The effect of Forced Slant on Automatic Writer Identification Performance

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August 2, 2007

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Bachelor's Thesis in Artificial Intelligence
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Abstract

The most common method used to forge handwriting is changing one's slant. Forensic experts ignore slant and automatic writer identification programs usually simply shear the handwritten text to an upright orientation. However, this last method has never been evaluated and there might be changes to the handwriting other than slant. The purpose of this research is to find out if there are such changes. In this research the performance of an automatic writer identification program on texts with changed slants is compared to texts with natural slant. This program uses the techniques 'hinge' and 'run-length' to identify handwriting.

Without any preprocessing the program matches half of the authors of text with a changed slant to their original handwriting. When the text is deslanted before processing, the performance increases. However, there are indications that the forced slant causes changes to the handwriting, depending on the direction in which the slant is changed.

1 Introduction

Automatic writer identification

One type of forensic investigation is finding out who has written a piece of handwritten text (questioned document). The usual approach is to let several suspects write another text and then manually compare the characteristics of the two texts. When the experts decide that the documents are from the same author this becomes evidence which can be used in court.

The development of automatic writer identification is important because much more data can be analysed and the results will be more objective. A lot of new insights into the field of pattern recognition are available and these could lead to better software. To aid forensic handwriting experts the TRIGRAPH project was started two years ago. It's goal was to develop better software for writer identification. For more details, please read Niels, Vuurpijl, Schomaker (2005).

Nowadays, several programs are able to identify authors with high levels of accuracy. One of these is developed at the department of Artificial Intelligence at the University of Groningen by Bulacu and Schomaker (2007). This one was used in this research.

Modified handwriting

However, an unsolved problem with automatic writer identification is that the programs have a hard time recognising an author who has forged his or her handwriting. The original author of the questioned document might try to modify the handwriting in order to avoid detection. Harris (1953) has studied the modifications people employ to do this and in his research 52% of the subjects changed their slant, making this the most employed technique to forge one's handwriting. Morris (2000) agrees with Harris that slant change is the most common technique used to disguise handwriting. If this often-employed technique could be countered by normalising the slant in written text, this would benefit the process of automatic writer identification in, for example, forensic investigations.

The most commonly used method to remove the slant from text is straightening the words automatically. There have been a few studies about removing slant from handwriting automatically. However, most of these studies are focussed on recognising the content of the message, for which deslanting is useful because upright text is easier to recognise since it looks more like printed text. The question whether the change of one's slant has an effect on the letters has never been answered.

This question can be answered by looking at the letters in detail and trying to find the changes, if these changes exist. However, such an analysis is hard to quantify and would require the help of an expert on handwriting recognition. In this research, another path was chosen, comparing the performance of an automatic writer identification algorithm on texts with changed slant that has been deslanted to the performance on texts with natural slant. If there are no changes to the letters other than the slant, the program should have no trouble recognising the slanted texts that has been straightened. If there are changes to the handwriting when written with a unnatural slant, the program will have a lower performance compared to the performance on texts with natural slant.

2 Methods

To do this comparison, handwriting with a natural slant and handwriting with a different slant is needed. In the next paragraphs the procedure used to obtain these is described. Next the algorithms for deslanting words and extracting the features that are used to analyse the handwriting are described. And finally the tests are presented. All the angles in this paper are in degrees, where 0 degree is a line to the right and 90 degrees is a line straight up.

Obtaining the data

Six subjects were used in this test, aged twenty to eighty with an average age of 43. One was left-handed, the others were right-handed. All subjects used a black ballpoint pen and wrote on paper on a smooth table. The experiment took place in a well-lit environment.

The subjects had to perform three tasks. First the subjects were asked to fill out the form in Figure 1 with 55 words that were provided. These words form a short story in Dutch: “Mijn prachtige, bruine hond zat vroeger wel eens tussen de deur met zijn poot. Daardoor begon hij vreselijk te janken. Het dier maakte hiermee de hele buurt wakker. Terwijl ik sliep kwam een klaaglijk gejammer vanuit het trapgat naar boven. Een bezoek aan de dierenarts was nodig. De gewonde Pluto werd haastig naar binnen gebracht.”

There was one yellow box for every word

Figure 1: The first form, this subject writers with a slant of 72.0 degrees

and a line they were asked to write along. Because each box contained one word it was easy to isolate every word. The colour of the boxes and lines was chosen to easily remove them from the images, without leaving a mark on the letters.

When the subject was done, the slant of the handwriting on the first form was measured. To determine the slant, a method proposed by Maarse and Thomassen (1983) was used. This method consists of using 25 transparent sheets with lines ranging from 28.8 to 118.8 degrees, where 90 degrees was straight up. This covered the range of the most common slants. The lines on the sheets between two following sheets differ 3.6 degrees. Each of these sheets are put on top on the first form from the subject, until the lines of the sheet match the downstrokes of the subjects handwriting. Figure 2 shows one of these sheets for a slant of 72 degrees.

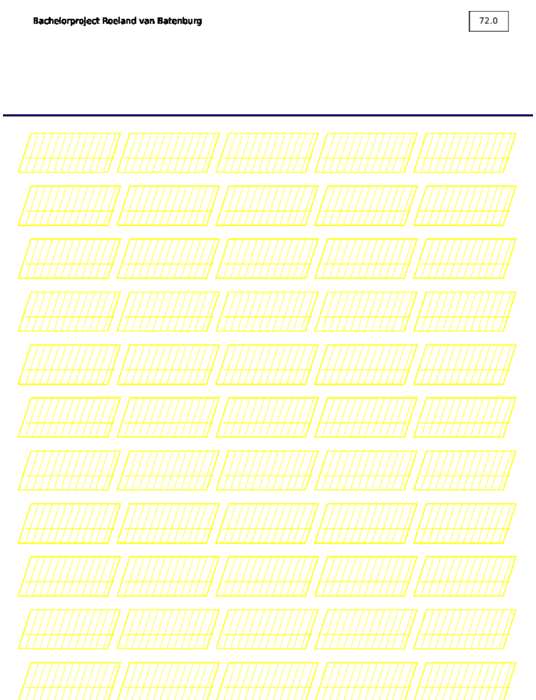

Figure 2: This is the transparant for a slant of 72.0 degrees

Then the subject received two new forms: the first had lines inside the boxes slanted 20 degrees to the left of the subjects original slant (Figure 3), the lines of the second form were slanted 20 degrees to the right. The subject was asked to fill out these other two forms using the same words as in the first form, but this time with a slant following the lines inside the boxes.

When the subjects were done there were three forms for each subject. Form 1 is written with the subjects natural slant. Form 2 with a slant 20 degrees to the left of the subjects natural slant and form 3 with a

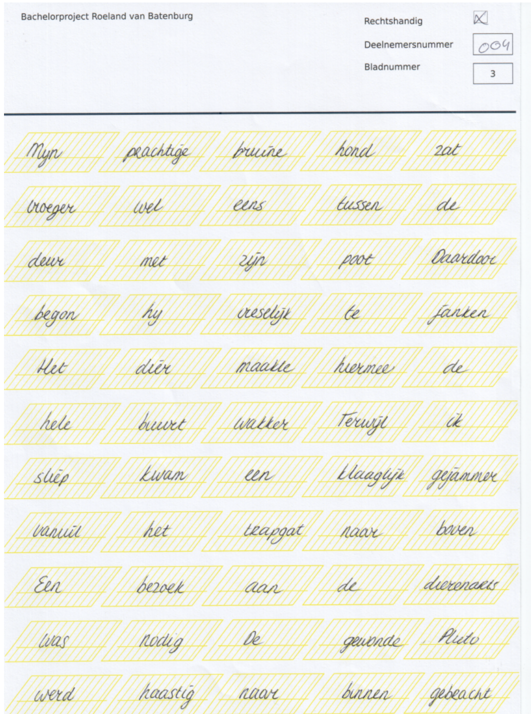

Figure 3: The third form for a person with natural slant of 72 degrees, the lines are slanted at 52 degrees

slant 20 degrees to the right of the subjects natural slant.

Processing the data

When all the data was collected, the words were deslanted using an algorithm developed by De Zeeuw (2006). This algorithm was translated to C++ because it runs faster than the original python code. For each angle between -50 and 50 degrees with steps of 1 degree the program shears the text. The slant is determined by choosing the angle which has the highest average of the five highest peaks in a vertical (to the x-axis) projection histogram. This algorithm is based on the theory that the peaks will have maximized values when the text is straight up. Figure 4 shows an example of a deslanted word with the projection histogram beneath it. Although this works for a lot of words, De Zeeuw already mentioned in his paper that the algorithm fails on some words with few vertical lines like 'en'. To solve this problem, the program keeps track of the average slant. The newly calculated slant must be within a range of this average otherwise the current average is taken. This assumes that people do not change their slant much while writing. This method does not use the information that is available about the slant which the subject used.

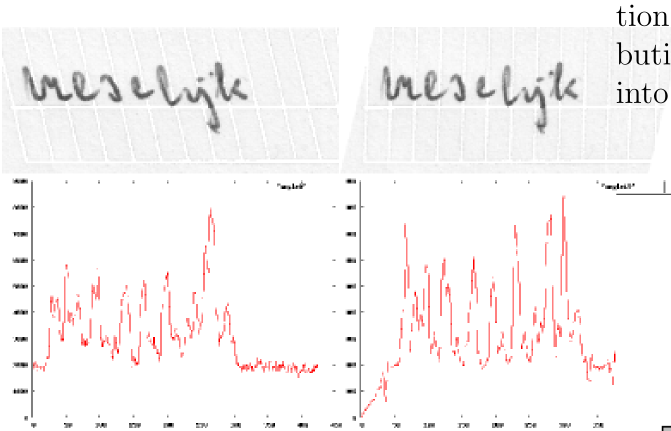

Figure 4: The word 'vreselijk', the original on the left and the deslanted(with 15 degrees) with the vertical projection histograms beneath them

When all words were deslanted, they were processed by the method that was developed by Bulacu and Schomaker (2007). This method needs several lines of text to recognise authors. To achieve this each form was split in two and the two parts each formed one line by putting the words one after one another. Two features that were calculated by the program were used, the hinge and the run-length. The hinge is a measure of roundness and slant of the text. This feature was chosen because it has been used to achieve good results on identifying writers. To calculate the hinge, the program determines for every edge pixel at which angles there is another edge pixel bordering it. All these angles are normalised into a probability distribution. Figure 5 shows the hinge of one pixel. The other feature is the run-length, which measures how close the letters are to each other. Run-length is the length of the white spaces between the letters on the horizontal axis. This feature is also returned as a probability distribution. Combining the two probability distributions from the features turned each line into a point in a multi-dimensional space.

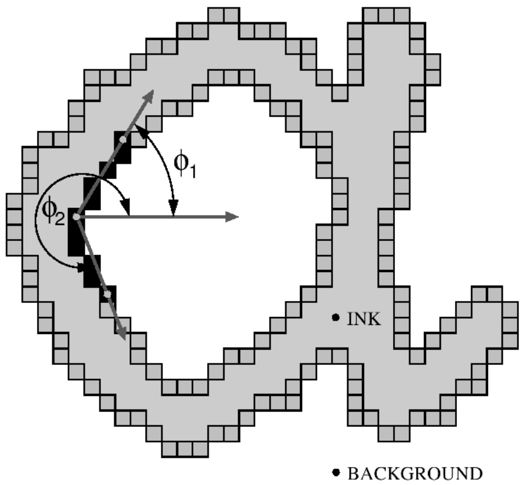

Figure 5: This shows the hinge from one pixel. The picture is taken from Bulacu and Schomaker (2007).

Testing

For the tests a nearest neighbour algorithm was used, this selects the point from the training data which has the smallest Euclidean distance. In all the tests the first halves of the first forms were used as training data. The diagram in Figure 6 shows which test were performed. Each test was performed twice, first without deslanting the words, then with deslanting. That means that there were six tests.

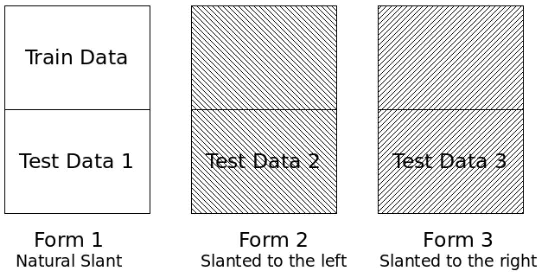

Figure 6: This diagam shows from what part of which form the data was acquired

First a base test was performed, to see how well the software could recognise the slanted text without using De Zeeuw's algorithm. The test data consisted of the second halves of all the forms. No text was deslanted during this test.

Next all forms were deslanted and then analysed by Bulacu and Schomakers method. Again the first halves of the first forms were used as training data and the second halves of the first, second and third form formed the test data.

3 Results

The results from all six tests are shown in Figure 7 to 12. Each figure shows for each subject the squared Euclidean distance to all six training points. The correct answer is indicated with a dot in the centre. When this is the leftmost cross the nearest neighbour picked the right answer.

Base tests

The base tests, with the unprocessed texts, show a six out of six correct identification on the texts with a natural slant (Figure 7), three out of six on the texts slanted to the left (Figure 8). From the texts slanted to the right, four out of six were correctly identified (Figure 9).

Deslanted handwriting

Next all the forms were deslanted and the same tests performed again. The texts with natural slant shows a 100% correct identification (Figure 10), six out of six on the texts slanted to the left are correctly identified (Figure 11). From the texts slanted to the right, three out of six were correctly identified (Figure 12).

The changes in performance seem rather high. However, because there were only six subjects in this test, the results can only show an indication of a general feature of slanted handwriting.

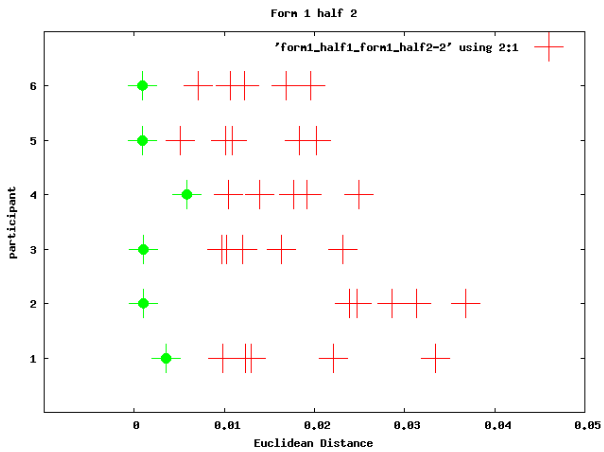

Figure 7: The first half of the first form is the train set, the second half of the first form the test set. For each subject the Euclidean distances to all the test points are plotted

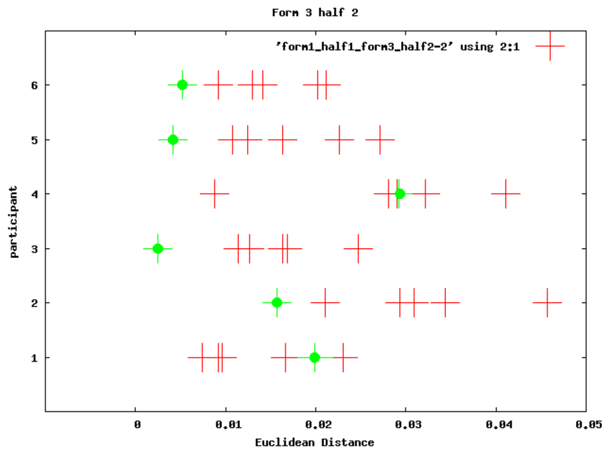

Figure 9: The first half of the first form is the train set, the second half of the third form the test set. For each subject the Euclidean distances to all the test points are plotted

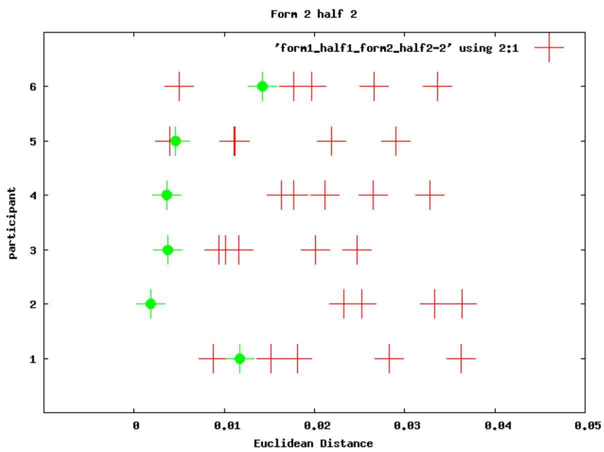

Figure 8: The first half of the first form is the train set, the second half of the second form the test set. For each subject the Euclidean distances to all the test points are plotted

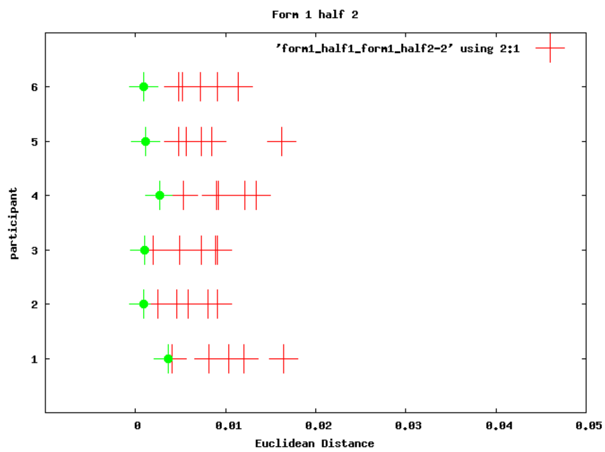

Figure 10: The first half of the first form is the train set, the second half of the first form the test set. Both were deslanted. For each subject the Euclidean distances to all the test points are plotted

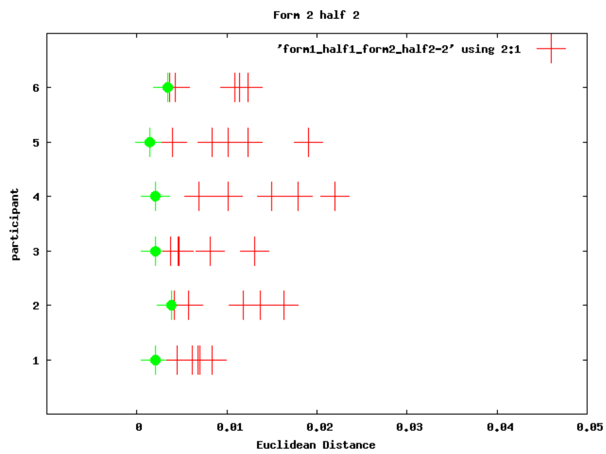

Figure 11: The first half of the first form is the train set, the second half of the second form the test set. Both were deslanted. For each subject the Euclidean distances to all the test points are plotted

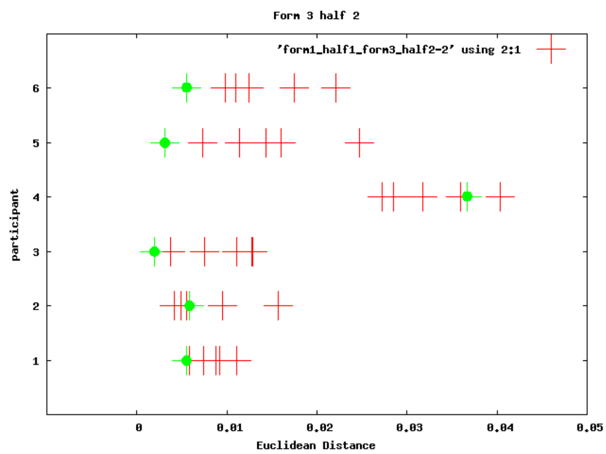

Figure 12: The first half of the first form is the train set, the second half of the third form the test set. Both were deslanted. For each subject the Euclidean distances to all the test points are plotted

4 Discussion

From the performance of the program on the slanted texts it can be seen that automatic writer identification has trouble recognizing the correct author when the original author changes his or her slant. This might be possible to solve by finding a feature that is not as dependent on slant as the hinge is instead of normalising the slant and then use the hinge.

The results indicate that applying the deslant algorithm has no negative impact on writer identification with the texts with natural slant. With the texts where the authors changed their slant to the left and which was then deslanted, the performance became as good as with the texts with natural slant. This means a great increase in performance and could indicate that there are no changes to the letters when people change their slant to the left. However the differences in Euclidean distance between the correct and incorrect answer has decreased. This could indicate that there are changes to the handwriting, but it seems that this is a result from the processing since the effect also occurs between Figure 7 and 10. It is possible that because the slant is normalised the hinge doesn't work as good as with the texts that had not been deslanted.

However, with the deslanted texts where the subjects changed their slant to the right the performance decreases. This seems to indicate that changes occur to letters when people use a slant to the right of their natural slant. This might be because to write with a slant further to the right than the natural slant the subjects have to force their wrist. One subject even reported he could not make the slant that he was asked to write with, while he had no such problems in the other direction.

Another possibility might be that the subjects were tired after writing two pages, because the third form was the last. So they had more trouble changing their slant and this resulted in a different handwriting. In future research this should be accounted for by letting half of the people first fill in form three and then form two.

Future work

There are several reasons to do more research on this subject. Only six subjects were used in this research, which is not enough to be certain of the effect seen here. Thus it is important to do the same research with a larger test group. Furthermore, it is interesting to look at the changes of the letters themselves, because there might be ways to counter the effect a slant to the right has on letters. Or determine that someone is trying to forge his or her handwriting.

Because there were so few subjects no difference could be observed between left-handed and right-handed writers. However if the reason why handwriting changes so much is that people have to strain their wrists, then this effect should occur among left-handed writers when they slant to the left instead of to the right.

Another interesting question is in which direction people usually change their slant. Harris does not mention this in his research and maybe people never change their slant to the right and only to the left.

It might also be useful to perform the same tests while looking at different features. The hinge is dependent of the slant of the text and maybe this is the main reason why the performance decreases on text with an unnatural slant.

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