Analytics of Reading Patterns Based on Eye Movements in an e-Learning System

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Abstract: We investigate relationships between a subject's impression of difficulty and the reading behaviors of teaching materials based on eye movement data of students learning in an e-learning system. The analyses are important to help revising difficult contents in teaching materials. In this study, we use complex teaching materials containing text, pictures, mathematical expressions, while a previous study in the content difficulty focused on simple teaching materials. We define reading pattern codes to analyze temporal and spatial information of eye movement data using non-negative matrix factorization and compute a backward reading pattern score to compute correlations of the relationships. Our summarization could extract unique reading patterns to understand overall reading behaviors, and we observed correlations between a subject's impression of difficulty and reading behaviors.

Introduction

Understanding students' learning behaviors has taken a key role in learning analytics for enhancing the student performance. Recent work has used eye movement data collected from eye trackers to analyze learning behaviors such as how to read texts and figures in a textbook (Blikstein & Worsley, 2016) (Sharma, Jermann, & Dillenbourg, 2014) (The & Mavrikis, 2016) (Buscher, Dengel, & Elst, 2008). Although clickstream data (Shimada, Taniguchi, Okubo, Konomi, & Ogata, 2018) are sparsely collected, eye movement data can represent detailed learning behaviors such as reading behaviors within pages in a textbook. For example, Jian and Ko showed that reading behaviors of the high-ability students were different from ones of the low-ability students in textbooks (Jian & Ko, 2017).

The analysis of eye movement data can be useful to improve teaching materials. Several previous works using eye movement data showed effective attention guidance techniques and contents of teaching materials. De Koning et al. investigated students' reading behaviors in an animation, and they showed effectiveness of spotlight-cueing in terms of attention guidance techniques (De Koning, Tabbers, Rikers, & Paas, 2010). Mason et al. found using text and pictures in teaching materials is more effective than using only text (Mason, Pluchino, Tornatora, & Ariasi, 2013). The findings did not suggest that we should revise which part of a teaching material. To solve this problem, estimating difficulty of each page in teaching materials is useful to revise the teaching materials. However, the previous study did not establish which pages of a textbook were difficult to understand for students. For example, Nakamura et al. estimated subjective impressions of difficulty of English word tests based on features using eye movements (Nakamura, Kakusho, Murakami, & Minoh, 2008).

In this study, we focus on subjective impression of difficulty of complex teaching materials such as textbooks containing text, pictures, and mathematical expressions. To understand learning behaviors within pages, we analyzed eye movement data of students using an e-learning system M2B (Ogata, et al., 2015). The research reported in this paper attempted to analyze relationships between pages with difficult content and eye movement data. We focused on the summarization of students' learning behaviors to understand reading behaviors and investigate relationships between a subject's impression of difficulty of pages and learning behaviors. To summarize learning behaviors, we defined reading pattern codes, which represented the reading order on a page by students. To analyze the relationships, we focused on the reading behaviors of students who read the same region again, and we defined a score of their reading behaviors.

Data Collection

We collected eye movement data from 15 university students engaged in M2B system. Our study focused on analyzing reading patterns of teaching materials from the eye movement of students. We used a Tobii eye tracker (Tobii pro spectrum 150 Hz). The eye tracker is attached to a monitor, and the sampling rate was 150 Hz. The distance between the eyes of the students and the monitor was 57 cm. Our experiment was conducted in a dark room for each student individually to reduce the measurement error of eye movements due to ambient noise.

First, the eye tracker device was calibrated for each student. Afterward, students learned by themselves using the teaching material in the online learning system. The teaching material was a statistical test, and it contained a variety of content, such as figures, tables, text, formulations, and images. In addition, the content alignment was free. All students answered subjective impressions of the page difficulty on a scale from 0 to 10 using a slider interface after they finished reading each page of the teaching material. The number 10 is considered as the most difficult page. A black page was displayed for one second before the next page was displayed. In addition, we allowed students to read previous pages freely, to collect their reading pattern in a realistic learning environment. After reading all pages, each student took an examination containing six questions to assess his/her understanding of the teaching material. We informed the students before the teaching material was provided that the examination would be performed to enhance their motivation for learning.

Preliminary Analysis

We computed the distribution of the students' achievements on the examination. The highest achievement was 83%. Almost half of the students achieved a score of less than 70% in the examination. This distribution indicates that the content of the examination was not easy for the students. A linear regression was applied to the relationship between students' achievements and reading time of the teaching material, with a Pearson correlation coefficient of the relationship of 0.553. Students were more likely to obtain higher scores on the examination when they spent more time reading the teaching material.

We confirmed that the students' achievements were related to their learning behaviors of students. In our experiment, it was useful to understand learning behaviors in order to improve students' performance. However, this analysis was insufficient to fully understand students' learning behaviors on each page of the teaching material because the analysis focused only on a summary of the learning behaviors. Consequently we analyzed learning behaviors using reading behaviors on each individual page.

Reading Pattern Analysis

We investigated a summary of reading behaviors of the 15 students to observe representative reading behaviors of the students. In this study, we identified several common reading patterns from the reading behaviors to analyze their reading behaviors easily. These reading patterns are referred to as the "reading pattern bases" in this study. The number of reading pattern bases was smaller than the number of observed reading behaviors. The reading pattern bases were useful to observe the overall reading behaviors of students.

To compute the reading pattern bases, we proposed a method for encoding eye movements. We encoded eye movements of each student to features called "reading pattern codes." The reading pattern codes provide the same scheme to compare the reading behaviors of all students. After encoding, we decomposed the reading pattern codes of the students to the reading pattern bases using non-negative matrix factorization (NMF) (Lee & Seung, 1991).

Reading Pattern Code

We encoded eye movement data from students to reading pattern codes, which represent temporal and spatial information of eye movements as a one-dimensional vector. The eye movement data of a student consist of a sequence of gaze points in the teaching material. The length of the sequence is not the same for every student because they could freely view pages of the teaching material in our experimental setting. Therefore, it is difficult to compare reading behaviors among the students. To avoid this problem, we normalized the duration of eye movement data by dividing the sequence into T time slots. This normalization keeps the order of reading part of a page. In this paper, T was set to 20, and $\boldsymbol{e}_{t,i}$ denotes the i-th two-dimensional gaze point on a page in the t-th time slot.

After the normalization, a density map m of gaze points at each time slot was computed on each page using a kernel density estimation:

$$m_t(\boldsymbol{x}) = \frac{1}{N_t}\sum_i \frac{1}{2\pi\sigma^2}\exp\left(-\frac{d\left(\boldsymbol{x}, \boldsymbol{e}_{t,i}\right)^2}{2\sigma^2}\right), \tag{1}$$

where $\boldsymbol{x}$ is the two-dimensional point on a page, N_t is the number of gaze points in t-th time slot, and $d(\cdot,\cdot)$ is the Euclid distance. σ is a hyper-parameter that controls a threshold for defining fixations of gaze points in computing the density map. In (Buscher, Dengel, & Elst, 2008), a fixation is detected as four gaze points within a square of 30 pixels, and gaze points, which are 50 pixels from the fixation, are classified as the same fixation. In this study, σ was set to $45 \times 0.5 = 22.5$, and we ignored gaze points separated by 75 pixels because the resolution was 1280×1024 (Buscher, Dengel, & Elst, 2008) and 1980×1080 in our monitor. We computed T density maps based on Eq. 1.

The resolution of the density map was the same resolution as the monitor. However, the dimensionality was much higher, (1980×1080). It is difficult to handle such density maps in high dimensional space because all pairwise similarities between density maps may be nearly identical as each other (Kabán, 2011). To avoid this problem, we reduced the resolution of the density map. We divided the density map into blocks and then summed the values of the density map in each block. $r_t(i)$ denotes the summation of the density map in the i-th block. The number of blocks was $B_H \times B_W$, where B_H and B_W are the height and width of the low-resolution density map, respectively. In this study, B_H and B_W were set to 6 and 8. Finally, the low-resolution density map r_t was concatenated using all time slots to form a one-dimensional vector as a reading pattern code.

Analysis of Reading Patterns Using NMF

After computing the reading pattern codes, we computed the reading pattern bases by applying NMF to a matrix of the reading pattern codes. Attributes of eye movement data contained student ID, pages, gaze points, and time. Analysis of the eye movement data were undertaken to determine relationships among these four attributes. However, the structure and content of the teaching material was different on each page. In this study, we focused on investigating the reading pattern bases of each page.

NMF decomposes a matrix $\boldsymbol{X}$ into the product of two matrices $\boldsymbol{W}$ and $\boldsymbol{H}$ as follows:

$$\boldsymbol{X} = \boldsymbol{WH}\,, \tag{2}$$

where $\boldsymbol{X}$ consists of reading pattern codes of students, and the i-th row vector is the reading pattern code of student i. If $\boldsymbol{X}$ is an $m \times n$ matrix, $\boldsymbol{W}$ is an $m \times p$ matrix, and $\boldsymbol{H}$ is a $p \times n$ matrix. p is the number of reading pattern bases. In this paper, $m = 15, n = TB_wB_H$, and $p = 3$. Therefore, $\boldsymbol{W}$ is a matrix of coefficients in the reading pattern bases, and $\boldsymbol{H}$ represents a matrix of the reading pattern bases. The row vectors of $\boldsymbol{H}$ corresponded to the reading pattern bases. In NMF, $\boldsymbol{W}$ and $\boldsymbol{H}$ contain only non-negative values, unlike other methods of analysis, such as principal component analysis. Therefore, it is easier to interpret the reading pattern bases because the reading pattern codes also have only non-negative values.

Figure 1 shows the reading pattern bases on pages where at least 10 students felt it was difficult. We superimposed the reading pattern bases onto the corresponding page at each time slot. Each row of the figure corresponds to each reading pattern base, and each column is a time slot. Red indicates a larger value than blue. This visualization represents a summary of students' learning behaviors. For example, the first and third rows visualize eye movements from the upper left to the bottom right of the page. In the second row, the reading pattern base has the

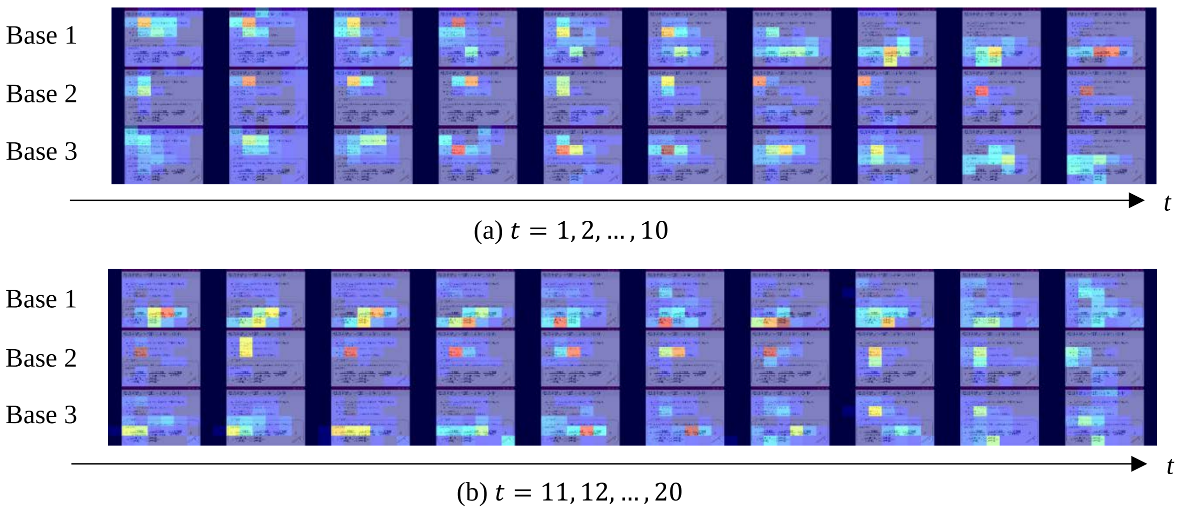

Figure 1: Visualization of reading pattern bases by non-negative matrix factorization in certain page where 10 students felt it was difficult.

same or similar gaze points in all time slots. This reading pattern means that some students read part of the page again. We can confirm overall reading behaviors on each page.

We further investigated students' learning behaviors on each page and conclude that the learning behavior analysis is useful for teachers. However, it is still hard for teachers to understand the reading pattern bases on all pages. To obtain additional information that is more useful, we hypothesized that students read the same regions more than once on difficult pages and call this the "backward reading pattern." We test this hypothesis in the next section.

Correlation Analysis on Reading Pattern and Subject Impression of Difficulty

In this section, we describe the relationship between reading patterns and the pages that the students felt were difficult to test the hypothesis that students read the same regions more than once on difficult pages. In this investigation, we especially focused on backward reading patterns based on the analysis as previously described. We designed a score to represent this backward reading pattern. The scores are used to compute correlations with students' subject impressions of difficulty.

We define backward reading as the reading pattern when a student watches the same region of a page again. The backward reading pattern is not a new feature and is used for gaze analysis in previous studies (Sharma, Jermann, & Dillenbourg, 2014) (The & Mavrikis, 2016). In previous studies, the pattern was computed based on an area of interest (AOI), such as user interface blocks and sentence regions. However, we do not need to define the AOIs because each element of the reading pattern code corresponds to each region on the page automatically. This was advantageous to our experimental setting because the teaching material contained a variety of content.

To analyze backward reading patterns, we compared all reading pattern codes of a student between two time slots on each page. The backward reading pattern score s was computed as the summation of values in a reading pattern code r on a page as follows:

$$s(r) = \sum_{t=1}^{T} \sum_{t'=t+1}^{T} \sum_{i} \delta_{t,t'}(i)\left(r_t(i) + r_{t'}(i)\right) , \tag{3}$$

where $\delta_{t,t'}(i)$ returns 1 if $r_t(i) > 0$, $r_{t'}(i) > 0$ and one $r_j(i)$ $(t < j < t')$ at least satisfies $r_j(i) < \alpha$, otherwise it becomes 0. We set α to 0.1 experimentally. $\delta_{t,t'}(i)$ can remove effects of fixation patterns from the computation of the score because values of reading pattern codes in fixation patterns are continually high, thus $\delta_{t,t'}(i)$ returns 0. To analyze the relationship between the backward reading pattern scores and pages the students felt were difficult, we computed the scores of each student on each page based on (Eq. 3), followed by calculation of the Spearman correlation coefficient for each student.

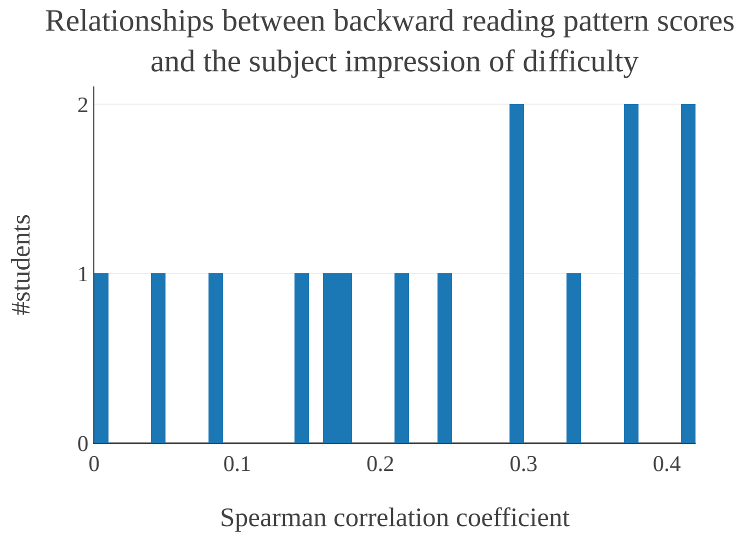

Figure 2: Histogram of the Spearman correlation coefficient between the backward reading patterns scores and students' subject impressions of difficulty.

In Figure 2, we show a histogram of the Spearman correlation coefficient between the backward reading pattern scores and students' subject impressions of difficulty. In Figure 2, five students whose correlation coefficient was greater than 0.3 are shown. This result indicates the existence of students whose backward reading pattern is related to subject impressions of difficulty on each page. However, we also observed results showing no correlation between the aforementioned two factors. This result indicates that the backward reading pattern score alone is not enough to understand difficult pages of teaching materials for students.

Discussion

The analysis undertaken in this study has enabled us to determine that a summary of reading behaviors allows us to understand the overall reading behaviors, and that an analysis of backward reading patterns can be used for detecting difficult pages. We confirmed a unique reading pattern base in the summary and observed a significant correlation between the backward reading pattern score and a subject's impression of difficulty for each page. This finding indicates that eye movement data are effective for improving teaching materials. The summary was based on the analysis of reading behaviors among students. The backward reading pattern score was computed from reading behaviors of each student individually. Thus, a combination of the two analyses provided findings across individuals and within individuals. For example, teachers may be able to find difficult pages based on the score and revise the page based on observations of the reading pattern basis. Further experiments are needed to evaluate education improvement arising from this methodology.

The major limitation of this study is that no evidence of cognitive status is provided after students did the backward reading. In all students, we did not find a correlation between the backward reading pattern score and subject impression of difficulty. We believe that some students in our experiment did not read parts of difficult pages again nor understood the content of the difficult page after reading it again. To further investigate the details of students' learning behaviors, measurements of cognitive status will be needed, such as an electroencephalogram (EEG).

Conclusion

In this study, we investigated a summary of reading behaviors of students and relationships between reading behaviors and backward reading patterns. Eye movement data were collected from students who read the teaching material by themselves. We focused on students' reading behaviors on each page of the teaching material. We proposed a reading pattern code to represent their reading behaviors and applied NMF to the students' reading patterns to analyze the reading pattern bases. The analysis based on the reading pattern bases may be useful for teachers to understand students’ learning behaviors within and across different pages. In addition, we proposed a backward reading pattern score based on the analysis and then performed correlation analysis between the scores and subject impression of difficulty for each page. In this analysis, the scores of five students showed correlations. We conclude that the score may be able to detect difficult pages automatically, thereby helping teachers, and we further conclude that eye movement is effective for assisting teachers.

We used only eye movement data in this study. However, eye movement data might be insufficient to reveal students’ learning behaviors completely. For example, the correlation analysis in this study did not show strong correlations in all students. Recently, other types of data such as clickstream event data and EEG have appeared in learning analytics. In the future, we will combine eye movement data and such other types of data to further study learning behaviors.

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