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Reading comprehension based on visualization of eye tracking and EEG data

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Using eye tracking technology can help us understand reading behavior. Furthermore, sharing the teacher's eye tracking features resulted in improving the students' comprehension of the same reading material [1]. On the other hand, a user's intention can be analyzed by physiological data, such as electroencephalogram (EEG) [2]. EEG is closely related to human cognition [3]. Recently, researchers have tried to use EEG-based engagement measures to augment learning activities. The BRAVO system constantly analyzes users' brain activity, and estimates their attention and meditation levels, and presents users with learning material that only results in high engagement [4]. FOCUS is an EEG augmented reading system that monitors a child's engagement level in real time, and it provides contextual brain computer interaction (BCI) training sessions to improve a child's reading engagement [5]. This study proposed an approach to serve novice readers, i.e., students, and recorded eye tracking and EEG data of the teacher and then converted the raw data into visualized measures. During the reading process, the students adjusted their reading patterns according to their teachers' visualization, and improved reading comprehension.

Eye tracking related measures. How fast a paragraph is read and how many times the person read the same paragraph are the most discriminative features for measuring comprehension [6]. We defined three measures: reading speed for a single area of interest (AOI), reading time for each AOI, switching frequency between two AOIs, and denote p as a time threshold in the AOI, and q as a time threshold between two AOIs (the values of p and q are set empirically) [1].

EEG related measures. Reading engagement has been referred to as general intent on reading and writing, the capacity to focus on text meaning and avoid distractions, and the state of immersion in the narrative [7]. We define reading engagement based on EEG measures and denote E as the value of reading engagement when an individual user is reading a specific AOI. It is calculated as follows [5]:

$$E = \frac{\beta}{\alpha + \theta}, \tag{1}$$

where α, β, θ represents the amplitude of the alpha wave rhythm, beta wave rhythm, and theta wave rhythm, respectively. E is able to identify changes in engagement related to external stimuli (e.g., AOI). To avoid differences across all individuals, we calculate a normalized value $E_{\rm norm}$ (0 to 1) as

$$E_{\rm norm} = \frac{E - E_{\min}}{E_{\max} - E_{\min}}, \tag{2}$$

where E represents the engagement of an individual, and $E_{\max}$ and $E_{\min}$ represent the maximum and minimum levels of engagement across all individuals, respectively. The smaller $E_{\rm norm}$ is, the lower the engagement level the individual user has.

Prototype system. The prototype system we developed includes two main modules: teacher module and student module. The teacher module is

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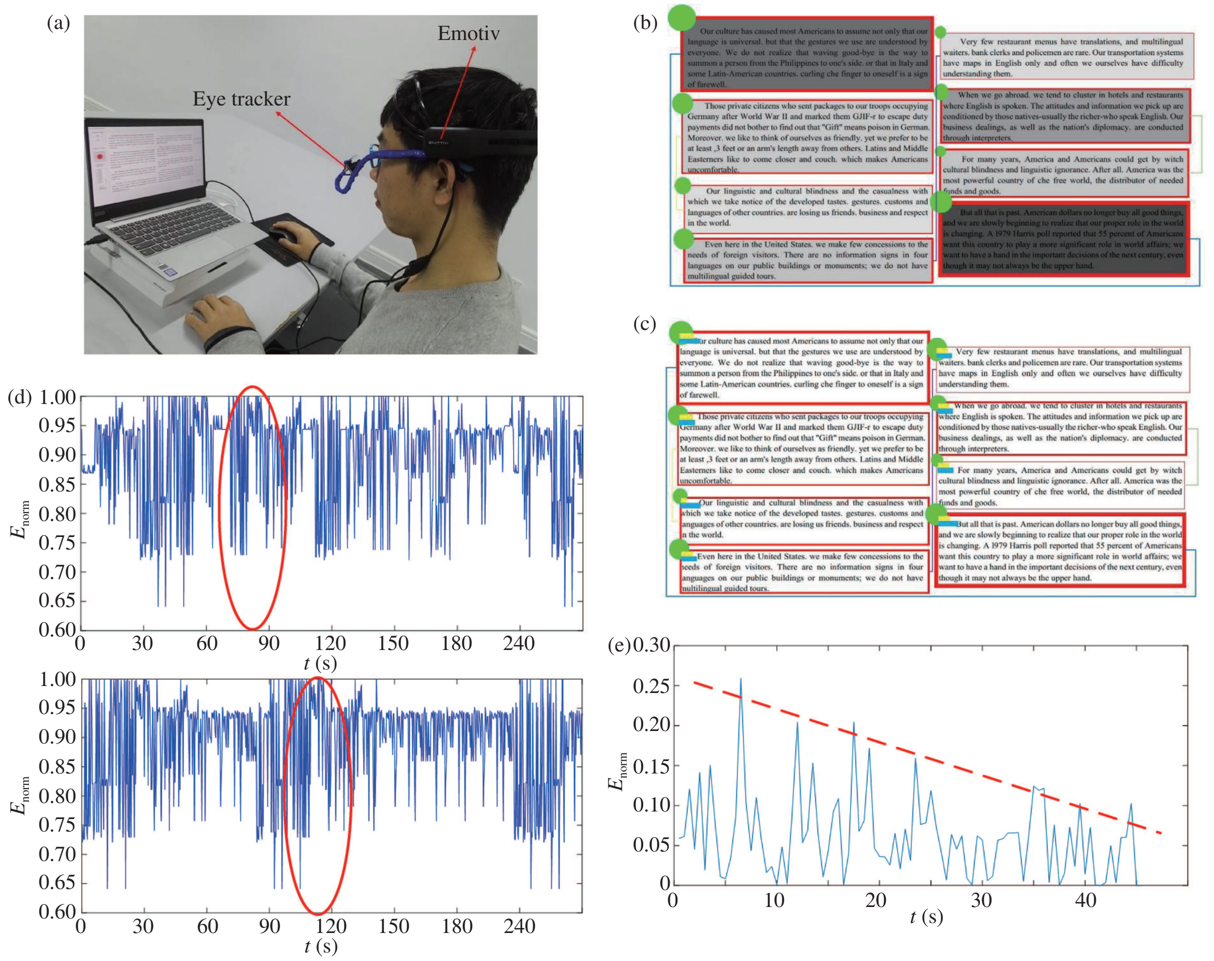

Figure 1 (Color online) (a) The usage scenario of prototype system; (b) teachers' visualizations of eye tracking and EEG data; (c) visualizations of difference between student's and teacher's eye tracking and EEG data; (d) example of engagement from teacher and student; (e) example of engagement difference for one student.

mainly composed of two components: data acquisition and data visualization. The former imports eye tracking and EEG data from the external eye tracker and EEG equipment. The latter generates visualization with eye tracking and EEG data. The system can detect if the user's gaze fixation enters the current specific AOI for a while (longer than the time threshold p), and then both the eye tracking and EEG data from this time are imported to data acquisition components, until the gaze fixation shifts to another AOI for a while (longer than the time threshold q). The student module displays the teacher's visualization while students are reading, and also engagement differences between students and teachers.

User study setup. Our study recruited two kinds of participants: teachers and students. We invited a teacher with a strong computer science academic background who was fluent in English. Twenty students were recruited from the local participant pool, and they majored in computer science. None of them had any visual impairment. To keep English comprehension level similar, students have similar scores in CET-4 (college english test band 4)1). The scenario is shown in Figure 1(a). The participant wears the eye tracker and Emotiv2) to record eye tracking and EEG data, respectively.

We used a headset eye tracker, which is based on the pupil center cornea reflection (PCCR) method [8] to collect eye movement data. We conducted the 9-point calibration achieved the tracking accuracy with 0.8 degree of the visual angle. We used Emotiv to record EEG data, which used 14 electrode sensors with two bipolar reference electrodes spatially organized using the International 10–20 system.

The study contained two phases: pre-study and formal study. With a pre-study , we excluded student participants who read very fast or slowly [1]. During the formal study, the teacher's eye track-

1) http://cet-bm.neea.edu.cn/.
2) https://www.emotiv.com/.

ing and EEG data were recorded and visualized for sharing with the students later. For student participants, all of them read the same paper that the teacher read. We divided students into experimental group and control group (each group had 10 students). The students in the experimental group could watch the visualizations, but the students in the control group could not watch the visualizations.

Results. Figure 1(b) shows the teachers' visualizations of eye tracking and EEG data: the lighter gray indicates fast reading, thicker border indicates more times, and the thicker linked line indicates more gaze switching [1]; and the green circle indicates reading engagement level (larger means higher). Figure 1(c) shows the visualizations while students are reading. Additionally, there are rectangles on the top left of each AOI representing the differences (between students and teacher). The blue rectangle indicates the difference in engagement, and the yellow rectangle indicates the difference in reading time. For rectangles, the increase in width corresponds with an increase in differences.

(1) Visualization influences engagement. We found that the engagement of students in the experimental group was similar to that of the teacher (highlighted with red ovals as shown in Figure 1(d)), but with time delay. That means that the student made engagement adjustments after seeing the visualizations. Furthermore, as shown in Figure 1(e), the engagement differences between student and teacher decreased gradually over the reading process. This means that, by watching the visualizations, the student's engagement pattern became more and more like that of the teacher.

(2) Comprehension performance increase. Students were asked to answer the comprehension questions (total score was 5) about the paper by recalling what they read. Paired T-tests showed that control group and experimental group had significant different scores (control group $M = 2.4$, $\mathrm{SD} = 0.7$, and experimental group $M = 3.3$, $\mathrm{SD} = 0.8$; $t = 2.377$, $p < 0.05$) and comprehension questions answering time (control group $M = 453.8$ s, $\mathrm{SD} = 69.3$ s, and experimental group $M = 409.6$ s, $\mathrm{SD} = 64.2$ s; $t = -2.089$, $p < 0.05$). It indicated that the experimental group spent less time to answer the questions with the help of the visualizations. We also found that the average engagement across all AOIs and all students in the experimental group was 0.84, and in the control group, it was 0.70.

(3) Subjective feedback. We used scale to ask participants to rate each type of visualization. They rated the yellow rectangle (the difference in reading time) to be the most helpful for reading comprehension, and rated the green circle (reading engagement level) and blue rectangle (the difference in engagement) as being "very helpful" for improving their concentration. We also found that students thought the reading time for each AOI and switching frequency between two AOIs were more useful.

Conclusion. We designed the visualizations of the eye tracking and EEG data to provide a guide for the students during their reading process. Our pilot study showed that the visualization provided a good guide for students to help them grasp the important content and to understand the logical structure of the paper, which improved their reading comprehension.

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Supporting information Videos and other supplemental documents. The supporting information is available online at info.scichina.com and link.springer.com. The supporting materials are published as submitted, without typesetting or editing. The responsibility for scientific accuracy and content remains entirely with the authors.

References

1 Cheng S W, Sun Z Q, Sun L Y, et al. Gaze-based annotations for reading comprehension. In: Proceedings of ACM Conference on Human Factors in Computing Systems, Seoul, 2015. 1569–1572
2 Ferreira A, Celeste W C, Cheein F A, et al. Human-machine interfaces based on EMG and EEG applied to robotic systems. J Neuroeng Rehabil, 2008, 5: 10
3 Szafir D, Mutlu B. Pay attention! Designing adaptive agents that monitor and improve user engagement. In: Proceedings of SIGCHI Conference on Human Factors in Computing Systems, New York, 2012. 1580–1586
4 Marchesi M. BRAVO: a brain virtual operator for education exploiting brain-computer interfaces. In: Proceedings of CHI'13 Extended Abstracts on Human Factors in Computing Systems, Paris, 2013. 3091–3094
5 Huang J, Yu C, Wang Y T, et al. 2014. FOCUS: enhancing children's engagement in reading by using contextual BCI training sessions. In: Proceedings of the 32nd Annual ACM Conference on Human Factors in Computing Systems, Toronto, 2014. 1905–1908
6 Buscher G, Dengel A, Elst L V, et al. Generating and using gaze-based document annotations. In: Proceedings of CHI'08 Extended Abstracts on Human Factors in Computing Systems, Florence, 2008. 3045–3050
7 Guthrie J T, Wigfield A. Engagement and motivation in reading. Handbook Read Res, 2000, 3: 403–422
8 Merchant J, Morrissette R, Porterfield J L. Remote measurement of eye direction allowing subject motion over one cubic foot of space. IEEE Trans Biomed Eng, 1974, 21: 309–317