Automatic Detection of Handwriting Forgery

Sung-Hyuk Cha and Charles C. Tappert
Computer Science Department, Pace University
861 Bedford Road, Pleasantville, New York, 10570 USA
{scha, ctappert}@pace.edu

Abstract

We investigated the detection of handwriting forgery by both human and machine. We obtained experimental handwriting data from subjects writing samples in their natural style and writing forgeries of other subjects' handwriting. These handwriting samples were digitally scanned and stored in an image database. We investigated the ease of forging handwriting, and found that many subjects can successfully forge the handwriting of others in terms of shape and size by tracing the authentic handwriting. Our hypothesis is that the authentic handwriting samples provided by subjects in their own natural writing style will have smooth ink traces, while forged handwritings will have wrinkly traces. We believe the reason for this is that forged handwriting is often either traced or copied slowly and is therefore more likely to appear wrinkly when scanned with a high-resolution scanner. Using seven handwriting distance features, we trained an artificial neural network to achieved 89% accuracy on test samples.

Key Words: *Forgery detection, Fractal, Handwriting Analysis*

1. Introduction

Since questioned document examinations play an important investigative and forensic role in many types of crime[1,2], it is necessary to build a system that objectively identifies forged handwriting. Various automatic writer identification computer techniques, feature extraction, comparison, and performance evaluation methods have been studied (see [3,4] for an extensive survey). In a study to establish the individuality in handwriting, Srihari, et al., successfully designed two models to establish the individuality with high confidence: a writer identification system and a writer verification system [5,6]. However, these models were based on the assumption that subjects provide their handwriting samples in their natural handwriting style, and the study did not cover forgery and disguised writing.

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It is unknown whether writership can be verified if some of the writing samples are forgeries. For this reason, we conducted a study to measure the capability of humans and machines to detect forgery. There were three stages in this study: *i)* handwriting sample collection, *ii)* feature extraction, and *iii)* statistical experiment. Subjects were asked to write test samples in their natural handwriting style and to forge other subject's handwriting samples. The resulting handwriting samples were scanned and stored digitally. Next, word-level features were computed from the writing samples. Finally, using these features as input, a neural network was trained using the dichotomy model [5,6,7] to distinguish between authentic handwriting and forgery.

One of the interesting features is a measure of the variability of the handwriting on a small scale. Although one can copy the shape of another's handwriting, it is difficult to mimic the dynamic aspects, such as speed and acceleration. Because forged handwriting tends to be drawn slowly, when scanned, it might be more wiggly than the authentic handwriting. This wrinkliness feature can be measured using the *fractal* dimension measure. For example, in the paper, "How long is the coastline of Great Britain?" a measure of the wrinkliness of the coastline was suggested [8]. Since the measured length of the coastline depends upon the size of the measuring stick, this problem can be answered in terms of *fractal* dimension. Hence, we applied this feature as one of the features to detect forgery.

This paper is organized as follows. In section 2, we explain the method of collecting both authentic and forged handwriting samples. Samples are digitally scanned and stored, and a database management system is used to facilitate the manipulation of the images and data. Section 3 discusses features extracted, section 4 describes the statistical experiment that tests whether forgery can be detected automatically, and section 5 draws conclusions of this work.

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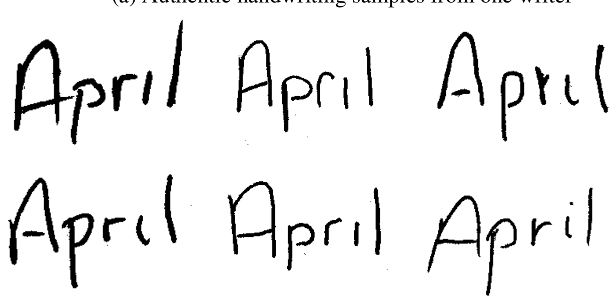
2. Forgery Database Construction

A database of English handwriting samples from ten subjects was created. Subjects were asked to write the following set of words, {*April, Bob, California, December, English, February, Greg, Halloween, Iraq, June, Kentucky, Los Angeles, Markov, November, October, Pennsylvania, Queen, Raj, States, Texas, United, What, Xray, York, Zorro, alumni, boy, come, date, enjoy, false, great, have, interest, jazz, keep, leave, millennium, now, of, picnic, question, run, six, time, unique, video, where, xenophobia, you, zero*}. This set is used because any word can be synthesized by using parts of these words [7], since it contains all word-initial alphabet characters for both upper and lowercase, and word middle and terminal positions for the lowercase alphabet.

Ten subjects were asked to write each of these words three times on provided ruled paper in their own most natural handwriting style. Thus, the handwriting image database contains both cursive and handprint word images depending on writers' natural handwriting styles. Subjects were also asked to forge one word from the handwriting samples of each of the nine other writers three times. Thus, we obtained 30 authentic writing samples of the full set of words (three from each of the ten writers) and 270 word forgeries (three word forgeries of the nine other writers from each of the ten writers). Figure 1 shows three authentic writing samples and six forgeries. All of the collected handwritten samples were scanned, digitized, and stored in an image database together with demographic information on the subjects.

(a) Authentic handwriting samples from one writer



(b) Forgeries of (a)

Figure 1. Images of handwriting samples: (a) authentic samples (b) forgeries by six other subjects.

3. Feature Extraction

We developed seven word-level features: some come from the handwriting recognition and identification literature, and one comes from *Fractal* theory. Since the dichotomy model, which transforms the features into a distance space is used to detect the forgery, features need not be homogeneous [6,7], and can be in any form as long as good distance measures are associated with them.

3.1. Computing Handwriting Features

The first feature is the centroid ratio. After counting all black pixels on each row and column, the centroid can be found by averaging them. After a bounding box is computed from a word, the centroid ratio is found by dividing the x-centroid by its height and y-centroid by its width. Hence, the centroid is in the form of a two dimensional vector. To compute the distance between the centroids from two different handwritings, the simple Euclidean vector distance is used.

We borrowed the next four features from those established in many document recognition systems: slant, stroke width, ascender, and descender. The slant feature is a simple numeric value. Average stroke width was computed separately from three parts of the word, since the average stroke width does not vary greatly when computed in pixel form, and thus it forms a three dimensional vector. The ascender and descender information was combined into a two-dimensional vector.

Other popular features are projected histograms. The side-projected histogram and bottom-projected histograms are stored separately and the histogram distance[10] is used to measure the distance. The gradient histogram is also computed and two gradient histograms are compared using the angular histogram distance. Finally, the wrinkliness, which is a simple numeric value, is computed, and the detailed description is given in the next section. As a result, we have three feature vectors, two numeric values, the projected histograms, and the gradient histogram.

3.2. Computing Handwriting Wrinkliness

One of the interesting features is the wrinkliness of the handwriting. One can copy the shape of another's handwriting, although it was found to be difficult for many subjects. However, the speed and acceleration are more difficult to mimic. Hence, forged handwriting tends to be written slowly and, when scanned, is more wrinkly than authentic handwriting. This feature can be measured using the *fractal* dimension measure. For example, in the paper, "How long is the coastline of Great Britain?" a measure of the wrinkliness of the coastline was suggested [8]. Because the measured length of the coastline de-

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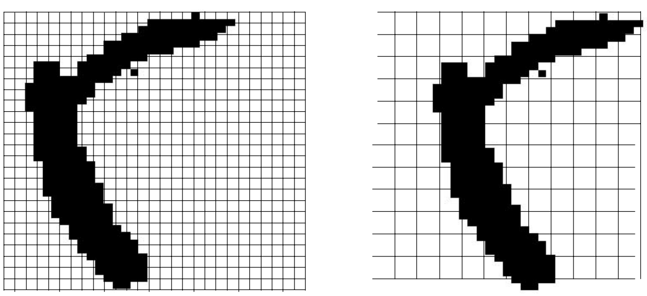
pends upon the size of the measuring stick, this problem can be answered in terms of *fractal* dimension. Hence, we applied this feature as one of the features to detect forgery.

Scanned digital handwriting images are typically binary images and they are represented by a rectangular array called pixel whose value is either 0 or 1. Whereas the wrinkliness of the coastline was computed using two different measuring sticks [8], the wrinkliness of handwriting in binary digital images can be computed using two different resolution pixels. One can simply count the number of high and low resolution pixels on the boundary of handwriting and the formula for the wrinkliness is:

$$Wrinkliness = \log\left(\frac{boundary\_in\_high\_res.}{boundary\_in\_low\_res.}\right) / \log(2)$$

If the character is a smooth straight line in either horizontal or vertical directions, the wrinkliness value is 1.



(a) (b)

(a) Number of □ in the boundary = 69

(b) Number of □ in the boundary = 32

Figure 2. Computing the Fractal Wrinkliness of handwriting in binary digital image format.

Figure 2 illustrates how to compute the Fractal wrinkliness. First, a high resolution count is obtained by counting the number of pixels on the boundary of the character. Then a low resolution count is obtained by considering the adjacent four pixels as one large pixel and recounting the number of larger pixels on the boundary of the character. In the example of Figure 2, there are 69 small pixels and 32 large pixels. The following measure is the wrinkliness of the above character.

$$Wrinkliness = \log(69/32)/\log(2) = 1.1085$$

4. Statistical Experiment

In this section, we discuss our experiment design to distinguish between authentic handwriting and forgery. Using the dichotomy model, we trained an artificial neural network. The dichotomy model transforms the feature space into a feature distance space and the forgery detection problem becomes a two class classification problem.

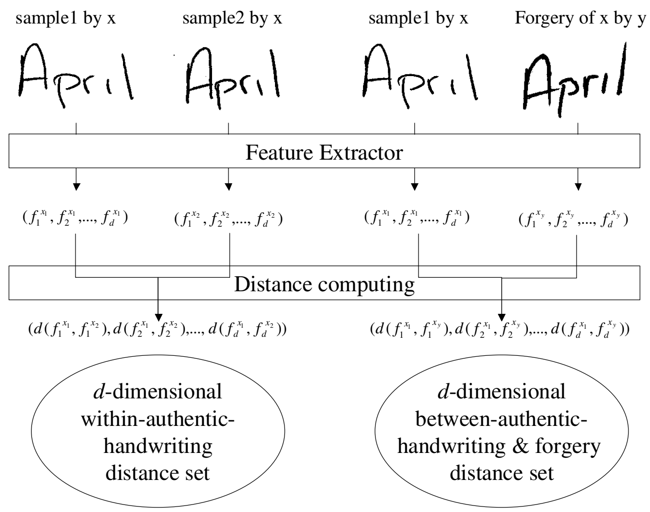


Figure 3. Generating the Training and Testing sets.

As depicted in Figure 3, we generate two different class sets: one is the within-authentic-handwriting distance set and the other is the between-authentic-handwriting-and-forgery distance set. The within-authentic-handwriting distance set is collected by taking two natural handwriting samples from the same person. Features mentioned in the previous section are extracted and their corresponding distance measures are computed. Consequently, the d-dimensional within-authentic-handwriting distance set is built.

Similarly, the between-authentic-handwriting-and-forgery distance set is collected by taking one natural handwriting of a subject x and one forgery of x attempted by a different subject y. These two sets are divided into training, validation, and testing sets to train and test an artificial neural network. Figure 4 illustrates our dichotomy artificial neural network model.

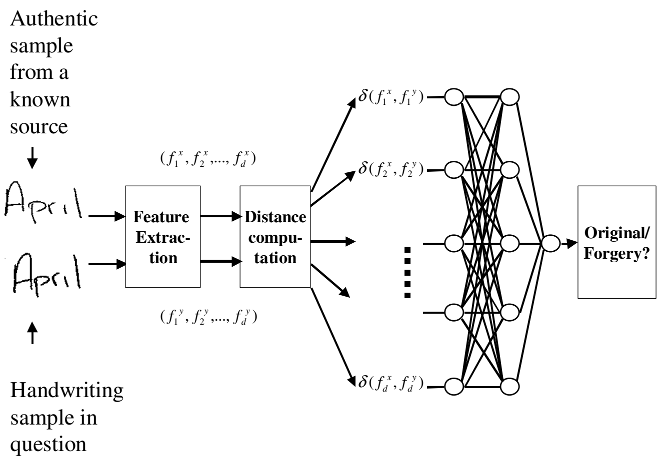


Figure 4. Artificial neural network using the dichotomy model to detect forgery.

We used a fully connected, feed forward, back-propagation artificial neural network with the dichotomy model for training. There are seven input units, five units in a hidden layer, one output unit. After training, forged handwriting samples can be detected in the following manner. Consider the case in which a person is presented with a document claimed to be in his or her handwriting but the person claims that it is a forgery. To prove whether the sample is authentic or a forgery, the person is asked to provide his or her handwriting sample. Then, the known sample and the sample in question are fed into the forgery detection system as depicted in Figure 4. We obtained 9.6% and 11.2% for type I and type II errors, respectively. Type I errors occur when the system classify an authentic handwriting as a forgery and vice versa for type II errors.

5. Conclusion

In this paper, we presented an automatic forgery detection system with an experiment. From the experiment, we observed the ease of forging handwriting, and found that many subjects can successfully forge the handwriting of others in terms of shape and size by tracing the authentic handwriting. We also observed that even though shape of handwriting can be easily traced by forgers, the exact speed and acceleration is impossible to forge. To this end, we suggested a measure of wrinkliness as forgery handwriting shows more wrinkliness than natural handwriting does.

We obtained experimental handwriting data from subjects writing samples in their natural style and writing forgeries of other subjects' handwriting. These handwritings were digitally scanned and stored in an image database. Seven distance features were computed usring various types of features extracted including the wrinkliness. Finally, an artificial neural network was trained using the dichotomy model to distinguish the authentic and forgery handwriting. We achieved 89% accuracy in detecting the forgeries.

In our final manuscript, we will include both results of human document examiners' performance and the computer forgery detector. Also, we will increase the training and testing set sizes to provide more valid results.

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