Title	Estimating Writing Neatness from Online Handwritten Data
Author(s)	Miura, Motoki; Toda, Takamichi
Issue Date	2014-11-20
URL	http://hdl.handle.net/10228/5873
Rights	富士技術出版

Paper:

Estimating Writing Neatness from Online Handwritten Data

Motoki Miura and Takamichi Toda

Kyushu Institute of Technology, 1-1 Sensui, Tobata, Kitakyushu, Fukuoka, 804-8550 Japan
E-mail: miuramo@mns.kyutech.ac.jp

[Received January 31, 2014; accepted April 15, 2014]

Handwriting is the most fundamental expressive activity in learning. To utilize the intuitiveness and the nature of handwriting, digital pen technology has emerged to capture and transfer notes. We developed AirTransNote, a student note-sharing system that facilitates collaborative and interactive learning in conventional classrooms. A teacher can use the AirTransNote system to share student notes with the class on a projected screen immediately to enhance the group learning experience. However, to improve the effectiveness of sharing notes, the teacher must be able to select an effective note for sharing. This can be difficult and time consuming during a lecture. Moreover, students should be encouraged to improve the presentation of their handwritten notes. Well-written notes are more accessible for other students and reduce irrelevant and careless mistakes.

To facilitate learning improvements based on note sharing, we require a method to estimate the neatness of a note automatically. If a method is established, the teacher can easily select effective notes. Furthermore, this method can help provide feedback to the student to improve their writing. We examined 14 basic features from handwritten notes by considering correlation coefficients and found that the variance of pen speed, angular point average, and pen speed average were the significant features for evaluating the neatness of handwritten notes.

1. Introduction

Handwriting is the most fundamental expressive activity in learning. Because the handwriting activity is common in modern culture, handwriting skills are developed from childhood in both drawing and writing. Handwriting is often regarded as the representation of personality. A Japanese proverb states that a beautiful hand drawing represents a person's character. Therefore, acquiring better handwriting skills is important.

Based on the intuitiveness and the nature of handwriting, digital pen technology has emerged to capture and transfer notes as digitized data. Using an Anoto-based pen, a handwritten paper note can be immediately and easily digitized. Utilizing this technology, we have developed AirTransNote, a student note-sharing system that facilitates collaborative and interactive learning in conventional classrooms [7]. With the AirTransNote system, a teacher can immediately share student notes with the class on a projected screen to enhance the group learning experience. Because of the simple writing interface, the proposed system does not impose any additional burden on the students who share notes.

However, to improve the effectiveness of sharing notes, the teacher must select an effective note for sharing. We have developed a function to classify notes based on the correctness of the answer [7]. However, selecting a suitable note during a lecture remains difficult because it requires significant time to review a substantial number of student notes. Moreover, students should be encouraged to improve the presentation of their handwritten notes. Well-written notes are more accessible for other students and reduce irrelevant and careless mistakes.

To facilitate learning improvements based on note sharing, we require a method to estimate the neatness of a note automatically. If a method can be established, the teacher can easily select effective notes for sharing. The students are expected to write more skillfully with improved content accuracy. Unfortunately, the habit of writing well is not always regarded as an important skill during conventional lectures, except for calligraphy class. When a method to accurately estimate the neatness is realized, it can be applied to making this habit a common practice.

Regarding the sharing of notes, learning through teaching [4] is one of the primary strategies for effective learning. Bielaczyc et al. examined the influence 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 [2]. Clearly, attitudes and strategies for explaining learning content are necessary and they can be improved by efforts to improve the manner in which explanations are provided.

In this paper, we investigate a method of estimating neatness from online stroke data. Our objective is to examine the writing activity of students during lectures, not the accuracy of the content of their notes compared to the teacher's presentation. In the latter approach, the neatness of the student note would be influenced by several factors including the speed at which the teacher delivers the lecture content and how the lecture is structured. We focus on students writing in response to short-term assignments or posed questions during lectures. In general, students are given sufficient time to consider and solve the questions.

We focus on the neatness of the notes, not how aesthetically the individual characters are written. The overall beauty of the character writing can be somewhat enhanced by writing carefully and should 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 the short term. Therefore, in this study, we focus on the care with which the students write their notes.

2. Related Works

Simard et al. [12] proposed a warping algorithm for ink normalization and beautification. They concentrated on the preprocessing of the recognition of handwritten text. 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. However, we focus on providing feedback based on the metrics of neatness.

Julia and Faure [5] presented an algorithm for recognition and beautification for graphical design applications on a pen-based computer. Their method recognized tables, gestures, geometric figures, and diagram networks and beautified the drawings for each drawing category. Miyao and Maruyama [9] proposed a method to segment and recognize online handwritten flowchart symbols using an SVM (Support Vector Machine) technique. They proved the effectiveness of their method and implemented a system that beautifies handwritten flowcharts. Paulson and Hammond proposed a new low-level recognition and beautification system called PaleoSketch [10] that could recognize eight primitive shapes and combinations of these primitives. Although the concepts of interactivity in handwritten drawings and demand for beautification have been commonly researched, our goal is to provide a method of diagnosis that determines the metrics of neatness.

Zhu and Jin [13] 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. Then, the method matched strokes with template characters. A portion 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 [1]. The aim of their research was to identify the consequences of alcohol and alcohol-related neurological deterioration on 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. Despite the fact that some of their metrics regarding handwriting are attractive for examining quality, the majority of their metrics were evaluated manually.

3. Method

In this section, we describe our candidate features for measuring the care with which students write their notes. We call this the level of neatness. To process substantial amounts of handwritten data, we required a simple writing activity model.

3.1. Presupposition

We gathered online handwritten note data to assess the level of neatness of the note-taking process. The online data can be captured using tablets or smartphones. In this study, we employed Anoto-based pens. The Anoto-based pen has the capability to store and send handwritten notes written on a specific dotted paper sheet. Using Anoto-based pens, we collected accurate student notes.

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

3.2. Basic features

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

$$dist_i = \sqrt{(x_i - x_{i-1})^2 + (y_i - y_{i-1})^2} \quad (1 \le i \le n-1),$$

$$velo_i = \frac{Dist_i}{1/75} \quad (pixels/sec) \quad (1 \le i \le n-1).$$

We made assumptions for estimating the neatness of the handwritten letters using stroke data. First, we attempted to estimate the level of neatness using fundamental features obtained from the handwritten data. We considered the following fundamental features.

- **Variance of pen speed:** This feature is calculated by $velo_i$ of a single stroke;
- **Average pen speed:** This feature 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 feature is also calculated using a single stroke.

Table 1. Expected relationships between character complexity and fundamental handwriting features

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

Table 1 illustrates the expected 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. Moreover, the average pen speed becomes slower than the average for writing simple strokes.

3.3. Calculation of stroke complexity (number of angular points)

To estimate the level of stroke complexity, we calculated feature points using the Ramer-Douglas-Peucker algorithm [11] (hereafter, called Ramer's method). The feature points of the algorithm are often utilized for handwritten recognition. They reduce the original points and capture the significant points. We utilize the number of feature points as a metric of stroke complexity.

Ramer's method is as follows. First, the start and end points of every stroke are captured as feature points (**Figure 1**, top-left). Then, the most distant point from the straight line between adjacent feature points is selected as a feature point if the distance to the straight line is greater than a threshold value (**Figure 1**, top-right). This selection is performed recursively until no additional feature points are selected.

We set the threshold value of Ramer's method as one fifth of the stroke height or width, whichever is greater. The number of feature points determined using Ramer's method represents the ratio of curves and number of angular points. By observing the Ramer feature with Japanese handwritten text, we found that the Ramer features of *Kanji* characters are smaller than those of *Hiragana* characters. This is because most *Kanji* characters consist of short, straight strokes compared to *Hiragana* characters.

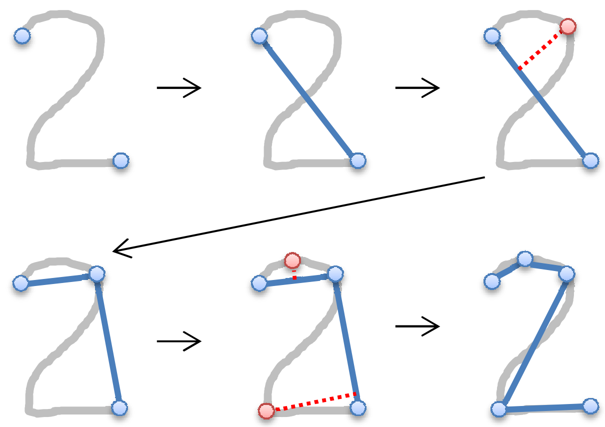


Fig. 1. Ramer-Douglas-Peucker algorithm

4. Experiment

In this section, we describe the method employed to collect and examine the data.

4.1. Collection of Note Data

We collected the handwritten note data of 10 undergraduate students in a lecture at our institute. The lecture was a Japanese literature and expression course. First, the students were required to write their report for their own topic based on research. The reports were shared among the students and the lecturer. The students were also given an assignment of reading reports and peer reviewing by writing short comments for each report. Anoto-based pens were used to digitize these comments. Some of the students prepared drafts of the short comments. Because the prepared drafts were stored in their personal smartphones, the students could refine the draft when they copied them onto a sheet of paper. We provided two A4 size papers. A 10 cm (wide) × 5 cm (high) area was provided for each comment and it was printed on the sheet. We did not place any limitations the size of the handwriting character or the length of the comment. We explained that the comments would be shared on a projected screen. We did not offer any commentary regarding neatness or care.

After the lecture, we grouped the digitized written data based on the short comments. To assess the possibility of detecting the neatness level from online stroke data and to estimate the relevance of the method, we attempted to collect the reference neatness scores for the digitized short comments by comparing all comments. However, we could not simply compare and score all 116 comments. The number of short comments was excessive to evaluate individually and the amount of text included in each comment varied. The size of the comments would affect the evaluation of the neatness score.

Therefore, we divided the short comments into nine groups of similar sizes. We eliminated the comments from the same writer in a group. Finally, we selected nine groups of four comments each. We prepared a PDF document that contained these comment groups, one per page (see **Figure 3**).

We then requested another 15 participants (twelve male and three female, aged 20 to 39) to evaluate the neatness of the writings as absolute scores using the five-point Likert scale (hasty: 1 – neat: 5). The participants browsed the nine page PDF document on their personal PCs and

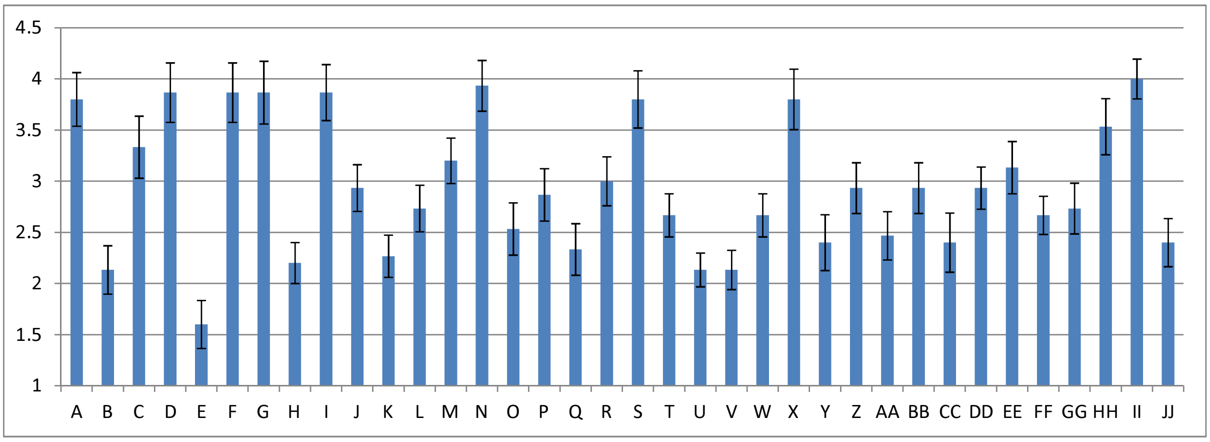


Fig. 2. Neatness (Average of 15 participants' ratings. The error bars represent standard errors)

	avg(Point)	avg(Dist)	avg(Ramer)	var(Ramer)	avg(Vsplog)	var(Vsplog)	avg(Ppd)
r	-0.133	0.002	-0.449	-0.244	0.179	-0.007	-0.440
t(34)	-0.781	0.011	-2.929	-1.466	1.063	-0.041	-2.853
p	0.440	0.991	0.006	0.152	0.295	0.967	0.007
rank	12	14	2	8	11	13	3
	var(Ppd)	var(PpdR0)	var(PpdR1)	var(PpdR2)	var(PpdR3)	var(PpdR4)	var(PpdR5)
r	-0.398	-0.286	-0.556	-0.354	-0.248	-0.207	-0.212
t(34)	-2.531	-1.738	-3.899	-2.209	-1.490	-1.231	-1.267
p	0.016	0.091	0.0004	0.034	0.145	0.227	0.214
rank	4	6	1	5	7	10	9

Table 2. Pearson's correlation coefficients (r) between the stroke features and the reference neatness rate

input their scores in the form of web pages. No time limit was specified. We instructed the participants to review the document and evaluate the neatness of the writings without considering the content - only the look and feel of the writings. We supplemented that the writer's carefulness level of presentation and his/her own handwriting skill on beautification should be separated for the reviewing. We mentioned the difference of comment size and that the participants should not compare the writings on the different pages directly. Further, we remarked that the green and light blue highlighted lines (see **Figure 3**) implied scratching out on unexpected or failure characters. Because the Anoto-based pen could not delete these characters, the students were permitted to ignote the mistakes. We also stated that the highlighted lines should not be considered. **Figure 2** presents the evaluated neatness scores. Owing to the grouping and limitation of four simultaneous writings, the variance of the score was moderate. Therefore, we adopted the average scores as the reference ratings of the neatness.

4.2. Candidate Features of Handwriting Data

We extracted the following candidate features for evaluating the neatness level. All features can be generated by a single stroke.

- **Point:** The number of sampling points in the stroke.
- **Dist:** The stroke length: $\sum_{i=1}^{n-1} dist_i$ (unit: pixel).
- **Ramer:** The number of angular points calculated by Ramer's method explained in Section 3.3. For example, a short straight line produces zero and a Z-shaped stroke produces two.
- **Vsplog:** Variance of pen speed (*dist*) per log(**Ramer**+2). This value was introduced in our former study [6]. This feature was significant under a controlled situation; however, it is not clear if this feature is effective in uncontrolled notes. The value increased when the writer changed the speed within a single stroke.
- **Ppd:** Point per distance (**Points/Dist**). This value represents the inverse of the average pen speed. This feature was introduced in our former study [8].
- **PpdR** n**:** Points per distance of Ramer = n stroke.

To compute the features of the multiple handwritten text strokes, we calculated the average and variance of the above features.

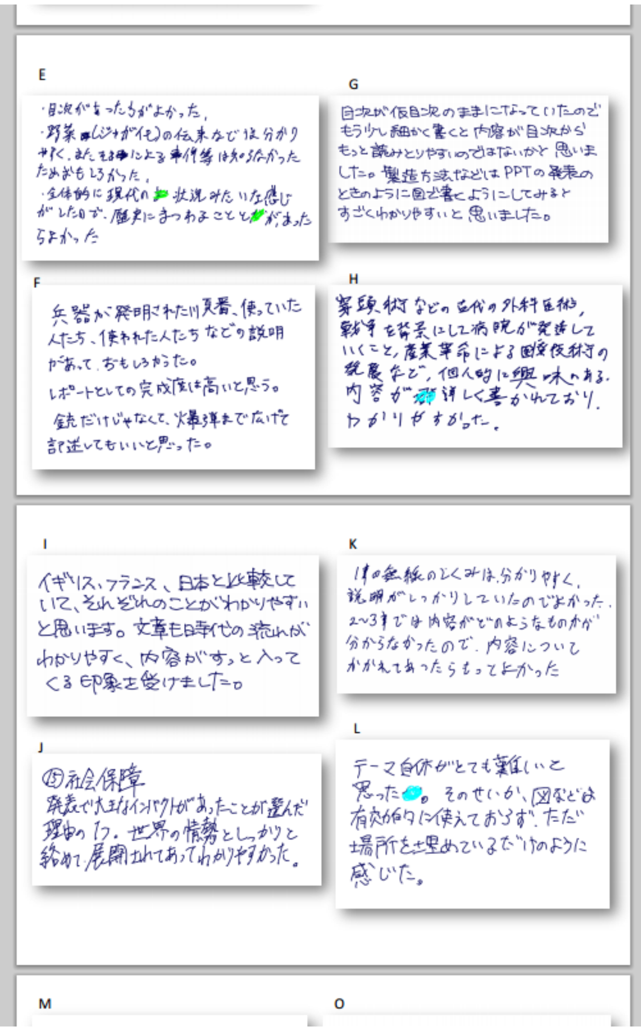


Fig. 3. PDF file for scoring (page 2 and 3 of 9)

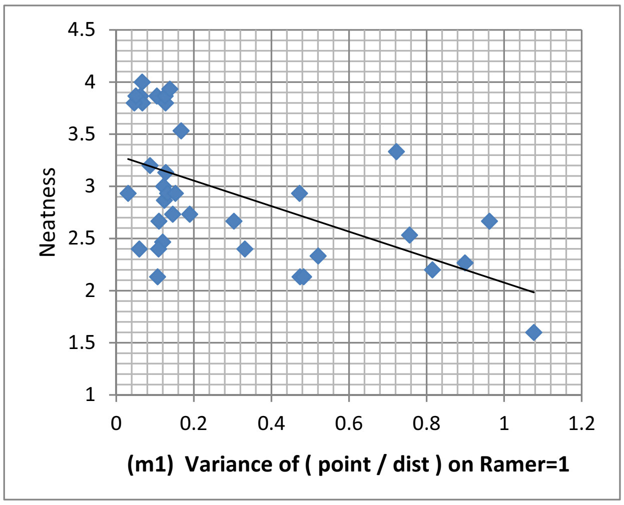


Fig. 4. (m1) Variance of (points/dist) on Ramer=1, $r = -.556$

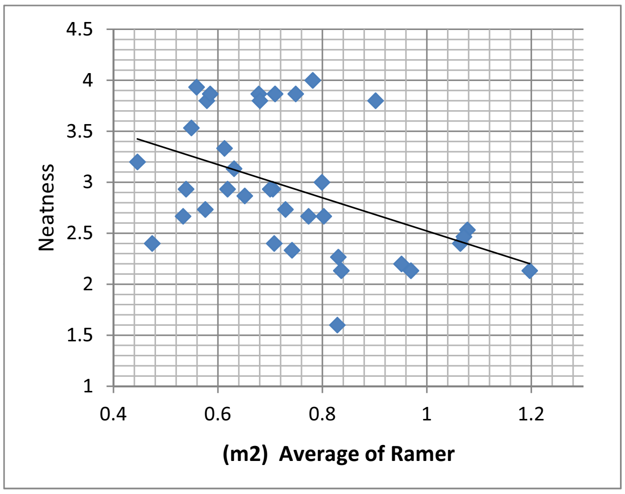


Fig. 5. (m2) Average of Ramer, $r = -.449$

4.3. Result

Table 2 presents the results of Pearson's Correlation Coefficients (r) between the 14 stroke features and the reference neatness rate. The most significant feature was the variance of points per distance on Ramer = 1 ($r = -.556, t(34) = -3.899, p = .0004$). **Figure 4** displays the scatter plot with a regression line. The second significant feature was the average of Ramer ($r = -.449, t(34) = -2.929, p = .006$). The third significant feature was the average of points per distance ($r = -.440, t(34) = -2.853, p = .007$). **Figure 5** and **Figure 6** are the scatter plot and a regression line of the two features. The following two features (the variance of points per distance and the variance of points per distance in Ramer = 2) were 5% significant.

Based on the above results, we attempted to evaluate two types of mixed features. The first, (mf_1), is a simple average:

$$mf_1 = \frac{m1 + m2 + m3}{3};$$

the second, (mf_2), is a weighted average:

$$mf_2 = \frac{m1 \times 3 + m2 \times 2 + m3}{6}.$$

Both mixed features were also significant on the correlation coefficients (regarding the mf_1 feature, $r = -.598, t(34) = -4.350, p < .0001$, and for the mf_2 feature, $r = -.607, t(34) = -4.450, p < .0001$). **Figure 7** and **Figure 8** display the scatter plot and a regression line of the two mixed features. Because mf_2 was the most significant in the above features, we are able to conclude that the mf_2 feature was the most effective metric for estimating the neatness of handwritten notes.

4.4. Discussion

In this section, we consider the reasons for the relationship between the significant features and the neatness rate. The variance of points per distance, which was the

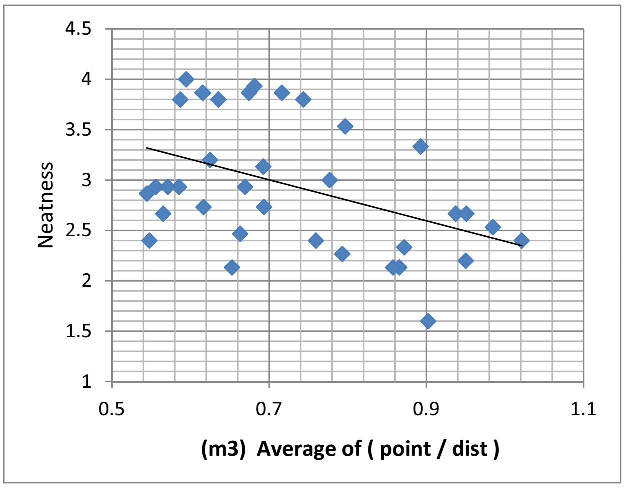


Fig. 6. (m3) Average of (points/dist), $r = -.440$

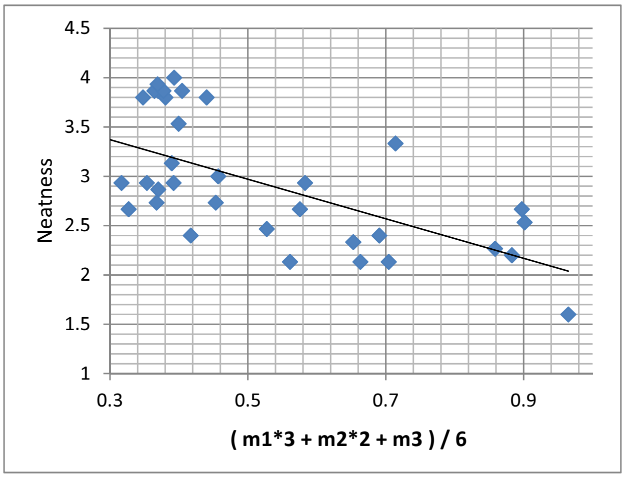


Fig. 8. Weighted mixed feature $(m1 \times 3 + m2 \times 2 + m3)/6$, $r = -.607$

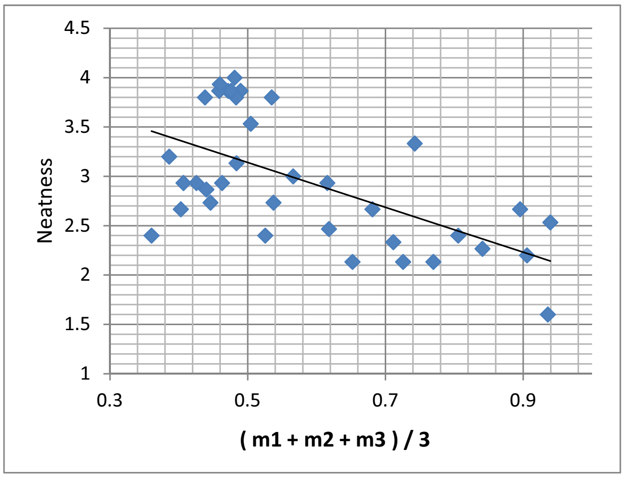


Fig. 7. Simple mixed feature $(m1 + m2 + m3)/3$, $r = -.598$

important feature, was reduced when the student maintained a constant writing speed. In particular, the strokes with Ramer = 1 were simple, yet curvy. Hasty students tended to write such strokes unconsciously. The notes of the careful students produced a low variance of points per distance.

The second feature, the average of Ramer, was straightforward. Careful students securely split their strokes even if the stroke was simple and short, especially in Kanji characters. Hasty students tended to concatenate these short strokes, which increased the percentage of higher Ramer values.

The third feature, average points per distance, was difficult to explain. Intuitively, the value increased when students wrote more slowly. From the results, however, when the average of points per distance increased, the neatness rate reduced. By observing the longest average note, we found that the student wrote smaller characters with shorter strokes. Because the distance of the shorter stroke was smaller, it increased the average value of points per distance. Incidentally, the student who wrote smaller characters did not maintain a constant pen speed.

5. Conclusion and Future Work

In this paper, we examined significant handwritten features for estimating the neatness rate of online note data. We calculated 14 basic features from handwritten notes and verified the correlation coefficients with a reference neatness rate. We found that (1) variance of pen speed, (2) average of angular point, and (3) average of pen speed were the significant features for evaluating the neatness of the handwritten notes. We illustrated that the weighted average of the above three features produced significant correlation coefficients ($r = -.607$). The metrics can be effectively used for estimating the neatness rate from the extensive amount of handwritten stroke data consisting of natural text written in Japanese.

We have not confirmed the effectiveness of the metrics for other languages such as English, Spanish, or Chinese. For future work, we will evaluate the applicability of these metrics. Furthermore, we will employ the metrics for our student note-sharing system to assess if the proposed method relieves the teacher's burden and encourages the students to improve the quality of their writings.

Acknowledgements

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

References:

[1] F. Aşıcıoğlu and N. Turan, "Handwriting changes under the effect of alcohol", Forensic Science International, 132(3):201 – 210, 2003.

[2] R. Barnard, "Peer tutoring in the Primary Classroom: A Sociocultural Interpretation of Classroom Interaction", New Zealand Journal

of Educational Studies, 37(1):57–72, 2002.

[3] K. Bielaczyc, P. L. Pirolli, and A. 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] A. Gartner, M. C. Kohler, and F. Riessman, ”Children teach children: Learning by teaching”, Harper & Row, 1971.

[5] L. Julia and C. Faure, “Pattern Recognition and Beautification for a Pen Based Interface”, In Proc. of the 3rd Int. Conf. on Document Analysis and Recognition, volume 1, pp. 58–63, August 1995.

[6] M. Miura, S. Akase, and T. Toda, “Estimating the Care with which Notes are Written from Online Handwritten Character Data”, In Proceedings of the 6th International Conference on Intelligent Interactive Multimedia Systems and Services, pp. 195–203, June 2013.

[7] M. Miura, T. Sugihara, and S. Kunifuji, “Improvement of Digital Pen Learning System for Daily Use in Classrooms”, Educational Technology Research, 34:49–57, October 2011.

[8] M. Miura and T. Toda, “Extraction of Writing Carefulness from On-line Handwritten Data”, In 22nd FIM Int. Conference on Interdisciplinary Mathematics, Statistics and Computational Techniques, pp. 113–118, November 2013.

[9] H. Miyao and R. Maruyama, “On-Line Handwritten Flowchart Recognition, Beautification and Editing System”, In Int. Conf. on Frontiers in Handwriting Recognition (ICFHR), pp. 83–88, 2012.

[10] B. Paulson and T. Hammond, “PaleoSketch: Accurate Primitive Sketch Recognition and Beautification”, In Proc. of the 13th Int. Conf. on Intelligent user interfaces, IUI ’08, pp. 1–10, New York, NY, USA, 2008, ACM.

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

[12] P. Y. Simard, D. Steinkraus, and M. Agrawala, “Ink Normalization and Beautification”, In Proc. of 2005 Int. Conf. on Document Analysis and Recognition (ICDAR’05), pp. 1182–1187, August 2005.

[13] X. Zhu and L. Jin, “Calligraphic Beautification of Handwritten Chinese Characters: A Patternized Approach to Handwriting Transfiguration”, In Proc. of ICFHR2008, pp. 135–140, 2008.

Name:
Motoki Miura

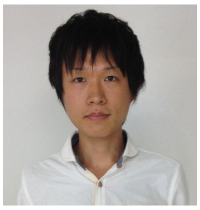
Affiliation:
Faculty of Basic Sciences, Kyushu Institute of Technology

Address:
1-1 Sensui, Tobata, Kitakyushu, Fukuoka, 804-8550, JAPAN

Brief Biographical History:
He received B.S., M. E., and D. E. degrees in electronics engineering from the University of Tsukuba in 1997, 1999, and 2001, respectively. From August 2001 to March 2004, he worked as a research associate at TARA Center, University of Tsukuba. From April 2004 to March 2009, he worked as an assistant professor in the School of Knowledge Science, Japan Advanced Institute of Science and Technology.

Main Works:
• Human-Computer Interaction, Learning Environments, and Creativity Support Systems

Membership in Learned Societies:
• IPSJ, JSSST, IEICE, JSAI, ACM, JSET



Name:
Takamichi Toda

Affiliation:
Graduate School of Engineering, Kyushu Institute of Technology

Address:
1-1 Sensui, Tobata, Kitakyushu, Fukuoka, 804-8550, JAPAN

Brief Biographical History:
He received B.E. degree from Department of Integrated System Engineering, School of Engineering, Kyushu Institute of Technology.

Main Works:
• Human Activity Sensing, Distributed Machine Learning

Membership in Learned Societies:
• IPSJ