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Statistical modeling for visualization evaluation through data fusion

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A B S T R A C T

There is a high demand of data visualization providing insights to users in various applications. However, a consistent, online visualization evaluation method to quantify mental workload or user preference is lacking, which leads to an inefficient visualization and user interface design process. Recently, the advancement of interactive and sensing technologies makes the electroencephalogram (EEG) signals, eye movements as well as visualization logs available in user-centered evaluation. This paper proposes a data fusion model and the application procedure for quantitative and online visualization evaluation. 15 participants joined the study based on three different visualization designs. The results provide a regularized regression model which can accurately predict the user's evaluation of task complexity, and indicate the significance of all three types of sensing data sets for visualization evaluation. This model can be widely applied to data visualization evaluation, and other user-centered designs evaluation and data analysis in human factors and ergonomics.

1. Introduction

The increasing volume and variety of data make it a computational and cognitive challenging task for one to obtain valuable information and insights from big data (Michael and Miller, 2013; Tien, 2003). How to deliver the right information to the right people at the right time in a specific scenario remains an open question (Keim et al., 2008). To address these issues, user-centered data visualization can graphically display raw data to help users rapidly narrow down to interested segments from a large scope, and effectively obtain the insights from data (Fekete et al., 2008).

Many data visualization techniques have been developed to efficiently reduce the mental workload and to enlarge user's perception of insights from data. Indeed, different visualization approaches should be selected according to the objectives. In addition to the static visualizations (DeLamarter, 1986; Rohrer and Swing, 1997), a large number of interactive designs have been proposed to visualize high dimensional, large-sample and dynamic data sets (Carlis and Konstan, 1998; Van Ham and Van Wijk, 2004; Wills, 1997). In the past twenty years, Virtual Reality (VR) also provided a platform to immerse the users in data visualization (Bryson, 1996). While its counterpart, Augmented Reality (AR), mixes up the real world and the visualization designs to present graphical visualizations (Azuma, 1997). These new VR and AR based visualization methods have been widely used in many applications, such as medical science (Bichlmeier et al., 2007; Hansen et al., 2010), education (Billinghurst, 2002; Kaufmann, 2003) and industry (Doil et al., 2003; Nee et al., 2012). Data analytics results were also integrated with AR platform for manufacturing applications (Chen et al., 2016).

Despite the tremendous needs of new visualization methods and platforms for wide applications, researchers and practitioners have long identified the need to evaluate the visualization tools to understand the potential and limitations (Lam et al., 2011; Plaisant, 2004). In the literature, a lot of visualization evaluation methods in Human-Computer Interaction (HCI) have been proposed. Field observations (Isenberg et al., 2008) and laboratory observations (Hilbert and Redmiles, 2000) are popular evaluation approaches to assess the visualization works via the understanding of the environments. Besides, heuristic evaluation, formative usability test and summative evaluation methods were also reported to evaluate user-centered designs (Hix et al., 1999). To evaluate the provided insights, a longitudinal study of visual analytics was developed and captured for the entire visualization and analysis process (Saraiya et al., 2006). Furthermore, the controlled experiment approach was used in evaluation study design to provide the objective measures (Willett et al., 2007). Although various evaluation approaches have been presented, they still show limitations in the following three aspects: (1) the lack of unobtrusive data collection during user's' operations in visualization evaluation, (2) the lack of

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consistent standards for evaluating different visualization tools, and (3) the lack of online data analytics for visualization evaluation in a timely manner.

In order to address the aforementioned limitations, various types of sensing techniques and the corresponding data analysis are considered. In Human Factors and Ergonomics (HFE), a typical unobtrusive and quantitative approach is used to use sensors, such as EEG devices, eye tracking systems, motion tracking systems, etc., to assess the mental workload. In this paper, a similar strategy was used.

EEG signals are highly sensitive to variations in mental workload and have been applied to mental workload assessment in several situations. Okogbaa et al. (1994) quantified the relationship between EEG signals and white collar worker mental fatigue for human reliability prediction. Driver' drowsiness, which had a close relationship to mental fatigue, was studied by analyzing the changes of EEG α, β, β/α, $(\alpha+\theta)/\beta$ indices among different driving periods (Åkerstedt and Torsvall, 1984; De Waard and Brookhuis, 1991; Eoh et al., 2005). EEG spectral features were extracted to assess working memory load when the participants were performing tasks with different difficulties (Gevins et al., 1998; Murata, 2005).

As another powerful tool, the use of eye movements has been established in Psychology as a means for analyzing user attention patterns in information processing tasks (Rayner, 2012). In recent years, eye movements have many applications in HFE research. For example, Dehais et al. (2012) used eye tracking techniques as an index of attentional focus to assess the cognitive conflicts in human-automation interactions. In military, Lin et al. (2014) addressed the significant influence of the camouflage patterns to the eye-movement behavior and evaluated the effects of different camouflage designs. To facilitate user experience design, eye tracking techniques were applied to understand, design and evaluate user experience by a lot of researchers and companies (Bergstrom and Schall, 2014). Because users' characteristics, such as cognitive abilities and personalities, have impacts on effectiveness of information visualization, eye movements were used to evaluate traditional information visualization techniques such as tree diagrams (Burch et al., 2011) and box plots (Toker et al., 2013).

In HFE research, motion tracking systems have also been widely adopted. For instance, motion tracking technique was used for interactive work design in occupational ergonomics (Ma et al., 2010). Besides, motion tracking systems were reported to be integrated in virtual environments to assess the work design and to predict real-world ergonomic measurements (Hu et al., 2011; Rajan et al., 1999). Furthermore, a mouse motion tracking system was used to measure the stress condition (e.g., frustration, difficulty) of users during the interaction with interfaces (Sun et al., 2014), which addressed its potential to be used in evaluating information visualization.

Despite the successful applications of individual new sensing technology in HFE, the integration of different types of sensor data has not been explored and reported so far. Such an integration may yield a more accurate user-centered evaluation online. Besides, the contribution of each type of data in user-centered evaluation cannot be evaluated until a data fusion framework is studied in this paper. This is an important issue, since it helps one to understand how to select the right sensing devices for cost-effective and unobtrusive user-centered evaluation.

Our motivation is to bridge the gap between the high demand of new data visualization tools and the low efficiency of user-centered evaluating processes by proposing a data fusion model for quantitative and online visualization evaluation. A wireless EEG device, a remote eye tracker, as well as a logging system (mouse motion tracking system newly developed in this paper) will be integrated to achieve this objective. The synchronized data will be correlated with participants' subjective ratings of task complexities (i.e., visualization evaluation scores). These three types of data can be obtained online when the user is interacting with the visualization designs, and can be further used to predict the evaluation scores online before the post-evaluation survey is performed.

The rest part of the paper is organized as follows. In Section 2, the study design is introduced. In Section 3, the results of the statistical analysis are presented. And the findings are discussed in Section 4. An application guideline of the proposed approach in HEF are discussed in Section 5. The limitations of the data fusion model are presented in Section 6. Finally, we draw the conclusions and summarize the future work in Section 7.

2. Study design

An overview of the study design is shown in Fig. 1. The objective of the study design is to identify if there is a strong correlation between the three types of sensing data and the subjective evaluation scores. In particular, three data sets of last and first names in hierarchical structure were used to generate three hierarchical visualization designs. These designs were visualized and evaluated by 15 participants. During the evaluation, a free exploration task and 11 predefined tasks were performed by participants. These tasks were mainly used to search information from the graphic designs with simple calculations. The experiment followed Institutional Review Board (IRB) approved procedure. For each participant, EEG signals, eye movements and visualization logs were collected. The features were extracted and used to predict the evaluation scores that the participants provided for each task during the experiment. Eight models were estimated to unveil the correlation of the sensing data and the evaluation scores.

2.1. Hierarchical data sets and visualization designs

Three arrays of 252 English names, including the last and the first names, were randomly generated from a name data base (Alan, 2011). Motivated by a data visualization example *flare* (UC Berkeley Visualization Lab, 2008), a hierarchical data structure was generated. Three data sets were automatically generated through randomly mapping the full name arrays to the data structure. These settings were designed to exclude the effects of different data types and structures, and reduce the learning effects to the participants' performances.

In this study, three designs of visualization from an open source visualization library D^3 were used to visualize the data sets (Bostock, 2011). Fig. 2 (a) presents the static node-link tree, in which full names and hierarchical relationships were mapped to the circles, texts and edges, respectively. The static node-link tree presents all semantic information at once without any interactions. Fig. 2 (b) shows an interactive version of static node-link tree. After a click on the node, the corresponding branch can be expanded or collapsed, which provides users with filtered information. Fig. 2 (c) implements a different layout of nested circles (Wang et al., 2006). The nodes sharing the same parents are mapped to the same circle, and the names are shown at the center of each circle. Hierarchical levels are represented by different level of packs and interactive field of views. By clicking on an interested circle, the circle will be zoomed in/out with more details on children circles inside it. Three visualizations were coded in HTML and JavaScript, and each of them used the web browser as the platform. Moreover, the diagrams shared the same screen with the resolution as 1920*1200.

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