Off-line Writer Verification Using Shape and Pen Pressure Information

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***Abstract*—This paper proposes an off-line writer verification method which uses a new hybrid feature. The characteristics of this new feature are the combination of shape and pen pressure information. For shape information, we use the Weighted Direction code Histogram (WDH), which is often used in Japanese handwriting recognition and writer verification methods. For pen pressure information, we use the texture features of infrared (IR) images obtained from a multi-band image scanner. Although the simple use of pen pressure information encoded in the infrared image can not improve verification error rate, the use of second order statistics and the clipping process can decrease the verification error rate from 4.8% to 3.7%.**

***Keywords*-off-line writer verification; pen pressure; infrared image; cost-sensitive learning; geometric mean; support vector machine;**

I. Introduction

Handwriting is an important means of communication and is used to record information in everyday life. The handwritten characters reveal specific traits of one's personality. There are many applications that automatically recognize handwriting. Amongst these applications, personal identification [1] requires highly accurate identification performance, and extensive studies have been carried out [2]–[4].

Writer verification methods can be categorized into two types: on-line methods and off-line methods. In on-line methods, the dynamic information such as the pen location, speed, and pressures are used for the analysis. On the other hand, in off-line methods, only static information, i.e., the shape of the written characters, is used. Since the off-line method does not require any special instruments, a lot of methods for automated off-line writer verification have been proposed [2]–[4]. These off-line methods try to identify writers from the written image of simple instruments such as mechanical pencils, ball-point pens and felt-tip pens etc.

However, writer verification performance conducted by a computer is still far behind that of human beings. Srihari et al. [5] have described that their automated system has been shown to perform better than lay-persons but less than questioned document examiners (QDEs). Coetzer et.al. [6] describe that a combined system which used both a human and machine classifier can perform better than just humans or a machine alone. Since applications of writer verification (e.g, criminal investigations and trials) sometimes result in grave consequences, further research, to improve the performance of automated writer verification, is required.

One of the more promising approaches is the use of pen pressure and stroke information. QDEs use an optical microscope to extract dynamic hand movements such as pen pressure even if they have been given information acquired using an off-line method [7].

In this study, we use an infrared (IR) image obtained by a multi-band image scanner to acquire the pen pressure and stroke information. Although the simple use of pen pressure information encoded in the IR image can not improve the verification error rate, the use of second order statistics and the clipping process can decrease the verification error rate from 4.8% to 3.7%.

The rest of this paper is organized as follows. First, Section II summarizes past research on off-line writer verification methods. Then, Section III proposes a method for writer verification using shape and pen pressure information. Section IV reports on the experimental results, Section V summarizes our findings.

II. Related works

Off-line writer verification methods mainly use shape information. Here, shape information is extracted from static images obtained by ordinal image scanners. To extract the feature of shape information, the Weighted Direction code Histogram (WDH) [8] is used, it is a popular feature in Japanese character recognition and writer verification systems [9].

To improve verification accuracy, recent research has attempted to use pseudo-dynamic information in off-line writer verification systems. The temporal order of stroke production is used in [10]. Stroke thickness, and intensity variation are used in [11].

In our study, we use new pseudo-dynamic information based on pen pressure. Recently, Furukawa [7] proposed a

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model to extract accurate pen pressure information using a multi-band image scanner. We have also used a multi-band image scanner to extract pen pressure information. However, we used simple texture statistics [11]–[13] to express pen pressure information. We also show that second order statistics can decrease the error rate by expressing pseudo-stroke information.

III. Proposed method

A. Outline

To analyze the shape and pen pressure information of written characters, we have used a multi-band image scanner which scans the visible and IR images simultaneously. It uses an oblique IR light source to make shades from wrinkles on the sheets. Since the wrinkles were caused by the pen pressure, we can analyze pen pressure information from IR images. Visible images are used to analyze shape information.

Here, we assume that the ink used to write characters is IR-transmittable. The multi-band image scanner requires the IR-transmitting ink to obtain pen pressure information. Since IR-transmitting ink is commonly used for popular ball-point pens [7], this assumption is acceptable for our practical use.

Figure 1 shows the outline of the analysis. After digitizing the handwriting images, the common process to correct the position and rotation of written character images are applied. Simultaneously, we apply a moment-based character normalization method to reduce the shape variation within the same characters. Here, this moment-based character normalization can regulate the position of the character without deforming the structures. Then, the shape and pen pressure information are extracted from both the visible and IR images. Finally, the Support Vector Machine (SVM) is used to make classifiers using the shape and pen pressure information. The following subsections explain the details of sub-processes.

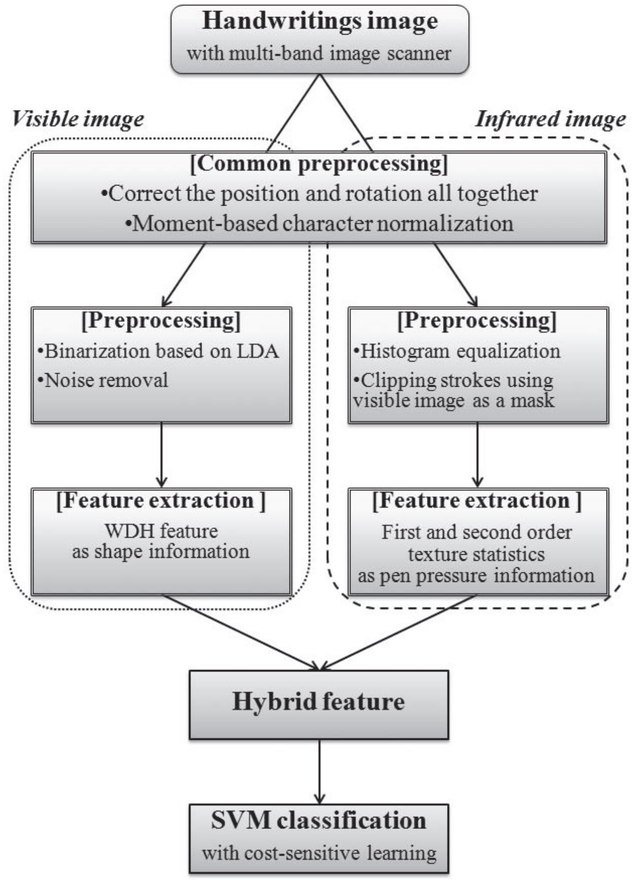

Figure 1. Outline of the Proposed Method

B. Shape Information from Visible Image

First, the gray-scale visible image scanned by the multi-band image scanner is converted into a binary-coded image. Linear discriminant analysis (LDA) is used to decide the threshold for the binary-coding [14]. The following techniques, smoothing filter and dilation of strokes are also applied to remove noise from the image.

After these preparations, we extract the WDH feature [8] from the visible image. WDH is a widely used shape feature in Japanese character recognition and writer verification systems [9]. Figure 2 shows the procedure to extract WDH features.

1) First, the contour tracking with 8-direction chain code is applied to the binary-coded image.
2) Then, the arithmetic mean of two-pair chain codes is taken to produce 16-directional codes.
3) The image is divided into 49 (7 horizontal $\times$ 7 vertical) blocks. The number of chain codes for each direction is counted in each block to produce 49 local direction code histograms.
4) The spatial resolution is reduced from 7×7 to 4×4 by down sampling every two horizontal and every two vertical blocks with a 5×5 Gaussian filter. Then, the directional resolution is reduced from 16 to 8 by down sampling with a weight vector $\begin{bmatrix} 0.5 & 1.0 & 0.5 \end{bmatrix}^t$.
5) The pair of opposite directions are combined into one direction (from 8 to 4 directional codes).
6) Finally, a feature vector of size 64 (4 horizontal $\times$ 4 vertical $\times$ 4 directional codes) is obtained.

C. Pen Pressure Information from IR Image

We have applied two preprocessing techniques on an IR image. 1) The original IR image is low contrast, and the shade intensity according to pen pressure is affected by the writing conditions such as the hardness of a desktop. To compensate for this difference, the histogram-equalization is applied to the IR image. 2) Slight wrinkles across the sheets

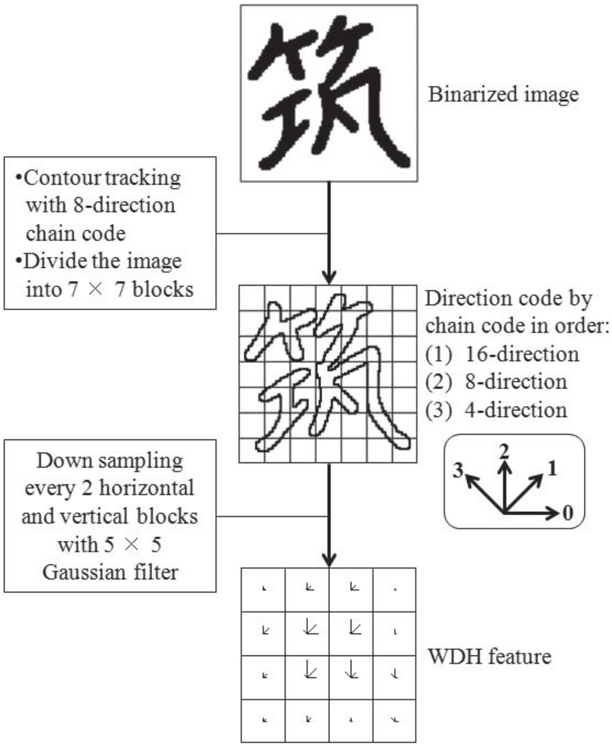

Figure 2. WDH feature of Visible image

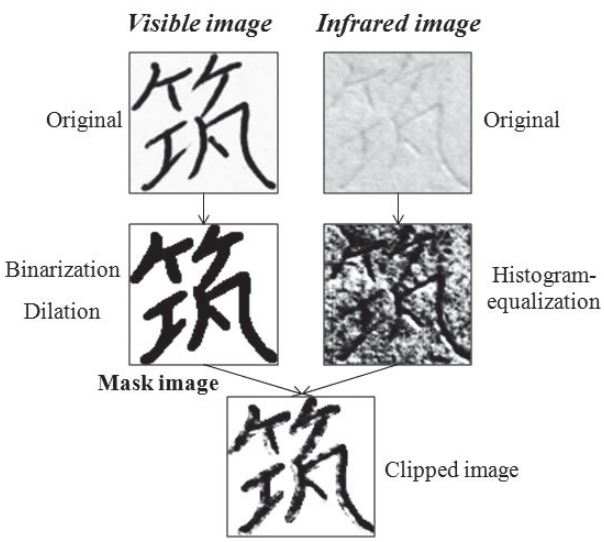

Figure 3. Clipping process of IR image

that contain the written characters make background noises, and disturb the analysis of pen pressure (See Fig. 3, right side examples). To remove the noise from these wrinkles, we use the dilationed visible image to clip the IR image. The dilationed visible image is used as the mask pattern to clip the IR image.

After the preprocessing mentioned above is done, we then extract pen pressure information from IR images. We use texture statistics which are widely used by many applications [11]–[13]. Here, the texture statistics can be categorized into first order, second order, and higher order statistics based on the number of the pixel combinations. In our study, first and second order statistics are used.

1) First order statistics: First order texture statistics depend on the histogram of each pixel values. We use the following six statistics:

$$\text{Mean } \mu = \sum_{i=0}^{L-1} ip(i) \tag{1}$$

$$\text{Variance } \sigma^2 = \sum_{i=0}^{L-1} (i-\mu)^2 p(i) \tag{2}$$

$$\text{Skewness} = \frac{1}{\sigma^3}\sum_{i=0}^{L-1} (i-\mu)^3 p(i) \tag{3}$$

$$\text{Kurtosis} = \frac{1}{\sigma^4}\sum_{i=0}^{L-1} (i-\mu)^4 p(i) \tag{4}$$

$$\text{Energy} = \sum_{i=0}^{L-1} \{p(i)\}^2 \tag{5}$$

$$\text{Entropy} = -\sum_{i=0}^{L-1} p(i) log_2\{p(i)\} \tag{6}$$

where $p(i)$ shows the probability of gray-level i ($0 \leq i \leq L-1$) of the image. Here, L is set to 256 in the experiments described in the next section.

2) Second order statistics: Second order texture statistics are calculated based on the Gray Level Co-occurrence Matrix (GLCM) [11]–[13]. The concept of GLCM is the analysis of the joint probability of gray-level i and j within a spatial relation of the image. Here, the spatial relation is defined with a distance d and an angle θ.

GLCM is represented in $G \times G$ matrix where G is the number of gray-levels in the image. If the image has an 8-bit gray level, GLCM is represented in a 256×256 matrix with a lot of zeros in the matrix. To reduce the calculating costs caused by this sparse GLCM matrix, we quantify the gray levels G from 256 to 8. After the calculation of the GLCM, we can obtain several statistics from it. In our study, we use the following five statistics:

$$\text{Energy} = \sum_{i=0}^{G-1}\sum_{j=0}^{G-1}\{p(i,j)\}^2 \quad (7)$$

$$\text{Contrast} = \sum_{i=0}^{G-1}\sum_{j=0}^{G-1}(i-j)^2 p(i,j) \quad (8)$$

$$\text{Correlation} = \frac{\sum_{i=0}^{G-1}\sum_{j=0}^{G-1} ijp(i,j) - \mu_x\mu_y}{\sigma_x\sigma_y} \quad (9)$$

$$\text{Homogeneity} = \sum_{i=0}^{G-1}\sum_{j=0}^{G-1}\frac{p(i,j)}{1+(i-j)^2} \quad (10)$$

$$\text{Entropy} = -\sum_{i=0}^{G-1}\sum_{j=0}^{G-1} p(i,j)log\{p(i,j)\} \quad (11)$$

where

$$\mu_x = \sum_{i=0}^{G-1} i \sum_{j=0}^{G-1} p(i,j)$$

$$\mu_y = \sum_{j=0}^{G-1} j \sum_{i=0}^{G-1} p(i,j)$$

$$\sigma_x = \sqrt{\sum_{i=0}^{G-1}(i-\mu_x)^2 \sum_{j=0}^{G-1} p(i,j)}$$

$$\sigma_y = \sqrt{\sum_{j=0}^{G-1}(j-\mu_y)^2 \sum_{i=0}^{G-1} p(i,j)}$$

and $p(i, j)$ is the probability of co-occurrence of gray-level i $(0 \leq i \leq G-1)$ and j $(0 \leq j \leq G-1)$ at distance d and angle θ. In this study, distance $(d = 1)$ and four angles $(\theta = 0°, 45°, 90°, 135°)$ are used. Finally, the feature vectors of 20 dimensions (5 statistics $\times$ 4 angles) are obtained.

Note that QDEs extract dynamic hand movements and stroke information even if they have given information acquired using the off-line method. Since the first order statistics only represent pen pressure information at each position, they do not seem to provide information on hand movements and stroke information. Second order information is used in our study to represent the correlation between pen pressure information generated by the stroke orders.

D. *Verification as an Imbalance Classification Problem*

For writer verification, we have to solve the 2-class classification (i.e., the writer of the character, and non-writer). In this study, we assume:

1) There is a set of characters written by an unknown suspected person.
2) There is also a labelled dataset of the same characters written by K candidate persons. The label shows the writer of the characters in the dataset. The unknown suspected person who wrote the first set of characters is one of the members of the K candidate persons.
3) The classifier will be trained using the labelled dataset. The trained classifier will be used to find the writer of the first characters.
4) The classification performance can be measured using the separate-validation test on the labelled dataset.

Since K is not small in practice (we use 54 as K in the experiments shown in the next section), the 2-class classification problem for the writer verification is extremely imbalanced.

1) Cost-sensitive learning with SVM: SVM is a popular machine learning method for classification. Geometrically, SVM constructs a separating hyper plane with maximal margins. To solve the imbalanced classification problem, we have applied the cost-sensitive learning method proposed in [15].

The idea proposed in [15] is the use of different penalty parameters. Given a set of labelled instances $X = \{\boldsymbol{x}_i, y_i\}_{i=1}^n$, a weight vector $\boldsymbol{w}$, a bias b, slack variable ξ_i, Lagrange multipliers $\{\alpha_i \geq 0\}$ and $\{r_i \geq 0\}$, positive error costs C^+, and negative error costs C^-, the Lagrangian to be optimized is:

$$\begin{aligned} L &= \frac{\|\boldsymbol{w}\|^2}{2} + C^+ \sum_{\{i|y_i=+1\}}^{n_+} \xi_i + C^- \sum_{\{i|y_i=-1\}}^{n_-} \xi_i \\ &\quad - \sum_{i=1}^{n} \alpha_i[y_i(\boldsymbol{w}\cdot\boldsymbol{x}_i + b) - 1 + \xi_i] - \sum_{i=1}^{n} r_i\xi_i \end{aligned}$$

where the constraints on α_i are:

$$\begin{cases} 0 \leq \alpha_i \leq C^+ \ (\text{if}\, y_i = +1) \\ 0 \leq \alpha_i \leq C^- \ (\text{if}\, y_i = -1) \end{cases}$$

C^+ and C^- are tuned using the simple grid search method in the experiments described in the next section.

2) Geometric mean: To evaluate the performance of classifiers on highly imbalanced datasets, we have used the following geometric mean (g-mean) proposed in [16]:

$$\begin{aligned} \text{sensitivity} &= \frac{TP}{TP+FN} \\ \text{specificity} &= \frac{TN}{TN+FP} \\ \text{g-mean} &= \sqrt{\text{sensitivity} \times \text{specificity}} \end{aligned}$$

where *TP, TN, FP,* and *FN* are “True Positive”, “True Negative”, “False Positive”, and “False Negative”, respectively. Finally, we calculate the g-mean based error rate (%) as follows:

$$\text{g-mean based error rate} = (1 - \text{g-mean}) \times 100$$

IV. Experimental Results

A. Settings of Experiments

To evaluate the performance of the proposed method, we have collected samples of Kanji-character strings. Figure 4 shows the Kanji-character strings we have collected. 54 volunteers who use Kanji-characters in daily life have provided samples. Each volunteer provided 20 different strings using ball-point pens with IR-transmittable ink which we had prepared. They were asked to write each character on a sheet which had pre-printed 1.1×1.1 cm cells on it. The volunteers were also asked to write the characters clearly.

20 sample strings from each volunteer are randomly split into 10 strings for the training and 10 strings for the test. With these independent test and training sets, we have evaluated character-based performance of the proposed method. Using each characters in the string for the training, 432 (i.e., 54 volunteers $\times$ 8 characters) SVM classifiers were trained so that each classifier can discriminate the character written by the assigned volunteer from other characters. Then g-mean based error rates are evaluated using the test sets.

Other details we have to mention are:

- The datasets are digitized with the multi-band image scanner at 300 dpi.
- RBF kernel $K(\boldsymbol{x}_i, \boldsymbol{x}_j) = e^{-\gamma \|\boldsymbol{x}_i - \boldsymbol{x}_j\|^2}$ was used as the kernel function of SVM.
- The parameters, i.e., error costs C^+, C^-, and RBF γ, were tuned using grid-search.

B. Results

1) Over All Performance: Figure 5 compares the g-mean based error rate of the proposed method with that of the WDH method. "WDH" indicates the results with WDH alone. "WDH+PP1,2" indicates the results with the proposed method, i.e., with WDH and first/second order statistics on pen pressure information. As shown in the figure:

- All the g-mean based error rates on each character decreases by using the pen pressure information.
- Averages of the g-mean based error rates decreases from 4.8% to 3.7%.

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Figure 4. Kanji Characters for the Experiments

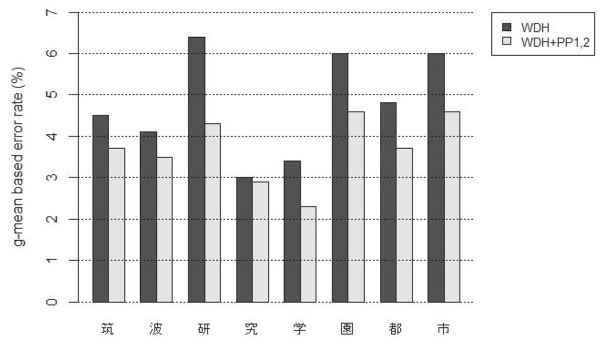

Figure 5. Comparison with WDH

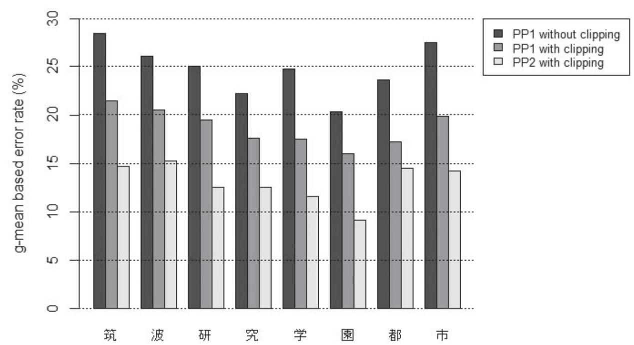

Figure 6. Effect of Clipping process and Second Order information

Thus we can confirm the effectiveness of the pen pressure information in the off-line writer verification methods.

2) Effect of Clipping and Second Order Statistics: The use of second order statistics and the clipping process are the concepts we employed to best use the pen pressure information. Figure 6 shows the effects of these ideas. It compares the g-mean based error rates among the first order statistics without the clipping process "PP1 without clipping", with the clipping process "PP1 with clipping", and the second order statistics with the clipping process "PP2 with clipping". Averages of the g-mean based error rates are 24.7%, 18.7%, and 13.0% respectively.

As shown in these results, the simple use of pen pressure information has room for improvement. The idea of second order statistics and the clipping process decreases the g-mean error rate of the proposed method.

V. Conclusion

In this study, we proposed a new off-line writer verification method. The characteristics of the proposed method are:

- Pen pressure information obtained by multi-band image scanner is used to improve verification error rate.
- Shape information expressed by the WDH and pen pressure information are the information used in the

proposed method.

- Experimental results show that the use of pen pressure information decreases the verification error rate from 4.8% to 3.7% on average.
- Although the simple use of pen pressure information could not improve the verification error rate, the additional use of second order statistics and the clipping process could decrease the verification error rate.

Since the study reported in this paper is our first attempt to improve the writer verification error rate using pen pressure information, there remains room for improvement. In shape information, the effort of other methods such as zoning technique [17] by considering dynamic topologies are worth examining to detect and exploit the most discriminating parts of the patterns. In pen pressure information, the effect of other features (e.g., wavelet transforms representation, local binary pattern, and texton) are worth examining. However, these actual investigations remain as future research issues.

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