Estimating the Care with which Notes are Written from Online Handwritten Character Data

Motoki MIURA [a,1], Shun AKASE [b] and Takamichi TODA [b]

[a] *Faculty of Basic Sciences, Kyushu Institute of Technology, Japan*

[b] *Department of Integrated System and Engineering, School of Engineering, Kyushu Institute of Technology, Japan*

Abstract. In our previous work, we developed AirTransNote, a student note-sharing system that facilitates collaborative and interactive learning during regular lectures in conventional classrooms. Because taking notes on paper is a regular activity, our system does not impose an extra burden on students who share notes. However, in order to improve the effectiveness of sharing notes on peer learning, students need to improve the presentation of their handwritten notes, because carefully written notes are more accessible for other students and reduce irrelevant, careless mistakes. To facilitate improvements in note-taking, we applied a set of metrics that determine how carefully the notes were written, and propose a system that provides feedback to students about how carefully they are writing notes.

Keywords. Consciousness, Neatness, Improved Handwriting, Attitudes, Anoto digital pen

1. Introduction

In our previous work, we developed AirTransNote, a student note-sharing system that facilitates collaborative and interactive learning during regular lectures in conventional classrooms [1]. Because taking notes on paper is a regular activity, our system does not impose an extra burden on students who share notes. However, in order to improve the effectiveness of sharing notes in peer learning, students need to improve the presentation of their handwritten notes, because carefully written notes are more accessible for other students and reduce irrelevant, careless mistakes.

Learning by teaching [2] is one of the primary strategies for effective learning. Bielaczyc et al. examined the impact of self-explanation and self-regulation strategies on student explanations and performance [3]. The results indicated that particular self-explanation and self-regulation strategies contributed to learning and problem-solving performance. Barnard reported peer-tutoring interactions and their interpretation from a socio-cultural perspective [4]. Therefore, attitudes and strategies for explaining learning

[1] Corresponding Author: Motoki Miura, Kyushu Institute of Technology, 1-1 Sensui, Tobata, Kitakyushu, Fukuoka, 804-8550 Japan; E-mail: miuramo@mns.kyutech.ac.jp.

content are necessary, and they can be improved by efforts to improve the way explanations are made.

Handwriting is a fundamental skill for humans. A Japanese proverb says that a beautiful hand-drawing represents a person's character. For the above reasons, students are expected to write better by hand as well as write accurate content; nevertheless, they do not share their notes. However, the habit of writing well is not always regarded as an important skill during most conventional lectures, except for calligraphy class. In order to make the habit a common practice, we identified the need for a system that could facilitate careful handwriting by providing proper feedback, based on our AirTransNote framework.

In this study, we consider how to determine from online stroke data the level of care that a student takes to write notes. Our target is to examine the writing activity of students during lectures—not the accuracy of the content of their notes compared to the teacher's lecture. Teachers usually check whether students understand the lecture content by asking questions soon after a topic is introduced, and students are expected to answer within a sufficient time. Therefore, our evaluation of the carefulness of the handwriting is independent of factors, such as the speed at which the teacher delivers the lecture or how the lecture is structured.

We focused on the care with which the students wrote their notes, not how beautifully the characters were written. The beauty of the character-writing can also be somewhat improved by writing carefully, and it should also be improved for better presentation of the student's notes. However, beautification depends on the student's motor skills, which are generally difficult to improve in short term. Therefore, in this study, we focused on the care with which students wrote their notes.

2. Related Works

Simard et al. [5] proposed a warping algorithm for ink normalization and beautification. They concentrated on the preprocessing of the recognition of handwritten text; therefore, their final goal was to reduce recognition errors. The concept of ink normalization could be applied to our research in terms of presenting beautified notes, but instead we focused on giving feedback based on metrics of carefulness.

Julia and Faure [6] presented an algorithm of recognition and beautification for graphical design applications on a pen-based computer. Their method recognizes tables, gestures, geometric figures, or diagram networks, and it beautifies the drawings for each drawing category. Miyao and Maruyama [7] proposed a method to segment and recognize online handwritten flowchart symbols by SVM technique. They also proved the effectiveness of their method and implemented a system that beautifies handwritten flowcharts. Paulson and Hammond also proposed a new low-level recognition and beautification system called PaleoSketch [8] that can recognize eight primitive shapes as well as combinations of these primitives. The concepts of interactivity in handwritten drawings and demand for beautification are commonly researched; however, our goal is to provide a method of diagnosis that finds metrics of carefulness.

Zhu and Jin [9] proposed a method for beautifying online handwritten Chinese-character calligraphy. They first applied a speed-based calligraphy simulation to produce a paint-brush style stroke. Afterward, the method matched strokes with template characters. Part of the transfiguration technique in their method can be applied to beautify our students' notes. However, our aim is to make the students improve their attitude about writing carefully while thinking.

Aşıcıoğlu and Turan examined the quality of the handwriting of subjects under the influence of alcohol [10]. The aim of the research was to learn how alcohol and alcohol-related neurological deterioration affected handwriting. The results revealed that the handwriting parameters, such as the length of words, the height of uppercase and lowercase letters, the height of ascending letters, the height of descending letters, the spacing between words, the amount of angularity, the amount of tremor, and the number of tapered ends, were all significantly increased under the effect of alcohol. Some of their metrics regarding handwriting are attractive for examining quality, but most of their metrics were evaluated by human examiners.

3. Method

In this section, we describe our proposed method for measuring how carefully students write their notes, which we call the level of carefulness. To process huge amounts of handwritten data, we needed to build a simple model of writing activity.

Table 1. Hypotheses of Carefully Written Characters

Metric	Carefully written Characters	Disorderly Characters
Variance of Pen Speed	Large	Small
Average of Pen Speed	Small	Large

Table 2. Expected Relationships between Character Complexity and Fundamental Handwriting Metrics

Metric	Complicated Characters	Simple Characters
Variance of Pen Speed	Large	Small
Average of Pen Speed	Small	Large

3.1. Presupposition

We gathered online data of handwritten notes to assess the level of carefulness of note-taking. The online data could be captured by tablet or smartphones, but we employed Anoto-based digital pens in this study. The Anoto-based digital pen has the capability to store and send handwritten notes written on a specific dotted paper sheet. Using the Anoto-based digital pens, we collected accurate and stable student notes.

The Anoto-based digital pen generates (1) the coordinates of the pen-tip (x,y) in a frequency of 75 times per second, and (2) the start time of the writing. Although the end time of the drawing is not captured, it can be estimated using the start time and the number of coordinates that represent a drawing. Therefore, a one-stroke drawing contains n coordinates $P_i(x_i, y_i)$ $(0 \leq i \leq n-1)$ and has a start time T_0 in milliseconds.

Based on the coordinates, we can define distance ($dist$) and velocity ($Velo$) between two coordinates P_i and P_{i-1} as follows:

$$Dist_i = \sqrt{(x_i - x_{i-1})^2 + (y_i - y_{i-1})^2} \qquad (1 \leq i \leq n-1)$$

$$Velo_i = \frac{Dist_i}{1/75} \quad (pixels/sec) \qquad (1 \leq i \leq n-1)$$

3.2. Hypotheses

We made some assumptions for estimating the carefulness of handwritten letters using stroke data. We first tried to estimate the level of carefulness using fundamental metrics obtained from the handwritten data. The fundamental metrics we considered were the following.

Variance of pen speed: This metrics is calculated by $Velo_i$ of a single stroke.
Average of pen speed: This metrics is also calculated by $Velo_i$ of a single stroke.
Complexity of the stroke: This method counts the number of angular points and feature points extracted by Ramer's method. This metric is also calculated by single strokes.

Table 1 shows our hypotheses of the differences between carefully written characters and disorderly characters. Because the writer is calm, the stroke should end accurately and precisely. Therefore, the variance of pen speed becomes larger in carefully written characters. In addition, the average pen speed becomes slower when the writing is done carefully instead of disorderly.

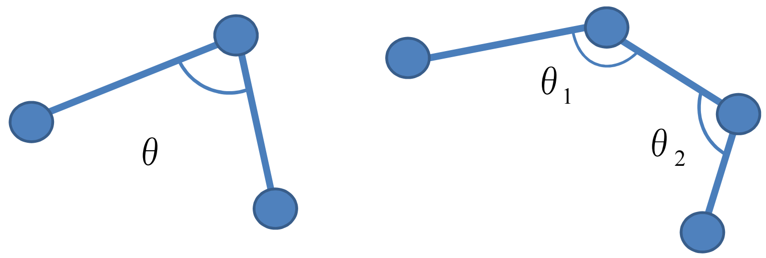

Figure 1. Detection of angular point: single point (left) and paired points (right)

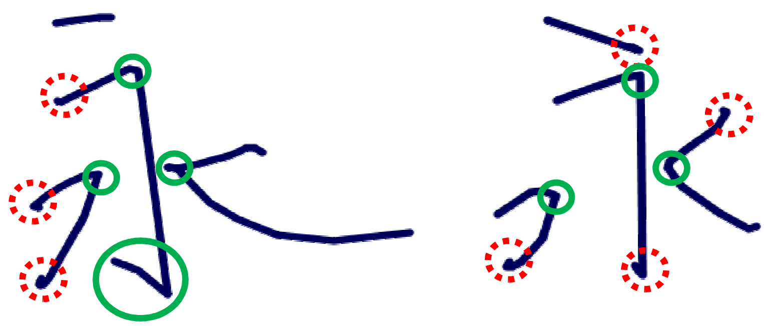

Figure 2. Example of irrelevant angular point (dotted circle) and relevant angular point (solid circle)

Table 2 shows our expectations of the relationship between the complexity of characters and the previously mentioned fundamental metrics. When the writer draws a complicated stroke, the variance of the pen speed will be greater than when writing a simple stroke. In addition, the average pen speed becomes slower than the average for simple strokes.

3.3. Detection of angular point

To estimate the level of stroke complexity, we counted a number of angular points for each stroke. First, we calculated the cosine and angle of all adjacent edges:

$$Cos_i = \frac{Dist_i^2 + Dist_{i+1}^2 - distance(P_{i-1}, P_{i+1})^2}{2 \times Dist_i \times Dist_{i+1}} \qquad (1 \leq i \leq n-1)$$

$$\theta_i = arccos(Cos_i) \qquad (0 \leq \theta_i \leq \pi) \quad (1 \leq i \leq n-1)$$

Then, we defined an angular point as follows: (1) if angle θ_i is greater than 80°, P_i is an angular point (**Figure 1** left) and (2) if the sum of the two adjacent angles $\theta_i + \theta_{i+1}$ is greater than 80°, Pi is an angular point (**Figure 1** right). Without the second condition, some angular points would not be detected, because the pen's scanning frequency (75 times per second) would cause over-resolution of the angular drawing. It is important to note that if the second condition is applied to P_i, then P_{i+1} cannot be an angular point.

This method of detecting angular point works well, but we found some detected points that were irrelevant owing to an unexpected characteristic of the Anoto-based pen data, which sometimes contained an inversed series of points at the beginning and end of the strokes. **Figure 2** shows examples of relevant and irrelevant angular points. At the beginning of strokes, we can simply reject any angular point. However, at the end of strokes, we should consider whether or not the angular point is relevant, because some of the characters must be drawn with a flick at end of the stroke (**Figure 2** left, lower center). Therefore, we accepted the angular point at the end as relevant if the distance of the final stroke after the angle $Dist_{n-1}$ is one-tenth of the distance of the stroke before the angle.

In addition to the simple angle-based detection, we calculated feature points using Ramer's method [11]. First, the start and end points of every stroke were captured as feature points (**Figure 3**, top-left). Then, the most distant point from the straight line between adjacent feature points was selected as a feature point if the distance to the straight line was greater than a threshold value (**Figure 3**, top-right). This selection was done recursively until no more feature points were selected.

We set the threshold value of Ramer's method at 5 pixels[2]. The number of feature points found using Ramer's method represents the ratio of curves to angular points, and it is somewhat larger than the number of the angular points we defined.

4. Experiment

In this section, we explain how we collected and examined the data.

[2] The threshold depends on resolution and size of characters in general. The resolution of the Anoto-based pen is 3 pixels per millimeter

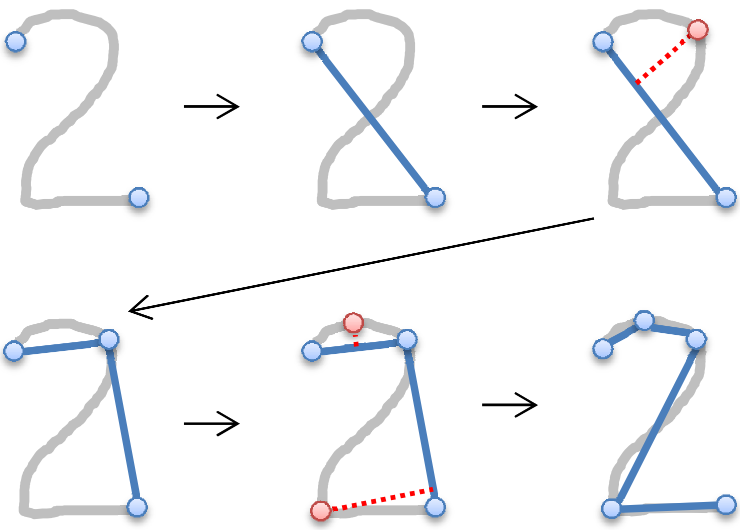

Figure 3. Ramer's method

4.1. Participants and tasks

We asked 10 participants to write Japanese characters that we specified, under a counsciousness of our specified mood. Participants wrote two types of letters: (1) 10 Hiragana letters (the Japanese cursive syllabary) and (2)10 Kanji letters (Chinese-based characters). We specified two sizes: 24 $\times$ 24 mm (large condition) and 12 $\times$ 12 mm (small condition). The participants wrote a total of 80 characters: 2 types $\times$ 2 sizes $\times$ 2 specified moods $\times$ 10 characters. The orders of the conditions were counterbalanced. We did not limit the time to write down the characters. **Figure 4** and **Figure 5** show part of the writing of large characters. The upper example of the characters was carefully written and the lower example of the characters was hastily written. The width of the both figures was the same width as an A4-sized paper sheet. Even though the hastily written characters were still readable, we examined the difference of the specified moods on the students.

4.2. Result

Because the meaning of the distance and velocity is almost the same, we adopted the distance between points in a stroke (*Dist*) as the pen-moving speed. We first eliminated stroke data for which the variance of distance was zero[3]. **Table 3** shows the basic statistics of the stroke data. Norig shows the number of strokes before the elimination, and N shows the number of strokes that were adopted as valid data. VarDist and AvgDist show the variance and average of the speed in the stroke, respectively. To determine stroke complexity, we calculated these metrics using the angular points and Ramer's feature points.

[3]In other words, short strokes were rejected owing to no variance.

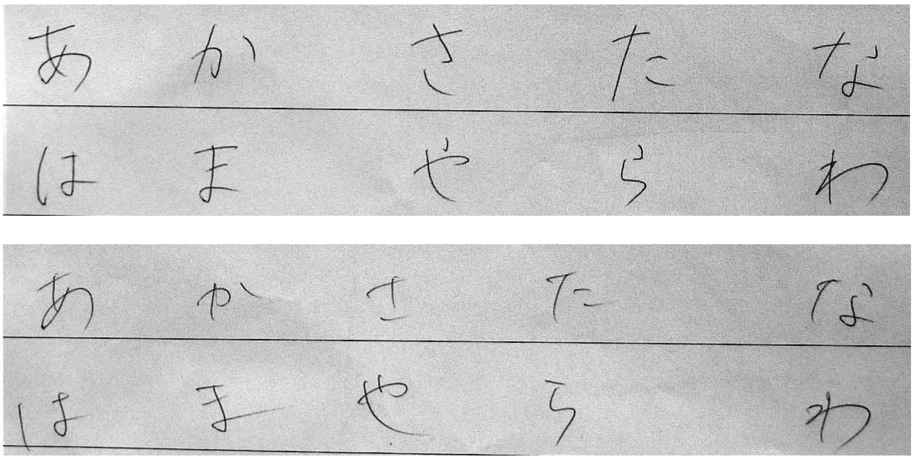

Figure 4. Participant's note in Hiragana characters (upper: carefully written; lower: hastily written)

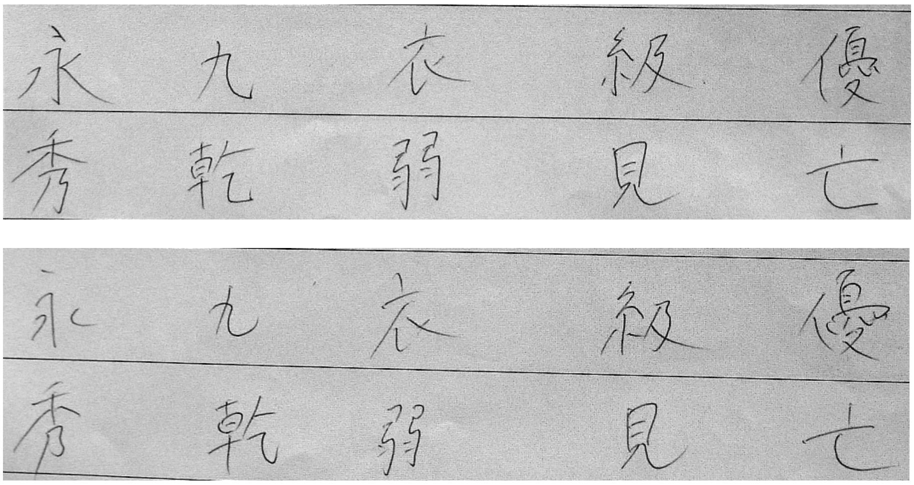

Figure 5. Participant's note in Kanji characters (upper: carefully written; lower: hastily written)

$$VarDist_{angular} = \frac{VarDist}{log(\text{num of angular point} + 2)}$$

$$VarDist_{ramer} = \frac{VarDist}{log(\text{num of Ramer's feature point} + 2)}$$

The result of VarDist partially supported our first hypothesis. The values of AvgDist were varied in character sizes, but not varied in the level of carefulness. To investigate the differences, we conducted a t-test. **Table 4** shows the results of students' t-tests for each character category. The number represents the probability value of the t-test. The bold font indicates that the significance level was under 5%. From the table, we can conclude

Table 3. Basic statistics of the stroke data. (Std.dev. denotes standard deviation)

Size–Type	Mood	VarDist	AvgDist	$\frac{VarDist}{log(angular+2)}$	$\frac{VarDist}{log(ramer+2)}$	N	Norig
Small-Hiragana	Carefully written	8.93	3.34	21.6	23.9	262	298
	(Std.dev.)	12.8	1.64	39.9	40.8		(87.9%)
Small-Hiragana	Hastily written	5.91	3.25	12.37	13.01	216	295
	(Std.dev.)	10.3	1.76	29.8	29.9		(73.2%)
Small-Kanji	Carefully written	8.11	2.94	16.2	19.1	555	740
	(Std.dev.)	13.5	1.22	1.88	36.3		(75.0%)
Small-Kanji	Hastily written	5.18	2.81	9.93	11.3	421	592
	(Std.dev.)	8.49	1.50	22.2	22.7		(70.8%)
Large-Hiragana	Carefully written	27.5	5.31	79.0	81.3	291	305
	(Std.dev.)	62.4	3.27	202.8	203.8		(95.4%)
Large-Hiragana	Hastily written	13.1	5.10	33.4	34.2	246	285
	(Std.dev.)	21.1	2.53	65.1	66.2		(86.3%)
Large-Kanji	Carefully written	15.8	4.54	36.1	40.4	657	755
	(Std.dev.)	24.1	2.47	67.9	73.5		(87.0%)
Large-Kanji	Hastily written	13.4	4.59	30.7	32.3	571	704
	(Std.dev.)	23.9	2.47	68.0	69.6		(81.1%)

the metric $VarDist_{ramer}$ has the potential to estimate the level of carefulness even when the character size s varied.

The metric $VarDist_{ramer}$ can be computed from a single stroke. This feature is convenient; however, to estimate trends in the levels of carefulness, we needed to summarize the metric results from several strokes. In this experiment, the participants wrote only one character. Usually, students write more than one character at a time. We first bundled the strokes according to gap-time, and then extracted the level of carefulness according to the number of bundled strokes.

Table 4. t-test probability (p-value)

Size	VarDist	AvgDist	$\frac{VarDist}{log(angular+2)}$	$\frac{VarDist}{log(ramer+2)}$
Small-Hiragana	**.0045**	.564	**.0014**	**.0002**
Small-Kanji	$<$ **.0001**	.223	**.0001**	$<$ **.0001**
Large-Hiragana	**.0003**	.396	**.0002**	**.0002**
Large-Kanji	.080	.723	.128	**.033**

5. Conclusion and Future Work

In this study, we developed a metric that measures how carefully students write notes based on online handwriting character data. The results supported our first hypothesis that the variance of strokes tends to increase when the strokes are written carefully. In addition to the variance, we revealed that the stroke complexity calculated by Ramer's method can improve the significance of the metric. In future work, we will apply the metric to general handwritten notes and evaluate the performance of the proposed method.

We did not consider the level of beautification in particular. The level of beautification is deeply related to the care with which the writing is done, but it requires special control skills for writers. To evaluate the level of beautification, how well students' writing matches preset character patterns will be calculated. However, the approach should be carefully adopted because it may force students to only imitate beautified samples. We hope that students would not be bound by unnecessary restrictions.

Acknowledgment

Our research is partly supported by Japan Society for the Promotion of Science(JSPS) KAKENHI Grant-in-Aid for Young Scientists (A): Grant Number 23680078.

References

[1] Motoki Miura, Taro Sugihara, and Susumu Kunifuji. Improvement of Digital Pen Learning System for Daily Use in Classrooms. *Educational Technology Research*, 34:49–57, October 2011.

[2] Alan Gartner, Mary Conway Kohler, and Frank Riessman. *Children teach children: Learning by teaching*. Harper & Row, 1971.

[3] Katerine Bielaczyc, Peter L. Pirolli, and Ann L. Brown. Training in Self-Explanation and Self-Regulation Strategies: Investigating the Effects of Knowledge Acquisition Activities on Problem Solving. *Cognition and Instruction*, 13(2):221–252, 1995.

[4] Roger Barnard. Peer tutoring in the Primary Classroom: A Sociocultural Interpretation of Classroom Interaction. *New Zealand Journal of Educational Studies*, 37(1):57–72, 2002.

[5] Patrice Y. Simard, Dave Steinkraus, and Maneesh Agrawala. Ink Normalization and Beautification. In *Proc. of 2005 Int. Conf. on Document Analysis and Recognition (ICDAR'05)*, pages 1182–1187, August 2005.

[6] Luc Julia and Claudie Faure. Pattern Recognition and Beautification for a Pen Based Interface. In *Proc. of the 3rd Int. Conf. on Document Analysis and Recognition*, volume 1, pages 58–63, August 1995.

[7] Hidetoshi Miyao and Rei Maruyama. On-Line Handwritten Flowchart Recognition, Beautification and Editing System. In *Int. Conf. on Frontiers in Handwriting Recognition (ICFHR)*, pages 83–88, 2012.

[8] Brandon Paulson and Tracy Hammond. PaleoSketch: Accurate Primitive Sketch Recognition and Beautification. In *Proc. of the 13th Int. Conf. on Intelligent user interfaces*, IUI '08, pages 1–10, New York, NY, USA, 2008. ACM.

[9] Xinghua Zhu and Lianwen Jin. Calligraphic Beautification of Handwritten Chinese Characters: A Patternized Approach to Handwriting Transfiguration. In *Proc. of ICFHR2008*, pages 135–140, 2008.

[10] Faruk Aşıcıoğlu and Nurten Turan. Handwriting changes under the effect of alcohol. *Forensic Science International*, 132(3):201 – 210, 2003.

[11] Urs Ramer. An iterative procedure for the polygonal approximation of plane curves. *Computer Graphics and Image Processing*, 1(3):244–256, 1972.