19th International Conference on Knowledge Based and Intelligent Information and Engineering Systems

Detecting Erase Strokes from Online Handwritten Notes using Support Vector Classification

Motoki Miura\textsuperscript{a}, Yusaku Kobayashi\textsuperscript{b}

\textsuperscript{a}Faculty of Basic Sciences, Kyushu Institute of Technology, 1-1 Sensui, Tobata, Kitakyushu Fukuoka, 804-8550, Japan
\textsuperscript{b}Department of Electrical and Electronic Engineering, Kyushu Institute of Technology, 1-1 Sensui, Tobata, Kitakyushu Fukuoka, 804-8550, Japan

Abstract

We have implemented a student note-sharing system, AirTransNote, that facilitates collaborative and interactive learning in conventional classrooms. With the AirTransNote system, a teacher can immediately share student notes with the class using a projection screen to enhance group learning. However, students tend to hesitate to share their notes, particularly when the notes contain embarrassing mistakes. Nevertheless, teachers want to focus on real mistakes students make while learning. We introduce an erase stroke detecting method for the student note-sharing system to reduce students’ discomfort regarding sharing mistakes, as well as to assist the teacher in finding mistakes. We collected and manually labeled free-style handwritten student notes. Based on the labeled notes, we extracted features for the erase symbols and deleted strokes. We have tested support vector machine techniques for classifying erase symbols and deleted strokes from typical handwritten notes.

1. Introduction

Digital devices such as tablets and smartphones are commonly used for learning and teaching in classroom lectures. Using these devices, teachers can collect students’ ideas and responses smoothly and immediately. Furthermore, the collected ideas and responses can be organized by similarity, encouraging students to share related thoughts. Although a device’s display can be used to present lecture materials freely using wireless data transmission, such digital devices require the students to learn the device’s interface.

To minimize students’ burden, we have proposed AirTransNote, a student note-sharing system that facilitates collaborative and interactive learning in conventional classrooms\textsuperscript{1}. AirTransNote uses digital pens and paper to collect students’ ideas and responses. Since notes written by the students are transmitted wirelessly, the teachers can immediately share the notes with the class using a projection screen to enhance group learning. Furthermore,
the students are familiar with the pen and paper and the interface is intuitive, lessening the burden imposed on the students.

Since AirTransNote uses Anoto-based pens, and the pen tip is that of a ballpoint pen, there is no means of erasing unwanted handwritten notes. The characteristics of the pen can benefit teachers, because it can track all student activities including errors and mistakes. However, students tend to hesitate to share their notes, particularly when the notes contain embarrassing mistakes. Nevertheless, teachers sometimes want to focus on real mistakes made during a lecture to further enhance students’ learning.

In this study, we introduce an erase stroke detecting function for our student note-sharing system. When the erase stroke function is implemented, mistakes in students’ notes can be hidden. We consider that reducing students’ discomfort regarding the sharing of mistakes is important for note-sharing lectures. Detecting erase strokes also assists teachers in finding mistakes during the lecture. Note-sharing lectures are effective when teachers can recognize students’ status. However, this is difficult because of the limited time of each lecture. The erase function can help teachers to focus on their mistakes. Real-time feedback from teachers improves the effectiveness of note-sharing lectures.

Moreover, the erase function can be useful for reviewing students’ notes after lectures. The timing and circumstances of mistakes can be analyzed and classified, and the results can assist in improving the quality of succeeding lectures.

To create an erase function, we collected and manually labeled free-style handwritten student notes. Based on the labeled notes, we extracted features for erase symbols and deleted strokes. We have tested support vector machine (SVM) techniques for classifying erase symbols and deleted strokes from typical handwritten notes.

2. Design Criteria

We decided on the following criteria for designing an erase function.

- To keep the interface natural and intuitive, the system must accept all possible erase symbols.
- Teachers can easily update the rules of the erase symbols based on student notes.
- The target writings contain not only characters or words but also figures and formulae. These writings are not always restricted by any form areas or rectangle fields, which are designed and printed on the sheet in advance.

For the first criterion, we collected as many erase symbols as possible. For the second criterion, we cannot define and implement the conditions of the concrete erase symbols in advance. Hence, we adopt a support vector classifier to detect erase symbols. Using the support vector classifier, teachers can update the classifier model by specifying new erase symbols. The third criterion is necessary because of our motivation. Student notes can contain any type of writing in a free form. The system must support such free-styled writing, rather than only fixed styles.

3. Related Works

Ahmad et al. applied SVM techniques to character recognition and tested the IRONOFF and UNIPEN datasets. Their result showed that SVM recognition rates are significantly higher at the character level. Bahlmann et al. proposed a novel classification approach that combines dynamic time warping and an SVM by establishing a new SVM kernel. Huang et al. presented a combined approach using a hidden Markov model (HMM) with an SVM. They used a set of left-right HMMs as a feature extractor and an SVM as a classifier to identify unknown symbols. This technique reduces the dimensions of feature vectors. They also tested the proposed methods with UNIPEN datasets. The authors also presented a fast feature selection model for handwriting symbol recognition by combining an HMM with a multilayer forward network. The approach to classifying handwriting using an SVM is similar, but these involve the results of isolated character recognition. We examine the classification of handwritten symbols of natural note writing, which includes formulae and figures, which are not separated into individual characters in advance.
4. Method

The aim of this study is to classify both erase symbols and deleted strokes. However, since deleted strokes are similar to normal strokes, they cannot be determined without data regarding erase symbols. In other words, deleted strokes are closely related to erase symbols. Therefore, we first predict erase symbols from all handwriting strokes. After determining the erase symbols, deleted strokes are classified using features of erase symbols. We call these steps Phases 1 and 2, respectively.

4.1. Phase 1: detecting erase symbols

Figure 1–Figure 3 show typical erase symbols observed in student notes: two or more horizontal, X, and scratch-out lines, respectively. To identify these erase symbols, we selected the following feature values for each stroke.

- Distance of the stroke. The distances of horizontal, X, and scratch-out lines are longer than those of normal strokes.
- Width and height of the bounding box of the stroke. The widths and heights of horizontal, X, and scratch-out lines are greater than those of normal strokes (“width” and “height” in Table 2).
- Number of angular points (using Ramer-Douglas-Peucker algorithm). Scratch-out lines usually contain many angular points rather than normal strokes (“ramer” in Table 2).
- Number of crossing points with previously written strokes. The strokes of erase symbols are typically overwritten on already existing strokes, increasing the number of crossing points (“cross” in Table 2).
- Cosine similarities of vectors with preceding and succeeding strokes. The vector contains (1) line slant (by simple linear regression), (2) straightness of a stroke (using principal component analysis), and (3) width and (4) height of a bounding box. This value is introduced to distinguish horizontal and X lines from others (“erase” in Table 2).

The Ramer-Douglas-Peucker algorithm (Ramer’s method) is used to extract angular points of a stroke. In that method, the start and end points of every stroke were first captured as feature points (Figure 4, 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 4, top-right). This selection was performed recursively until no further feature points were selected. We set the threshold value as one fifth of the stroke height or width, which is larger than others.

The distance and number of angular points can distinguish scratch-out strokes (Figure 3) from others. The width and height of the bounding box of a stroke increase, when the student writes X lines (Figure 2). To detect horizontal lines (Figure 1), we introduced the cosine similarities of line slant, straightness, width, and height of the bounding box with strokes just before/after the stroke is written.

4.2. Phase 2: detecting deleted strokes

For detection of deleted strokes, we chose the following feature values.

- Number of overlapped erase symbol strokes written after a stroke (“oc” in Table 3).
- Sum of areas overlapping with erase symbol strokes.
- Number of crossing points with erase symbol strokes written after a stroke (“crossa” in Table 3).
- Time duration from overlapped erase symbol strokes and a stroke. If multiple overlapping strokes exist, the maximum value is used (“otd” in Table 3).

Note that these feature values are calculated using the erase symbol stroke determined by Phase 1. For the condition of overlap, we use the bounding box of a stroke. We considered that when the entire bounding box of a stroke is contained in one of the erase symbols’ bounding boxes, the stroke is overlapping.

5. Experiment

To test the effectiveness of the proposed method, we conducted an experiment. We collected handwritten note data of undergraduate students in a lecture on material mechanics. Forty students attended the lecture. The students were asked to answer questions as an exercise using Anoto digital pens and paper during the lecture. Since the digital pen notes cannot be erased, we asked the students to create some erase symbols to identify the deleted region. We did not require specific erase symbols. Thus, the students defined their erase symbols by themselves. After the experimental lecture, we labeled each note manually according to our own judgment. Though the number of students was 40, timestamp data of several students’ notes were defective. Therefore, we chose only student note data for which the timestamp data were correct. Figure 5 shows the notes written by the students, which include the results of labeling with colors. Red and blue indicate erase symbols and deleted strokes, respectively.

Table 1 shows the fundamental data of the collected and labeled notes. Sheet ID comprises the lecture day (first digit) and penID (last two digits). There were 15 notes that did not contain erase symbols. Therefore, these notes did not have deleted strokes. We extracted feature values for each stroke, with those of Phase 1 and Phase 2 extracted separately. Table 2 and Table 3 show the basic statistics of the feature values classified according to our manual labeling results. The “cls” in Table 2 indicates the labeling types of stroke, i.e., 0 for normal and deleted strokes, and 1 for erase symbols. Since sheets 126 and 130 did not contain erase symbols, we omitted their cls1 results in both tables. The “erase” represents the cosine similarity value discussed in Section 4.1. The “cross” and “ramer” represent the number of crossing and angular points. Similarly, the “cls” in Table 3 indicates the labeling type of stroke, with 0 indicating normal and 2 deleted. The “oc,” “otd,” and “crossa” represent the number of overlappings counted with erase symbols, time duration, and number of crossing points in 4.2, respectively. From the tables, we can confirm the differences in the averages for each class (cls). The larger differences between classes are better for distinguishing strokes. Because of page limitation, only one third of the sheets are shown in the paper.

We incorporated LIBSVM for Java with the AirTransNote system and evaluated the features through cross-validation. Table 4 shows the results of Phase 1 classification. Since the number of erase symbols (355 strokes)
Table 1. Number of strokes in each sheet

| sheet | normal | erase | deleted | sheet | normal | erase | deleted | sheet | normal | erase | deleted |
|-------|--------|-------|---------|-------|--------|-------|---------|-------|--------|-------|---------|
| 109   | 533    | 11    | 49      | 209   | 399    | 4     | 12      | 242   | 581    | 0     | 0       |
| 111   | 518    | 10    | 374     | 211   | 584    | 16    | 101     | 243   | 492    | 2     | 3       |
| 113   | 630    | 10    | 64      | 213   | 418    | 18    | 37      | 318   | 435    | 0     | 0       |
| 118   | 604    | 6     | 43      | 214   | 496    | 17    | 13      | 319   | 433    | 10    | 5       |
| 119   | 384    | 16    | 13      | 218   | 894    | 18    | 45      | 322   | 250    | 2     | 17      |
| 122   | 435    | 15    | 133     | 219   | 630    | 0     | 0       | 323   | 320    | 0     | 0       |
| 123   | 532    | 8     | 25      | 222   | 716    | 3     | 6       | 326   | 274    | 3     | 3       |
| 126   | 433    | 0     | 0       | 223   | 563    | 0     | 0       | 327   | 306    | 0     | 0       |
| 127   | 624    | 11    | 39      | 226   | 540    | 4     | 15      | 328   | 329    | 0     | 0       |
| 128   | 555    | 2     | 34      | 228   | 824    | 9     | 150     | 329   | 264    | 2     | 4       |
| 129   | 358    | 22    | 196     | 229   | 467    | 4     | 14      | 330   | 355    | 0     | 0       |
| 130   | 388    | 0     | 0       | 230   | 323    | 0     | 0       | 331   | 483    | 5     | 2       |
| 131   | 515    | 16    | 307     | 231   | 501    | 14    | 79      | 332   | 163    | 2     | 3       |
| 132   | 411    | 10    | 69      | 232   | 137    | 0     | 0       | 334   | 368    | 2     | 23      |
| 134   | 381    | 1     | 2       | 234   | 627    | 9     | 148     | 335   | 171    | 0     | 0       |
| 135   | 348    | 2     | 62      | 235   | 579    | 17    | 65      | 336   | 145    | 4     | 29      |
| 136   | 901    | 1     | 2       | 236   | 951    | 6     | 43      | 338   | 225    | 0     | 0       |
| 138   | 330    | 20    | 207     | 238   | 791    | 3     | 38      | 339   | 39     | 4     | 248     |
| 142   | 365    | 4     | 16      | 239   | 523    | 0     | 0       | 340   | 293    | 2     | 20      |
| 143   | 386    | 5     | 62      | 240   | 482    | 2     | 5       | 343   | 92     | 3     | 77      |

is less than that of normal writing strokes, all features of erase symbols except the target note are used to learn and build models. In Table 4, num(normal) represents the number of normal and deleted strokes selected randomly from
Table 2. Fundamental statistics of Phase1 features (one third of sheets)

| sheet | cls | num | width  | height | erase | cross | ramer |
|-------|-----|-----|--------|--------|-------|-------|-------|
|       |     |     | Avg    | SD     | Avg   | SD    | Avg   |
| 109   | 0   | 582 | 12.7   | 11.6   | 9.7   | 7.0   | 0.04  |
|       | 1   | 111 | 138.0  | 98.3   | 11.7  | 6.6   | 0.73  |
|       | 0   | 586 | 10.5   | 11.8   | 8.9   | 5.7   | 0.02  |
|       | 0   | 577 | 72.9   | 55.9   | 107.6 | 96.3  | 0.60  |
|       | 0   | 694 | 6.4    | 9.2    | 6.3   | 4.8   | 0.04  |
|       | 1   | 10  | 34.5   | 27.7   | 12.7  | 9.0   | 0.40  |
|       | 0   | 647 | 9.9    | 16.2   | 8.5   | 6.9   | 0.04  |
|       | 1   | 6   | 132.5  | 59.4   | 11.7  | 6.6   | 0.73  |
|       | 0   | 397 | 10.1   | 7.6    | 10.9  | 8.6   | 0.05  |
|       | 1   | 16  | 29.5   | 5.5    | 23.6  | 2.3   | 0.56  |
|       | 0   | 568 | 10.5   | 22.1   | 10.4  | 15.2  | 0.04  |
|       | 1   | 15  | 63.4   | 62.5   | 36.5  | 25.9  | 1.00  |
|       | 0   | 557 | 8.6    | 11.1   | 7.5   | 5.8   | 0.05  |
|       | 8   | 18.4 | 7.6    | 13.0  | 6.5   | 0.38  |
|       | 0   | 433 | 9.4    | 16.0   | 9.8   | 7.7   | 0.03  |
|       | 0   | 663 | 9.2    | 12.9   | 9.1   | 7.7   | 0.03  |
|       | 1   | 30.3 | 32.1  | 31.4  | 22.3  | 0.00  |
|       | 0   | 589 | 9.2    | 13.6   | 7.2   | 5.1   | 0.04  |
|       | 2   | 202.8 | 14.5  | 10.9  | 1.9   | 1.00  |
|       | 0   | 554 | 9.6    | 19.7   | 9.1   | 6.7   | 0.04  |
|       | 2   | 33.5 | 54.9  | 43.3  | 67.8  | 0.23  |
|       | 0   | 388 | 7.5    | 14.2   | 7.2   | 5.6   | 0.03  |
|       | 0   | 822 | 10.1   | 11.8   | 11.7  | 38.0  | 0.03  |
|       | 1   | 16  | 77.2   | 56.3   | 54.6  | 73.7  | 0.50  |
|       | 0   | 480 | 10.1   | 18.0   | 8.4   | 8.7   | 0.06  |
|       | 10  | 70.9 | 75.5  | 19.5  | 15.0  | 0.40  |
|       | 383 | 10.9 | 19.3   | 10.7  | 7.6   | 0.03  |
|       | 1    | 7.8 | 0.0    | 5.3    | 0.0   | 0.00  |
|       | 10   | 410 | 10.0   | 15.9   | 8.5   | 7.7   | 0.04  |
|       | 1   | 2    | 237.2  | 68.2  | 5.5   | 1.4   |
|       | 903 | 10.1 | 24.3   | 10.6  | 28.7  | 0.04  |
|       | 1    | 9.7 | 0.0    | 7.8    | 0.0   | 0.00  |
|       | 537 | 9.7   | 16.0   | 8.6   | 8.5   | 0.05  |
|       | 20   | 106.2 | 76.8  | 19.6  | 23.8  | 0.50  |
|       | 821 | 8.2   | 6.4    | 9.1    | 7.3   | 0.05  |
|       | 29.1 | 6.6  | 14.0   | 1.5   | 0.75  |
|       | 448 | 8.1   | 4.2    | 8.0    | 6.5   | 0.03  |
|       | 5    | 86.9 | 81.6   | 26.8  | 47.7  | 0.60  |

The F-value is calculated from precision and recall. The values are the best result of grid search in different C and γ values in RBF kernel. The results indicate that the recognition ratio improved when the number of normal strokes increased. We confirmed that 70%-80% of strokes can be correctly classified, if the kernel parameters are appropriately selected.

The result of Phase 2 recognition is shown in Table 5. The “num” represents the sampling numbers of both normal and deleted strokes. The sampling strokes were also randomly selected for building models. Since we assume that all detection of erase symbols in Phase 1 succeeded, no erase symbols were included in the sampling strokes in Phase 2. As for the result (Table 5), the number of samples was not affected for the result of recognition (Avg(F)). In the Phase 2 experiment, we assumed that all the erase symbols were appropriately detected in Phase 1. Therefore, the recognition rate of Phase 2 in a real situation will be worse than the result shown in Table 5.
Table 3. Fundamental statistics of Phase2 features (one third of sheets)

| sheet | cls | num | Avg(oc) | SD(oc) | Avg(otd) | SD(otd) | Avg(crossa) | SD(crossa) |
|-------|-----|-----|---------|--------|----------|---------|-------------|------------|
| 109   | 0   | 533 | 0.00    | 0.00   | 0.00     | 0.00    | 0.00        | 0.00       |
| 109   | 2   | 49  | 0.53    | 0.86   | 12.02    | 18.98   | 1.14        | 1.51       |
| 111   | 0   | 518 | 0.00    | 0.06   | 0.95     | 15.23   | 0.00        | 0.00       |
| 111   | 2   | 374 | 1.17    | 0.69   | 321.60   | 192.17  | 0.21        | 0.75       |
| 113   | 0   | 630 | 0.00    | 0.06   | 0.27     | 4.77    | 0.00        | 0.00       |
| 113   | 2   | 64  | 0.38    | 0.52   | 26.22    | 38.74   | 1.48        | 2.02       |
| 118   | 0   | 604 | 0.00    | 0.00   | 0.00     | 0.00    | 0.00        | 0.00       |
| 118   | 2   | 43  | 0.16    | 0.37   | 2.37     | 6.63    | 0.95        | 1.35       |
| 119   | 0   | 384 | 0.00    | 0.00   | 0.00     | 0.00    | 0.00        | 0.00       |
| 119   | 2   | 13  | 1.54    | 1.01   | 14.00    | 8.43    | 3.08        | 4.16       |
| 122   | 0   | 435 | 0.00    | 0.10   | 0.06     | 1.20    | 0.00        | 0.00       |
| 122   | 2   | 133 | 0.86    | 0.81   | 21.08    | 21.13   | 0.38        | 0.76       |
| 123   | 0   | 532 | 0.00    | 0.00   | 0.00     | 0.00    | 0.00        | 0.00       |
| 123   | 2   | 25  | 0.36    | 0.48   | 6.84     | 11.50   | 1.32        | 1.57       |
| 127   | 0   | 624 | 0.00    | 0.00   | 0.00     | 0.00    | 0.00        | 0.00       |
| 127   | 2   | 39  | 0.97    | 0.60   | 7.49     | 7.08    | 6.69        | 6.09       |
| 128   | 0   | 555 | 0.00    | 0.00   | 0.00     | 0.00    | 0.00        | 0.00       |
| 128   | 2   | 34  | 0.50    | 0.61   | 76.09    | 85.86   | 0.56        | 0.69       |
| 129   | 0   | 358 | 0.01    | 0.12   | 1.14     | 15.25   | 0.00        | 0.00       |
| 129   | 2   | 196 | 1.40    | 0.96   | 99.95    | 75.31   | 1.07        | 2.48       |
| 131   | 0   | 515 | 0.01    | 0.09   | 0.36     | 4.55    | 0.00        | 0.09       |
| 131   | 2   | 307 | 0.70    | 0.62   | 34.52    | 38.46   | 0.42        | 1.06       |
| 132   | 0   | 411 | 0.00    | 0.05   | 0.01     | 0.20    | 0.00        | 0.05       |
| 132   | 2   | 69  | 0.78    | 0.41   | 21.19    | 17.98   | 1.30        | 2.37       |
| 134   | 0   | 381 | 0.00    | 0.00   | 0.00     | 0.00    | 0.00        | 0.00       |
| 134   | 2   | 2   | 0.00    | 0.00   | 0.00     | 0.00    | 0.00        | 0.00       |
| 135   | 0   | 348 | 0.00    | 0.00   | 0.00     | 0.00    | 0.00        | 0.00       |
| 135   | 2   | 62  | 0.10    | 0.30   | 2.79     | 9.28    | 0.44        | 0.66       |
| 136   | 0   | 901 | 0.00    | 0.00   | 0.00     | 0.00    | 0.00        | 0.00       |
| 136   | 2   | 2   | 0.00    | 0.00   | 0.00     | 0.00    | 8.50        | 0.50       |
| 138   | 0   | 330 | 0.00    | 0.00   | 0.00     | 0.00    | 0.00        | 0.00       |
| 138   | 2   | 207 | 0.59    | 0.81   | 13.43    | 20.77   | 0.38        | 0.66       |
| 142   | 0   | 365 | 0.00    | 0.00   | 0.00     | 0.00    | 0.00        | 0.05       |
| 142   | 2   | 16  | 0.69    | 0.68   | 11.44    | 12.32   | 0.69        | 0.92       |
| 143   | 0   | 386 | 0.00    | 0.00   | 0.00     | 0.00    | 0.00        | 0.00       |
| 143   | 2   | 62  | 0.71    | 0.45   | 39.95    | 27.82   | 0.40        | 1.30       |

6. Conclusion and Future Work

In this study, we proposed feature values for classifying erase symbols and deleted strokes from free-form handwritten notes. We tested the effectiveness of the feature values with students’ notes. For the detection of erase symbols, we confirmed that 70%-80% of strokes can be correctly classified, if the kernel parameters are appropriately selected. For the extraction of deleted strokes, 84% of the strokes were classified appropriately.

To improve accuracy, we must consider the features particularly for Phase 1, because the detection rate of the erase symbols directly influences the detection of deleted strokes. In this experiment, the labeling of strokes was not perfect, and there were some inconsistencies in labeling patterns between notes. We hope to refine the method to assist teachers in finding noteworthy student mistakes, and to reduce students’ burden on note sharing.

Acknowledgements

The part of this research was supported by the fund of Telecommunication Advancement Foundation and JSPS KAKENHI Grant-in-Aid for Scientific Research (C): Grant Number 15K00485.
Table 4. Grid search result of Phase1.

| num(normal) | Avg(F)  | SD(F)  | Avg(logC) | SD(logC) | Avg(logγ) | SD(logγ) |
|-------------|---------|--------|-----------|----------|-----------|----------|
| 100         | 0.428   | 0.198  | 10.80     | 4.00     | -13.1     | 1.73     |
| 200         | 0.483   | 0.207  | 10.20     | 3.76     | -13.0     | 1.73     |
| 300         | 0.537   | 0.219  | 10.20     | 3.89     | -13.4     | 1.78     |
| 400         | 0.583   | 0.215  | 8.00      | 4.88     | -12.6     | 2.11     |
| 500         | 0.584   | 0.223  | 7.10      | 4.65     | -11.9     | 2.93     |
| 600         | 0.646   | 0.202  | 7.00      | 6.62     | -12.2     | 3.49     |
| 700         | 0.655   | 0.216  | 6.65      | 5.67     | -12.4     | 2.91     |
| 800         | 0.666   | 0.229  | 6.55      | 5.28     | -12.6     | 2.34     |
| 900         | 0.671   | 0.233  | 6.45      | 5.16     | -12.2     | 3.89     |
| 1000        | 0.670   | 0.227  | 7.70      | 5.51     | -13.1     | 1.87     |
| 1200        | 0.705   | 0.213  | 6.50      | 5.53     | -12.2     | 2.36     |
| 1500        | 0.713   | 0.205  | 6.55      | 5.50     | -12.7     | 2.59     |
| 1800        | 0.742   | 0.212  | 5.50      | 5.86     | -11.6     | 3.32     |
| 2100        | 0.757   | 0.193  | 5.55      | 5.97     | -11.7     | 3.05     |
| 2400        | 0.779   | 0.196  | 6.25      | 5.89     | -11.8     | 2.99     |
| 2700        | 0.786   | 0.168  | 5.31      | 5.07     | -12.0     | 3.03     |
| 3000        | 0.807   | 0.181  | 5.25      | 5.46     | -11.4     | 2.89     |

Table 5. Grid search result of Phase2.

| num | Avg(F) | SD(F) | Avg(logC) | SD(logC) | Avg(logγ) | SD(logγ) |
|-----|--------|-------|-----------|----------|-----------|----------|
| 200 | 0.840  | 0.127 | -5.00     | 0.00     | -2.38     | 2.26     |
| 300 | 0.840  | 0.127 | -5.00     | 0.00     | -2.42     | 2.33     |
| 400 | 0.842  | 0.126 | -4.78     | 1.47     | -2.64     | 2.81     |
| 500 | 0.840  | 0.127 | -4.87     | 0.88     | -2.64     | 2.57     |
| 600 | 0.840  | 0.127 | -5.00     | 0.00     | -2.56     | 2.45     |
| 700 | 0.840  | 0.127 | -4.60     | 2.65     | -2.82     | 3.06     |
| 800 | 0.840  | 0.127 | -4.87     | 0.88     | -2.73     | 2.69     |
| 900 | 0.840  | 0.127 | -5.00     | 0.00     | -2.73     | 2.72     |
| 1000| 0.840  | 0.127 | -4.64     | 2.36     | -3.13     | 3.02     |
| 1200| 0.840  | 0.127 | -4.64     | 2.36     | -3.22     | 3.19     |
| 1500| 0.840  | 0.127 | -4.60     | 2.65     | -3.36     | 3.38     |

References

1. Miura, M., Sugihara, T., Kunifuji, S.. Improvement of Digital Pen Learning System for Daily Use in Classrooms. Educational Technology Research 2011;34:49–57.
2. Ahmad, A.R., Khalia, M., Viard-Gaudin, C., Poisson, E.. Online Handwriting Recognition using Support Vector Machine. In: TENCON 2004. 2004 IEEE Region 10 Conference. IEEE; 2004, p. 311–314.
3. Bahlmann, C., Haasdonk, B., Burkhart, H.. Online Handwriting Recognition with Support Vector Machines—A Kernel Approach. In: Frontiers in handwriting recognition, 2002. proceedings. eighth international workshop on. IEEE; 2002, p. 49–54.
4. Huang, B., Du, C., Zhang, Y., Kechadi, M.T.. A Hybrid HMM-SVM Method for Online Handwriting Symbol Recognition. In: Intelligent Systems Design and Applications, 2006. ISDA ’06. Sixth International Conference on; vol. 1. 2006, p. 887–891. doi:10.1109/ISDA.2006.61.
5. Huang, B., Kechadi, M.T.. A Fast Feature Selection Model for Online Handwriting Symbol Recognition. In: Machine Learning and Applications, 2006. ICMLA ’06. 5th International Conference on. 2006, p. 251–257. doi:10.1109/ICMLA.2006.6.
6. Ramer, U.. An Iterative Procedure for the Polygonal Approximation of Plane Curves. Computer Graphics and Image Processing 1972;1(3):244–256. URL: http://www.sciencedirect.com/science/article/pii/S0146664X72800170. doi:10.1016/S0146-664X(72)80017-0.
7. Chang, C.C., Lin, C.J. LIBSVM: A Library for Support Vector Machines. ACM Transactions on Intelligent Systems and Technology (TIST) 2011;2(3):27.
8. Hsu, C.W., Chang, C.C., Lin, C.J., et al. A Practical Guide to Support Vector Classification. 2003.