Writer Verification	33 (without text indication) 19 (with text indication)

5. Conclusion

In this paper, aiming for further reliability of on-line writer verification, we have introduced an HMM-based text-indicated writer verification which can indicate any kind of text including ordinary characters for writer verification. We also have shown the reliability of the proposed method by presenting some simulation results using handwritten data. Our further research may involve the determination of appropriate thresholds for the text verification and the writer verification, and the suitable method for selecting an indicated text.

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