Off-Line Skilled Forgery Detection Using Stroke and Sub-stroke Properties

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Abstract

Research has been active in the field of forgery detection, but relatively little work has been done on the detection of skilled forgeries. In this paper, we present an algorithm for detecting skilled forgeries based on a local correspondence between a questioned signature and a model obtained a priori. Writer-dependent properties are measured at the sub-stroke level and a cost function is trained for each writer. When a candidate signature is presented, the same features are extracted and matched against the model. We present a description of the features and experimental results.

1 Introduction

Research has been very active in the fields of on-line and off-line forgery detection. Most of the work in off-line detection, however, has been on random and/or simple forgeries, in part because random forgeries are a large fraction of forgery cases [1], and because of the difficulties encountered in analyzing detailed information embedded at the stroke level necessary to detect skilled forgeries. A general survey of signature verification research is presented in [2, 3], but in this paper we focus on skilled forgeries.

Skilled forgeries are often sub-classified into traced and simulated forgeries. Unlike random (signer uses own name and style) and simple (signer uses name of victim, but own style), skilled forgeries often differ only in subtle stroke and sub-stroke features that may require an experienced document examiner to identify. Often such forgeries have significant differences in line quality resulting from properties of handwriting related to movement, including speed, continuity and uniformity, pen pressure, freedom or hesitation, rhythm and writing skill [1]. Although skilled forgers attempt to mimic the style of the author, making skilled forgeries difficult to detect based only on shape, the fact that the forger has to concentrate on mimicking the style makes skilled forgeries very difficult to perform ballistically. Hence skilled forgeries often differ from genuine signatures in the rhythm and uniformity of the writing. These subtle differences can be compared locally on the stroke level and used for detection.

In previous work [4], we presented algorithms that segment a questioned signature and make a correspondence between the signature and a model. This makes it possible to examine a questioned signature on the stroke level. We assume this correspondence has been established.

2 Previous Work

The task of detecting a skilled forgery requires one to distinguish between natural variations among genuine signatures and unnatural variations between signatures and forgeries. In the case of automatic signature verification, noise and degradation of the image introduced during the scanning and digitization process make this task even harder. Unlike random forgery detection, not much work has been done on skilled forgeries, and what work has been done has focused on global or regional stroke properties.

As early as the 80's, Ammar et al. [5] did work on detection of skilled forgeries. They calculated statistics of dark pixels and used them to identify changes in the global flow of the writing. This was also one of the first attempts to extract "dynamic" information from a static image for signature verification.

Later work of Ammar [6] was based on reference patterns, namely the horizontal and vertical projections of the signature image. The projection of the questioned signature and the reference are compared using Euclidean distance. Using the leave-one-out method, the best result achieved was a 10.25% error rate.

The work we present in this paper is different from the research discussed above in that we focus on information embedded at the stroke and sub-stroke level. Instead of obtaining global statistics, we try to measure stroke properties that

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are writer-dependent.

Many of the features are used for descrimination can be linked back to properites of the writing process. For example, the pressure on the pen tip varies as a stroke is generated. We can observe that a person who writes normally does so ballistically, so changes in pressure are continuous and occur in a unique rhythmic fashion. In a forgery, the forger typically writes with great precision, so the pen pressure changes less, or in an unconventional way.

Since the pressure put on the pen tip changes along a stroke, the width of the stroke also changes. When trying to forge a signature, however, due to the careful study of the signature or the careful action involved in tracing the signature, the pressure is more evenly distributed along the stroke, making the stroke width more uniform, or change in ways that are not consistent with the genuine signature. Similarly, we observe that for genuine signatures, horizontal strokes usually taper off whereas forgeries, may tend to end abruptly. Although such differences are difficult to detect on a case by case basis, they are reflected in the types of features we extract.

3 Our Approach

Our approach is based on building a set of detailed observations using the correspondence between the model and the candidate signature. We first identify edge pixels of corresponding strokes, then extract features corresponding to gradient magnitude, gradient direction, gray level and stroke width. We then use these features to compute the cost of matching the model to the signature.

3.1 Finding the edges

The contour edges contain edge points on both sides of the strokes. When moving along a stroke, the contour edge points on the left form a curved line, defined here to be the *left edge* of the stroke, while the contour edge points on the right form a curved line, defined here to be the *right edge*.

First, each traced stroke point is compared with its previous point and a stroke direction is calculated for each point. Each quadrant is divided into four angular regions, each representing an angular range of 22.5^o. For each pair (current point p, previous point p_o), dx and dy are defined by

$$dx = p_x - (p_o)_x$$

$$dy = p_y - (p_o)_y$$

A direction value is assigned to each stroke point depending upon which range its dx and dy fall into.

All the left edge points are grouped into left edge segments according to the order of their associated stroke points, and all right edge points are grouped into right edge segments in the same order. However, because the stroke segments may not be smooth, the left and right edges may not be correctly ordered.

When we obtain the left and right edge points of a stroke segment, we obtain an ordered set of labels(i, p). i is the contour segment number and p is the the index number, i.e., the point number on that contour. We then examine these ordered sets. We break up a contour segment into sections called edge segments. For each edge segment, the minimum index number p_{min} and maximum index number p_{max} on the same contour segment are obtained. The portion of contour segment i between points p_{min} and p_{max} is the edge segment. This edge segment is guaranteed to be smooth and continuous.

3.2 Feature Extraction

To compare the model and the questioned signature, we compute average feature values for each stroke segment. We use the gradient magnitude feature as an example, but we also compute features based on gradient direction, gray level and changes in stroke width. As in [4], we segment the strokes at the local vertical minima and maxima. Averaging the gradient magnitude in each stroke segment greatly reduces the effect of noise.

Let $E_m(i, j), j = 0, 1, \ldots, M-1$ denote the gradient magnitude along one of the edges of the model stroke segment i. Let $E_s(i, j), j = 0, 1, \ldots, N-1$ denote the gradient magnitude along the corresponding edge of the corresponding signature stroke segment. Then

$$F_m(i) = \frac{1}{M-1} \sum_{j=0}^{M-1} E_m(i, j)$$

$$F_s(i) = \frac{1}{N-1} \sum_{j=0}^{N-1} E_s(i, j)$$

are the average of the gradient magnitude of segment i for the model and signature, respectively.

To compare the gradient magnitude of the questioned signature with that of the model, we compute

$$C_{mag} = \sum_i (F_m(i) - F_s(i)) * (F_m(i) - F_s(i))$$

for both edges.

Similarly, we compare the gray levels by computing the sum of the squared differences of the average gray levels of the stroke segments for the model and the questioned signature. The same method is used to compare the stroke widths.

To compare the gradient directions we proceed as follows. We first define a 16-component vector, where the components are the numbers of steps in the segment, from

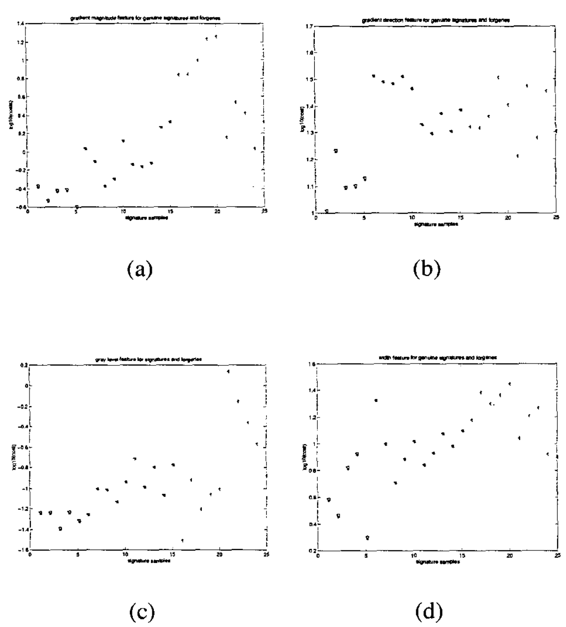

Figure 1. Cost distributions: a) gradient magnitude, b) gradient direction, c) gray level, d) width. The first five samples are genuine

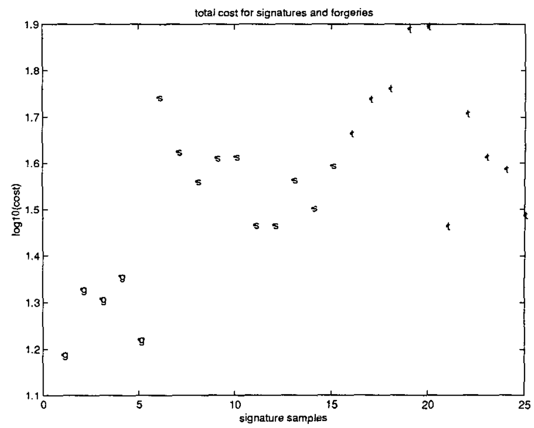

Figure 2. Example of total cost distribution

features used	Type I error	Type II error
grad. magnitude	7/50(14%)	30/200(15%)
grad. direction	6/50(12%)	34/200(17%)
gray level	9/50 (18%)	44/200(22%)
width	10/50 (20%)	35/200(18%)
combined	3/50(6%)	23/200(12%)

Table 1. Skilled Forgery Error Rates

sample point to sample point, in each of the 16 directions. These numbers are normalized by the total number of sample points in the segment, so that each component of the vector represents the fraction of moves that the segment makes in a specific direction. The difference between the two vectors is defined as the sum of the squares of the differences between corresponding components. We compare these gradient directions by computing the sum of the squares of the differences between corresponding components in the model and the questioned signature.

4 Experiments

We studied the differences between genuine signatures, simple forgeries, simulated forgeries and traced forgeries using a database of 350 signatures that we collected. There were ten authors: each was asked to produce five genuine signatures, as well as ten simple forgeries, ten simulated forgeries and ten traced forgeries of other authors in the group.

4.1 Results

Simple forgeries can be easily detected using the structural cost function we used in [4] for random forgery detection. The error rates for simple forgery detection on our database were $1/50$ (2%) for false rejection and $5/150$ (3.33%) for false acceptance.

For each model, edge profiles are obtained using the method described in Section 3. We compare the average values of gradient magnitude and gradient direction over each stroke segment and compute the cost for each feature as the sum of the costs over all the segments. The stroke width is also calculated using the gradient direction information along each stroke segment.

In Figure 1a we show an example of the costs for gradient magnitude. In this Figure, the genuine signatures are labeled "g", the simulated forgeries are labeled "s" and the traced forgeries are labeled "t". Similar results for gradient direction, grey level and stroke width are shown in Figures 1b, c and d. The costs do in fact tend to be lower for the genuine signatures. The total costs are plotted in Figure 2; they show a good separation between the genuine signatures and the forgeries.

Table 1 shows the the error rates obtained using each feature separately and together.

Different features reflect different aspects of the changes along strokes. All four features contribute to the distinctiveness of a person's writing. Among them, which one is the dominant feature depends on the individual.

In most of the cases, the gray level cost for traced forgeries seems to be higher than that for freehand forgeries. When tracing a signature, the differences between different portions of a stroke will not be as obvious as in natural writing. Similar arguments hold for gradient magnitude, and here too we find that the costs are usually higher for traced forgeries than for freehand forgeries.

5 Discussion of Results

In summary, the production of a signature is affected by a combination of many factors. As discussed above, traced forgeries may have high costs for gradient magnitude, gray level and stroke width, but the direction feature cost for traced forgeries is likely to be smaller than that for freehand forgeries. This is because a traced forgery closely follows a genuine signature, which determines the direction histogram of the stroke segment. Another observation is that traced forgeries have a bigger standard deviation of costs because tracing is almost never done ballistically, and drawing can be more inconsistent from instance to instance compared with writing.

The four features together have considerable distinguishing power. Since the four feature values in the cost are not in the same numerical ranges and the feature that works best for a given writer varies from person to person, intuitively, we should weight each feature by the standard deviation of that feature for the available genuine signatures.

An advantage of having a sub-stroke-wise correspondence between the model and the questioned signature is that it provides us with an opportunity to prioritize the strokes. Expert document examiners know which strokes to pay more attention to. Different stroke segments play different roles in a signature. If we can pick only stroke segments that are characteristic of each model, or weight different stroke segments differently according to their discriminating power, we should be able to improve our results.

In Figure 3, about $1/3$ of the stroke segments that are relatively long are used to compute the costs of gradient magnitude to illustrate the concept of using selected stroke segments for verification. We see that when this is done, the difference between the average costs of genuine signatures and forgeries becomes larger.

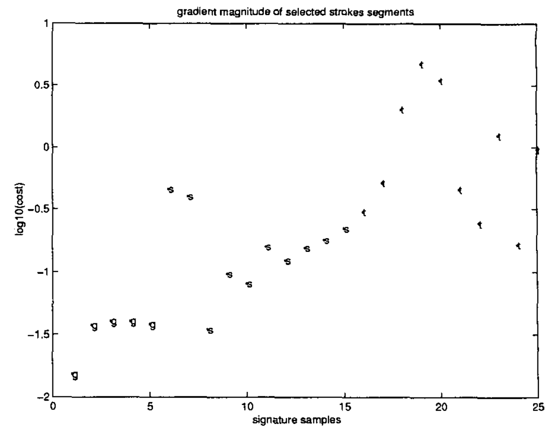

Figure 3. An example of the cost of gradient magnitude using a selected set of stroke segments (log scale).

6 Conclusion

Making a correspondence between a model and a questioned signature [4] enables us to do a local comparison between them on a stroke or sub-stroke level. In this paper, we describe the use of local features to detect skilled forgeries. The features studied are gradient magnitude, gradient direction, gray level, and stroke width. These features directly relate to the position and angle at which a person holds a pen while writing.

We have shown that these features can be used for skilled forgery detection. Future research could involve introducing weights for the different features for each writer. Another topic for future research is how to more effectively measure the features.

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