Statistical Displacement Analysis for Handwriting Verification

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Abstract. In this paper, it is assumed that each writer has his or her own statistics of handwriting displacement, therefore a statistical displacement analysis for handwriting verification is proposed. Here, a regularization method with the coarse-to-fine strategy computes the displacement function in questionable handwritten letters, and then it is normalized to remove the noisy displacement that arises from the position drift and scaling variation. Finally, the normalized displacement function and the statistics of displacement obtained in advance from registered authentic letters are used to calculate the distance from a standard handwritten letter to a questionable one. A fundamental simulation was conducted in order to evaluate the performance of the proposed method.

1 Introduction

Handwriting is one kind of biometrics and has played a major role in proving documentary evidence. As shown in the review of Plamondon et al. [1], many researchers are involved with this topic. Until now, several groups have tried to measure distance or similarities between a registered signature and a questionable signature after computing the displacement contained in the questionable one. For instance, de Bruyne and Forre[2] devised a linear deformation method for signature verification and Naske[3] suggested a block matching method. Mizukami et al.[4] computed the non-linear displacement in questionable signatures based on March's regularization algorithm[5, 6], which has been successfully applied to handwritten character recognition[7].

After reviewing previous attempts, it was noted that most of the researchers and engineers have been computing a displacement in order to eliminate it, while human handwriting experts are focusing on analyzing the tendency of the displacement. In this study, therefore, we propose a statistical displacement analysis method for handwriting verification based on an assumption that each writer has his or her own statistics of handwriting displacement, such as its average and variance of displacement. The following sections describe the details of the proposed method, the simulation results and the conclusion.

2 Proposed Method

In the field of computer vision, March[6] suggested a regularization method for acquiring disparity in two stereo images. This study utilizes March's method and the coarse-to-fine strategy together to compute 2-dimensional displacements in questionable handwriting[4], normalizes the obtained displacement, and computes the distance based on the statistics of displacement to verify the questionable handwriting (See Fig. 1). In this section, first the computation of displacement with the coarse-to-fine strategy is described, and then the procedures for normalizing the computed displacement and measuring the distance are explained.

Fig. 1. statistics of displacement in handwriting

2.1 Displacement Computation Based on Coarse-to-Fine Strategy

The computation procedure of optimum displacement field between two isolated handwritten letters is described here. A handwritten letter is denoted as a binary image $f(x, y)$, where $1 \leq x \leq n_x$ and $1 \leq y \leq n_y$, another handwritten letter as $g(x, y)$. In the framework of regularization theory[5], the optimum displacement is given as a 2-dimensional functions $(u(x, y), v(x, y))$, which minimize the following functional $E(u, v)$,

$$E(u, v) = P(u, v) + \lambda S(u, v), \quad (1)$$

$$P(u, v) = \iint \{f(x+u(x, y), y+v(x, y)) - g(x, y)\}^2 dx dy, \quad (2)$$

$$S(u, v) = \iint \left\{ \left(\frac{\partial u}{\partial x} \right)^2 + \left(\frac{\partial u}{\partial y} \right)^2 + \left(\frac{\partial v}{\partial x} \right)^2 + \left(\frac{\partial v}{\partial y} \right)^2 \right\} dx dy, \quad (3)$$

where the functional $P(u, v)$ represents the difference between f and g with taking into account the displacement function (u, v) , the functional $S(u, v)$ represents the penalty of departure from smoothness in (u, v) and λ is a regularization parameter balancing them[8]. According to calculus of variation, the following Gauss-Seidel iterative equations give the optimum displacement function (u, v) ,

$$\begin{aligned} u^{[t+1]}(x, y) = & \bar{u}^{[t]}(x, y) - \frac{1}{4\lambda} \frac{\partial f(x + \bar{u}^{[t]}(x, y), y + \bar{v}^{[t]}(x, y))}{\partial x} \\ & \times \{f(x + \bar{u}^{[t]}(x, y), y + \bar{v}^{[t]}(x, y)) - g(x, y)\}, \end{aligned} \quad (4)$$

$$v^{[t+1]}(x, y) = \bar{v}^{[t]}(x, y) - \frac{1}{4\lambda} \frac{\partial f(x + \bar{u}^{[t]}(x, y), y + \bar{v}^{[t]}(x, y))}{\partial y} \\ \times \{f(x + \bar{u}^{[t]}(x, y), y + \bar{v}^{[t]}(x, y)) - g(x, y)\}, \quad (5)$$

where the subscript t stands for the number of iteration and $(\bar{u}, \bar{v})$ is an average of four neighboring (u, v) 's.

We describe the coarse-to-fine strategy, which is adopted to keep its solution from being trapped by local minima and compute the displacement function (u, v) efficiently. The number of layers for the coarse-to-fine strategy is assumed to be K and two images in the k -th layer is referred as f_k and g_k , where $1 \leq k \leq K$. Note that f_K and g_K represent the original images of two handwritten letters. By applying the smoothing filter with size of 3×3 pixels to both of f_k and g_k and sampling at regular intervals, the coarser images, f_{k-1} and g_{k-1} , are generated. The same procedure is repeated until f_1 and g_1 in the first layer are obtained. The computation of the displacement function begins at the first layer. The obtained results are used as the initial values in the next finer layer. Consequently, the displacement function (u, v) with the same size of the original images is acquired.

2.2 Normalization Procedure for Computed Displacement

As described in Section 1, the uniqueness of the proposed method is to compute the displacement function and analyze it for handwriting verification. Since the computed displacement does not only contain the individual tendency in handwriting but also the effects of the position drift and scaling variation, we should remove such kinds of noisy effects from the computed displacement. Most of previous studies normalized the pattern on the image so as to fit the specified outer frame, while this study proposed a displacement normalization procedure that estimates the position drift and scaling variation according to the computed displacement. The details of the proposed normalization are described below.

It is assumed that (u', v') is the displacement caused by handwriting f 's shift drift for g and that (z_x, z_y) is the horizontal and vertical scaling ratio of f for g , therefore the following equations are given,

$$u' = \frac{\sum g(x, y)u(x, y)}{n_p}, \quad (6)$$

$$v' = \frac{\sum g(x, y)v(x, y)}{n_p}, \quad (7)$$

$$z_x = \frac{n_p \sum g(x, y)u(x, y)x - \sum g(x, y)x \sum g(x, y)u(x, y)}{n_p \sum (g(x, y)x)^2 - (\sum g(x, y)x)^2} \quad (8)$$

$$z_y = \frac{n_p \sum g(x, y)v(x, y)y - \sum g(x, y)y \sum g(x, y)v(x, y)}{n_p \sum (g(x, y)y)^2 - (\sum g(x, y)y)^2} \quad (9)$$

where n_p is the number of pixels composing the handwriting g and given as $\sum g(x, y)$. We adopted a very simple idea, that is, if f has the horizontally

z_x -times scaled shape compared with g , the computed horizontal displacement $u(x, y)$ should increase with the gradient of z_x to x . The relationship of z_y and $v(x, y)$ is also the same as described here.

According to the obtained (u', v') and (z_x, z_y) , the normalized displacement function (U, V) is given as

$$U(x, y) = u(x, y) - u' - z(x - \frac{n_x + 1}{2}), \quad (10)$$

$$V(x, y) = v(x, y) - v' - z(y - \frac{n_y + 1}{2}), \quad (11)$$

where z is the average of z_x and z_y . It means that the 2-dimensional scaling ratio of f for g is determined by balancing the horizontal and vertical scaling ratio.

2.3 Statistical Displacement Analysis for Handwriting Verification

The method of obtaining the statistics of displacement and applying them for calculating the distance of the questionable handwriting (See Fig.1 again) are described. It is assumed that N registered authentic handwritings are available in advance and that the n' -th handwriting, $g_{n'}$, is used as a standard one, where $1 \leq n' \leq N$. The average displacement function (μ_U, μ_V) and the variance (σ_U^2, σ_V^2) are given with the following equations,

$$\mu_U(x, y) = \frac{1}{N} \sum_{n=1}^N U_{n,n'}(x, y), \quad (12)$$

$$\mu_V(x, y) = \frac{1}{N} \sum_{n=1}^N V_{n,n'}(x, y), \quad (13)$$

$$\sigma_U^2(x, y) = \frac{1}{N-1} \sum_{n=1}^N (U_{n,n'}(x, y) - \mu_U(x, y))^2, \quad (14)$$

$$\sigma_V^2(x, y) = \frac{1}{N-1} \sum_{n=1}^N (V_{n,n'}(x, y) - \mu_V(x, y))^2, \quad (15)$$

where $(U_{n,n'}, V_{n,n'})$ is the normalized displacement function obtained in the case that the n -th and n' -th registered handwritings are used as f and g , respectively.

In order to verify a questionable handwriting f , after obtaining the normalized displacement function between f and g , the statistical distance d_{DA} is calculated with the following equation,

$$\begin{aligned} d_{DA} = & \sum_{x,y} \frac{g(x, y)}{(1 - \alpha_{DA}) + \alpha_{DA} \sigma_U^2(x, y)} (U(x, y) - \mu_U(x, y))^2 \\ & + \sum_{x,y} \frac{g(x, y)}{(1 - \alpha_{DA}) + \alpha_{DA} \sigma_V^2(x, y)} (V(x, y) - \mu_V(x, y))^2, \end{aligned} \quad (16)$$

where α_{DA} is a parameter controlling the effect of (σ_U^2, σ_V^2) . By comparing the obtained distance d_{DA} with the advance-specified threshold d_{th} , the questionable handwriting is judged if it is genuine or not.

3 Simulation Results

In order to evaluate the performance of the proposed method, a fundamental simulation was conducted. One volunteer offered twenty authentic handwritten letters for registration, $G_{reg} = \{g_{reg,1}, \dots, g_{reg,20}\}$, and ten genuine handwritten letters for the evaluation, $F_{gen} = \{f_{gen,1}, \dots, f_{gen,10}\}$, while ten other volunteers also offered ten skillfully forged handwritten letters for the evaluation, $F_{fog} = \{f_{fog,1}, \dots, f_{fog,10}\}$. They were allowed to practice imitating one of the genuine handwritings and write a forged handwriting while looking at the genuine letter. Handwritings used in our experiment are a subset of the handwritten signature database produced in M. Yoshimura and I. Yoshimura's research[9]. The size of the image was 128×128 pixels. The horizontal and vertical widths of all the handwritten letters on the image were shorter than 100 pixels. Each letter was shifted on the image so that the center of gravity could be located at the center of the image. Figure 2 illustrates the examples of a handwritten letter. It is a typical Chinese character that means 'big' or 'large' in English.

Fig. 2. examples of Chinese handwriting sets

First we acquired the statistics described in 2.3, that is, (μ_U, μ_V) and (σ_U^2, σ_V^2) . The first registered authentic handwriting, $g_{reg,1}$, was used as a standard one. Figure 3(a) and (b) illustrate the standard one and the handwriting deformed with the average normalized displacement function (μ_U, μ_V) . On the other hand, Fig. 3(c) and (d) illustrate the variance (σ_U^2, σ_V^2) of the normalized horizontal and vertical displacement functions, respectively, where more dark area means that its variance is larger. Note that, as shown in Eq. 16, only the statistics whose pixel is on the handwritten letter is utilized for calculating the distance d_{DA} .

Next the procedure for calculating the statistical distance d_{DA} of a questionable handwriting is described. The regularization method with the coarse-to-fine

(a) standard handwriting, $g_{reg,1}$. (b) average displacement, (μ_U, μ_V) . (c) variance of horizontal displacement, σ_U^2 . (d) variance of vertical displacement, σ_V^2 .**Fig. 3.** standard handwriting and displacement statistics

strategy computed the displacement function in the questionable handwriting, and then it was normalized so as to remove the noisy displacement that arose from the position drift and scaling variation. Finally, according to the displacement statistic obtained in advance from registered authentic signatures, the statistical distance d_{DA} between the questionable and standard handwritings is calculated. In this simulation, K was set to 5 and λ 's were set to 5.0×10^{-3} .

Most of the previous studies evaluated the performance of the signature verification methods from the viewpoint of two types I and II error ratio, i.e., error ratio for false judgment on genuine signatures and that for false judgment on forged signatures. In this study, however, we employed the degree of separation to keep the performance evaluation from being complicated due to the configuration problem of the threshold d_{th} . The degree of separation (DoS) is defined by the following equation,

$$\eta = \frac{(\mu_{gen} - \mu_{for})^2}{\sigma_{gen}^2 + \sigma_{for}^2}, \quad (17)$$

where μ_{gen} and μ_{for} are the average of the measured distances from the standard handwriting to the genuine and forged ones, respectively. In addition, σ_{gen}^2 and σ_{for}^2 are the variance to each of them, respectively.

For the comparison, the result of a conventional template matching is also shown, where the average image $\mu_g(x, y)$ and the variance $\sigma_g^2(x, y)$ was computed based on twenty registered authentic handwriting g_{reg} 's. This conventional method defines the distance d_{TM} by the following equation,

$$d_{TM} = \sum_{x,y} \frac{1}{(1 - \alpha_{TM}) + \alpha_{TM} \sigma_g^2(x,y)} (f(x,y) - \mu_g(x,y))^2, \quad (18)$$

where α_{TM} is a parameter controlling the effect of $\sigma_g^2(x,y)$.

Figure 4 shows the relationships of α and DoS of the proposed and conventional method. In the case of $\alpha = 0$, the DoSs were 2.27 and 1.61, respectively. The proposed method gave the best DoS of 2.44 at $\alpha_{DA} = 0.75$, while the conventional method gave that of 1.72 at $\alpha_{TM} = 0.97$. These results implied the superiority of the proposed method.

Fig. 4. degree of separation with proposed and conventional method

In order to investigate the improvement of DoS by combining the proposed method with the conventional one, the combined distance described below was introduced.

$$d_{mix} = (1 - \beta)d_{TM} + \beta d_{DA}, \quad (19)$$

where β is a parameter balancing the proposed and conventional distance.

Figure 5 illustrates the relationship between β and DoS. The best DoS was 2.56 at $\beta = 0.9$, which means that this combination can give further performance.

Fig. 5. degree of separation with using proposed and conventional method together

4 Conclusion

In this paper, it was assumed that each writer has his or her own statistics of handwriting displacement, therefore a statistical displacement analysis for handwriting verification was proposed. Here, a regularization method with the coarse-to-fine strategy computes the displacement function in questionable handwritten letters, and then it is normalized to remove the noisy displacement that arises from the position drift and scaling variation. Finally, the normalized displacement function and the statistics of displacement obtained in advance from registered authentic letters are used to calculate the distance from a standard handwritten letter to a questionable one.

In order to evaluate the performance of the proposed method, a fundamental simulation was conducted. One volunteer offered twenty authentic handwritten letters for registration and ten genuine handwritten letters for the evaluation, while ten volunteers also offered ten skillfully forged handwritten letters for the evaluation. An indicator, degree of separation, was employed for studying how far the method separates the genuine and forged handwritings. The simulation results show that considering the statistics in handwriting displacement is effective for handwriting verification, and that the use of the proposed method with the conventional template matching method together gives further performance.

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