PG23

Daejeon, Korea

Revisiting Visualization Evaluation Using EEG and Visualization Literacy Assessment Test

Soobin Yim, Chanyoung Jung, Chanyoung Yoon, Sangbong Yoo,

Seongwon Choi and Yun Jang

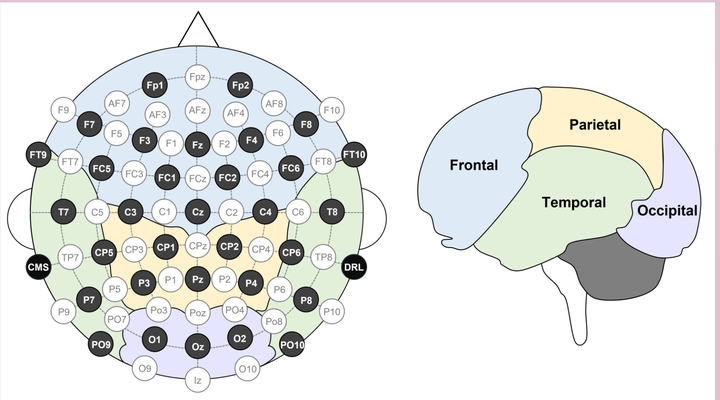
Sejong University

Motivation

Electroencephalogram (EEG) signals can offer a quantitative assessment of human cognitive workload, rendering it a valuable tool for assessing visualizations. Nonetheless, prior studies that assessed visualizations using EEG did not juxtapose their mental workload estimations with established research on visualizations. Consequently, it is impossible to affirm the suitability of their proposed approach for evaluating visualizations through EEG.

EEG

EEG (Electroencephalogram) is an electric signal that reflects human brain activity. We used the Emotiv Epoc FLEX to collect EEG data using saline sensors. This device has 32 electrodes. All electrodes were attached to the EasyCap, which is configurable according to the international 10-20 system.



Item Difficulty Index

The item difficulty index is a metric representing the ratio of subjects who answered an item correctly, and its value ranges from 0 to 1.0.
where P_i represents the index of item i, S_c is the number of subjects who answered item i correctly, and S is the total number of subjects

P_i > 0.85 are considered easy.
0.5 < P_i < 0.85 are considered moderate.
P_i < 0.5$ are considered hard.

$$P_i = \frac{S_c}{S}$$

Acknowledgements

This work was supported by Institute of Information & communications Technology Planning & Evaluation (IITP) grant funded by the Korea government (MSIT) (No.2022-0-00305, Development of automatic data semantic information composition/expression technology based on augmented analysis for diagnosing industrial data status and maximizing improvement, 50%) and (No.2021-0-00469, Development of heterogeneous fusion data detection and tracking technologies, 50%)

SEJONG UNIVERSITY

Experiment Design

This experiment was designed as a benchmark for the Visualization Literacy Assessment Test (VLAT). We chose to benchmark VLAT because it encompasses visualization types and task types commonly used in information visualization, allowing us to compare the relevance of EEG evaluation across various visualizations. Six subjects were recruited for the study. We asked the subjects to skip questions they did not know the answer to. Also, movement can introduce noise in the EEG data, we did not include any interaction techniques within the visualizations. EEG data were collected from the subjects while they were conducting the tasks.

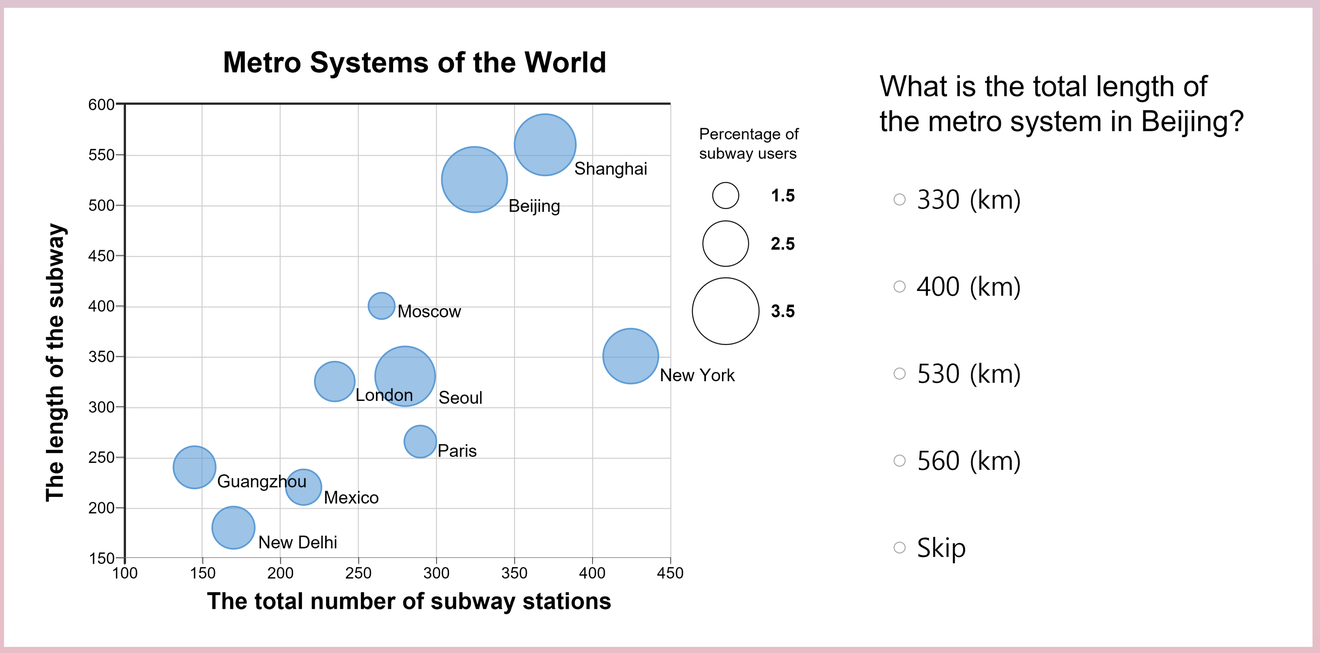
Model

The individual mental workload estimation CNN model is trained to incorporate cognitive differences that differ from person to person in the experiment. We compare the mental workload estimated by the model. The model achieved a training accuracy ranging from 96.73% to 99.72% and a test accuracy ranging from 88.54% to 91.54%.

Subjects	Train Loss	Train Acc	Test Loss	Test Acc
0	0.5523	99.72	0.5525	91.36
1	0.5536	99.55	0.5539	91.19
2	0.5573	97.51	0.5546	89.71
3	0.5542	96.86	0.5536	91.54
4	0.5577	96.65	0.5579	88.54
5	0.5586	96.73	0.5597	90.38

VLAT

VLAT was proposed to measure visualization literacy. Visualization tasks in VLAT are composed of varying difficulty levels, making it suitable for measuring cognitive load induced by visualizations of varying complexity. There were 53 potential test items, including 35 four-option multiple-choice items, 3 three-option multiple-choice items, and 15 true-false items.



Finding

Table compares the difficulty of visualizations measured by Lee et al.[2] with those measured in this work. Based on the item difficulty index, Lee et al.[2] classified problems into 17 hard items, 19 moderate items, and 17 easy items.
According to the behavioral data we collected, we classified problems into 0 hard items, 7 moderate items, and 46 easy items.
Also, our model classified problems into 17 low items, 15 low and moderate items, and 21 moderate items.
This difference is interpreted as the EEG-based model being able to capture complex cognitive mechanisms not seen in the item difficulty index, which is calculated by a simple formula. Therefore, an EEG-based evaluation is valuable for visualization because EEG data contain the mental workload the subjects experience.

Item Difficulty Index	VLAT's Item Difficulty Index	The Estimated Mental Workload in the Model				Count
		Low	Low and Mid	Mid	High	
Easy	Easy	1, 4, 17, 21, 23, 25, 42	7, 38, 56	2, 6, 20, 32, 44, 57, 61	-	17
	Moderate	35	8, 22, 27, 33, 34, 59	3, 5, 18, 19, 28, 29, 48, 52, 54	-	16
	Hard	11, 15, 31, 47, 49	10, 16, 37, 41, 55	9, 36, 60	-	13
Moderate	Moderate	14	-	12, 51	-	3
	Hard	45, 53	40, 46	-	-	4
Count		17	15	21	0	53

REFERENCES

[1] ANDERSON E. W., POTTER K. C., MATZEN L. E., SHEPHERD J. F., PRESTON G. A., SILVA C. T.: A user study of visualization effectiveness using eeg and cognitive load. Computer graphics forum 30, 3 (2011), 791–800.
[2] LEE S., KIM S.-H., KWON B. C.: Vlat: Development of a visualization literacy assessment test. IEEE transactions on visualization and computer graphics 23, 1 (2016), 551–560.
[3] NUAMAH J. K., SEONG Y., JIANG S., PARK E., MOUNTJOYD.: Evaluating effectiveness of information visualizations using cognitive fit theory: a neuroergonomics approach. Applied Ergonomics 88 (2020), 103173.
[4] PAREKH V., BILALPUR M., JAWAHAR C., KUMAR S., WINKLER S., SUBRAMANIAN R.: Investigating the generalizability of eegbased cognitive load estimation across visualizations. In Proceedings of the 20th International Conference on Multimodal Interaction: Adjunct (2018), pp. 1–5.
[5] THORNDIKE R. M., CUNNINGHAM G. K., THORNDIKE R. L., HAGEN E. P.: Measurement and evaluation in psychology and education. Macmillan Publishing Co, Inc, 1991.
[6] YIM S., YOON C., YOO S., JANG Y.: A mental workload estimation model for visualization using eeg. In The proceedings of the 56th Hawaii International Conference on System Sciences (HICSS) (2023).