Subspace method with multi scale wavelet for identification of handwritten lines

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Abstract. This article proposes a new indicator for handwriting examination in text independent framework. Experiments of writer identification are addressed using only handwritten short lines instead of a whole character. After preprocessing such as binarization and contours extraction, profiles of contours of handwritten lines were decomposed with fifth scales wavelet decomposition. As the result, we obtained indicators which showed qualities of handwritten lines such as smooth or jaggy. The indicators were analysed with Principle Component Analysis (PCA), and eigen vectors were obtained. In a phase of writer identification, using Kernel Orthogonal Mutual Subspace Method (KOMSM), subspace was calculated by the eigen vectors. The result obtained through the experiments was not enough to satisfy. In future works, the proposed method will be applied to whole handwritten characters.

1. Introduction

This article proposes a new indicator for handwriting examination in forensic science. Main method to identify individuals by handwriting in today is observing features of handwriting by eyes of document examiners. There are several problems in the conventional method because different features are selected in processes of identification by even in a same document examiner and by also between different those examiners. In that situation, it is proposed that methods to extract features using pattern recognition in computer science such as strokes directions, or start, end, cross points on coordinates of strokes (Franke, 2007). However, the above structural features of handwriting are visible by human naked eyes. As the result, it is easy for disguiser to imitate the genuine handwriting and to disguise the forgery. In addition, it is easy for even ordinary people to control their handwriting consciously in order to change their habit in handwriting.

To overcome the problem, we proposed a method to utilize almost invisible features such as depths and widths of strokes. It had already reported in a previous article that there was strong correlation between depths, widths of strokes and pen-tip force (Furukawa, 2012). Consequently, these indicators measured from handwriting reflected pen-tip movements. In addition, there were individual differences among subjects, in particular, of which widths and depths in strokes of handwriting at each four direction. In previous our articles (Furukawa, 2013), short lines of four directions were tested in experiments, because the set of Chinese characters contains a lot of kinds of characters which range from simple shapes to complicated those so that we are not able to obtain same kinds of handwritten characters to compare. In this difficult situation, we use text independent framework to overcome the difficulty using only short lines as shown in Figure 1. We also use wavelet decomposition to acquire the degree of qualities of handwritten strokes. In a field of character recognition, wavelet decomposition was widely used in handwriting analysis (Wen et al., 1996, Deng et al., 1999, and He et al., 2005). Also in a field of signal analysis, Mallat used zero-crossing points as indicators which were intersections between decomposed profiles and zero along y-axis (Mallat, 1991). In our previous work, we used the zero-crossing, the result of the work showed that eigen values of each three scale indicated individualities of each subject. The detail is shown in the previous article. In this our paper, however, we use the whole decomposed profiles instead of the zero-crossing because the zero-crossing is a useful feature which shows a degree of a fluctuation with a compact size, at the same time, there is lost information from a whole profile. To use the information, fifth whole decomposed profiles are analyzed. In addition, we improve a process of identification, i.e., applying subspace method. The experiment we conduct is to identify writers using several subspace methods such as Kernel Orthogonal Mutual Subspace Method (KOMSM). Subspace methods have been used in many areas such as face recognition. Superior points which subspace method has simple and easy implement for wide variety of real data in spit of data has multi classes. (Fukui et al., 2007, and Ohkawa et al., 2009). We explain details of our experimental methods in the following section. In the section of experimental results, we indicate potential of our proposed method. Finally, in the last section, we show the conclusion.

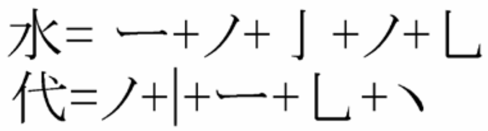


Figure 1. Conceptual diagrams of decomposition of whole characters to strokes.

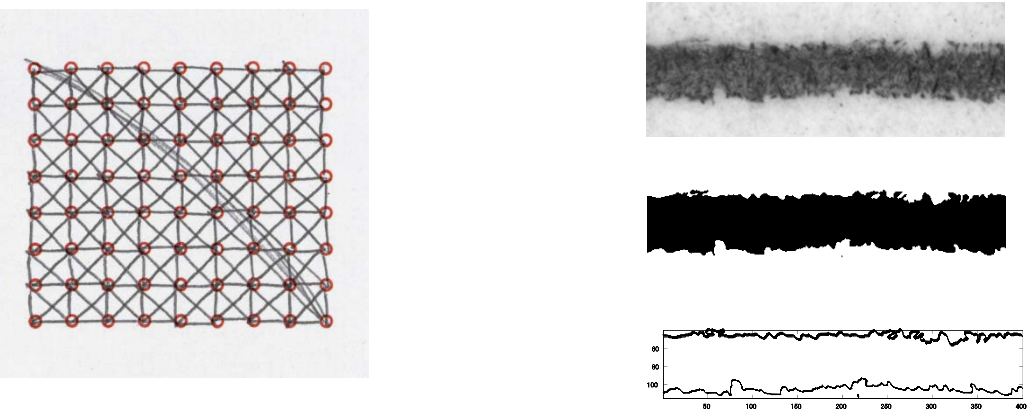


Figure 2. An image used in the experiment and pre-processing. The top column: raw image, the middle column : binary image, and the bottom column : contour image

2. Method

This article improves on identifying writers from written short lines which were composed of four directions of strokes using subspace method. Firstly, ten subjects (eight males and two females) were asked to draw short lines on a sheet of paper which was put on a digitizer tablet. The short handwritten lines were scanned by a flat bed type image scanner (Creo, iQsmart[3]) with high resolution (5400dpi). After binarization, using Otsu method (Otsu, 1979), contours of the short lines were extracted from the binarized handwritten lines as shown in Figure 2. Profiles were obtained by being subtracted from upper (right) contours to lower (left) contours. These profiles were determined to the features. The profiles were decomposed using fifth scales of wavelet decomposition. Finally, five decomposed profiles were extracted from the whole contours profile.

Firstly, the profiles were analyzed with PCA (Principle Component Analysis) in order to obtain eigen vectors among subjects. Secondly, test of identifying writers, between 20 training data and 44 trial data was yielded using several subspace methods such as Mutual Subspace Method (MSM), Kernel Mutual Subspace (KMSM), and Kernel Orthogonal Mutual Subspace (KOMSM). Kernel method is effective for recognition of objectives when a distribution of objectives has nonlinear structures.

In this section, the subspace methods are briefly explained. A common main idea is making subspaces which represent features of samples in low dimensions from learning samples. In learning stages, autocorrelation of sample data is calculated. Autocorrelation matrix is conducted by eigen extension so that eigen vectors are obtained. The subspaces are usually expressed as the eigenvectors. In stages of identification, similarities between objects to recognize and learned samples are estimated to be calculated inner products between vectors of objects to recognize and eigen vectors. Similarities are determined angles between input vectors and subspace, i.e., dictionary as shown in Figure 3. Mutual subspace method (MSM) also makes subspace from input samples to recognize as same as learning samples as shown in Figure 4.

$$\cos^2\theta = \frac{\sum_{i=1}^{N}(\mathbf{p}\cdot\Psi_i)^2}{\|\mathbf{p}\|^2} \tag{1}$$

$(\mathbf{p}\cdot\Psi_i)^2$ denotes inner product between input vector. **p** and *i*th denotes orthogonal base vector in dictionary subspace.|| **p**|| denotes norm of **p** vector.

$$\cos^2\theta_i = \max_{\substack{u_i \perp u_j (j=1,\ldots,i-1) \\ v_i \perp v_j}} \frac{(u_i\cdot v_i)^2}{\|u_i\|^2\|v_i\|^2} \tag{2}$$

$\mathbf{u}_i$ denotes *i*th input vector subspace, $\mathbf{v}_i$ denotes *i*th dictionary subspace.

Orthogonal subspace method (OMSM) contains procedures that relationship among dictionary subspaces is orthogonal to improve ability of discrimination of classes. In using SM, MSM, and OMSM, similarities are defined the following equation.

$$\mathrm{Similarity} = \frac{1}{N}\sum_{i=1}^{N}\cos^2 \tag{3}$$

Recently, Fukui et al. proposed KOMSM as shown in Figure 5. This method is able to improve on conventional methods such as MSM, and OMSM. These conventional methods use multiple input vectors to increase accuracy meanwhile simple subspace method uses only a single input vector. As increasing numbers of class of input images, however, similarities among classes are also increasing so that accuracies were decreasing.

In order to overcome the defects of OMSO, the relationship among classes in dictionary space is orthogonal. Although OMSM has high accuracies to discriminate classes, the accuracy is decreasing when relationship among classes have nonlinear structures. For example, in individual face recognition system, directions of faces, facial expressions, and illumination conditions are changed in nonlinear. To adapt nonlinear data classes, KOMSM uses kernel trick so that nonlinear distribution is mapped to high dimension spaces to discriminate classes. Firstly, original pattern **x** in *m*th dimensions are mapped high dimensions nonlinear feature spaces using nonlinear transform ϕ.

$$\phi : x \rightarrow \phi(x) = (\phi_1(x, . . . , \phi_{d_\phi}(x))' \tag{4}$$

In order to project maps in nonlinear spaces to nonlinear subspaces, it is necessary to calculate inner product between the map $\phi(x)$ and $\phi(y)$. It is difficult to calculate the inner product because there is data in high dimensions. Defined nonlinear transform ϕ through kernel function, $h(x; y)$, however, inner product, $(\phi(x).\phi(y))$ is able to calculate from original pattern vectors x and y. This is called kernel trick. For example, there is following Gaussian function.

$$h(x \cdot y) = \exp\left(-\frac{\| x - y \|^2}{2\sigma^2}\right) \tag{5}$$

Kernel Principal Component Analysis (KPCA) to pattern $x_i (i = 1,\ldots,m)$ is attributed to eigen value problem of m x m matrix **K**, i.e., kernel matrix which is obtained through kernel functions.

$$\begin{aligned} xKa &= \alpha a \\ k_{ij} &= (\phi(x_i) \cdot \phi(x_j)) \\ &= h(x_i, x_j) \end{aligned} \tag{6}$$

Base vector of *i*th, $\mathbf{e}_i$ in nonlinear subspace which is obtained from KPCA is expressed by linear summation of map of *m*'s learning pattern, $\phi(x_i)$.

$$e_i = \sum_{j=1}^{m} a_{ij} \phi(x_j) \tag{7}$$

$\mathbf{a}_{ij}$ is *j*th component of eigen vector, **a***i* which is correspond to *i* the largest eigen value, *i* in kernel matrix, **K**, This base vector, $\mathbf{e}_i$ is not able to directly calculate, however, inner products between components of projections in map, $\phi(x)$ or between base vectors are able to calculate. KOMSM uses the above parameters.

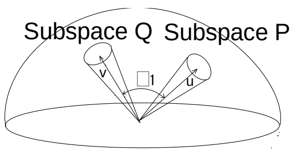


Figure 3. Conceptual diagrams of SM

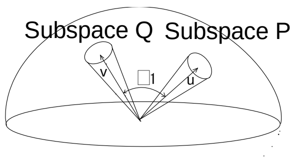


Figure 4. Conceptual diagrams of MSM.

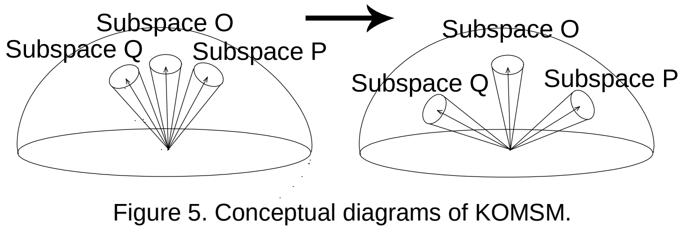


Figure 5. Conceptual diagrams of KOMSM.

3. Results

The results we conduct using several subspace methods are indicated in Table 1. The lowest equal error rate (EER) was obtained when KOMSM or KMSM was used, i.e., the EER was 0.440. The accuracy was not enough to identify the subjects. Figure 6 shows FRR and FAR of the experiment using KOMSM.

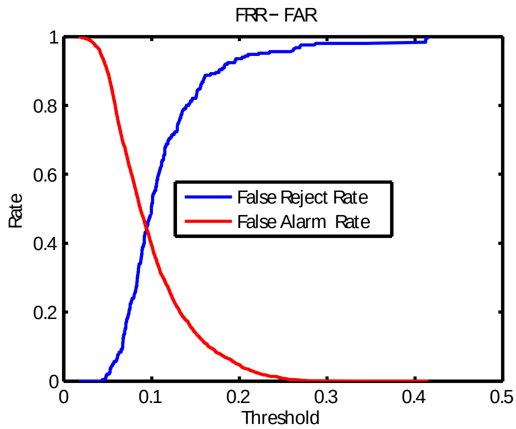


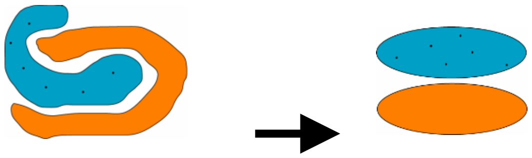
Figure 6. FRR and FAR of the experiment using KOMSM.

4. Conclusion and Future Works

We challenge an ideal method which is able to cover all kinds of characters that are composed of four directions strokes. The method we propose has possibility of being applied to not only same languages system but also different language system. In this work, however, the results were not satisfied for our document examiners. The reason why our method was failure was several causes such as not be considered orders of written strokes. One cause which we should point, in our experiments, subjects drew sequentially the only one direction, for example, firstly, they drew 64 horizontal strokes, next, 63 vertical strokes, 56 right-down and, finally, 56 left-down. If subjects drew in order of horizontal, vertical, right-down, and left-down at one time such as Chinese character '木' , we were able to obtain another results. Another cause we pointed is distribution of data which are detected from human writing movements. As shown in Figure 7, we were able to predict that distribution of handwriting which the subjects conducted contained nonlinear structures because the error rates of linear method such as MSM were lower than nonlinear method such as KOMSM. Consequently, we should find more robust method to classify handwriting. We will apply our proposed method to not only four directions lines but also normal characters such as Chinese characters and English characters.

Table 1. The result of the experiment

Method	EER
SM	0.472
MSM	0.452
KMSM	0.440
KOMSM	0.440



Conduct nonlinear map to high dimensional space

Figure 7. Conceptual diagrams of Kernel method.

Acknowledgement

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