SubjectBook: Hypothesis-Driven Ubiquitous Visualization for Affective Studies

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Abstract

Analyzing affective studies is challenging because they feature multimodal data, such as psychometric scores, imaging sequences, and signals from wearable sensors, with the latter streaming continuously for hours on end. Meaningful visual representations of such data can greatly facilitate insights and gualitative analysis. Various tools that were proposed to tackle this problem provide visualizations of the original data only; they do not support higher level abstractions. In this paper, we introduce *SubjectBook*, an interactive web-based tool for synchronizing, visualizing, exploring, and analyzing affective datasets. Uniquely, SubjectBook operates at three levels of abstraction, mirroring the stages of quantitative analysis in hypothesis-driven research. The top level uses a grid visualization to show the study's significant outcomes across subjects. The middle level summarizes, for each subject, context information along with the explanatory and response measurements in a construct reminiscent of an ID card. This enables the analyst to appreciate within subject phenomena. Finally, the bottom level brings together detailed information concerning the inner and outer state of human subjects along with their real-world interactions - a visualization fusion that supports cause and effect reasoning at the experimental session level. SubjectBook was evaluated on a case study focused on driving behaviors.

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Introduction

The focus of affective studies is on measuring and analyzing the psychophysiological state of subjects under various stressors. Such studies illuminate the hidden factors influencing operator performance in human-machine interactions and other critical tasks. Examples include monitoring of driver performance under distractions [12], and how loss of proprioception affects sympathetic and motor responses in novice and experienced laparoscopic surgeons [7].

In recent years, there has been growing interest in collecting and analyzing multimodal affective datasets [4, 5, 9, 11]. This is due to the advent of ubiquitous devices capable of measuring different aspects and factors of human affect [8]. Indeed, one challenge affective studies face nowadays is data variety, as routinely encompass biographic, psychometric, physiological, observational, and performance sets. Bringing all these pieces of information together and presenting them in a way that facilitates comprehension is not a straightforward task. Another challenge is the longitudinal nature of affective studies, where measurements are recorded on individual subjects over a period of time [10]. This leads to data explosion, complicating analysis further.



Figure 1: Levels of visualization in SubjectBook.

Data visualization is indispensable in coping with complexity in affective studies. Appropriate visualization facilitates insights by focusing the analysts' attention on important trends and patterns. There are a number of tools for visualizing multimodal affective datasets. Typically, these tools provide detailed visualizations of the original data. Little work has been done to communicate information at higher levels of abstraction, integral to hypothesis-driven research.

In this paper we describe SubjectBook, an interactive webbased visualization tool for exploring and analyzing multimodal affective datasets. This tool was designed not only to bring together different forms of data, but also to support hypothesis-driven reasoning. Toward this end, a visualization scheme with three levels of abstraction is supported. In the first level, the SessionPortrait, the covariates are presented at the top, followed by the time-registered explanatory and response variables. This visualization fusion aims to bring together possible cause, effect, and context. In the second level, we extend our work from [3] to help analysts appreciate within subject phenomena. Context information along with the explanatory and response measurements per subject are summarized in a construct reminiscent of an ID card - the SubjectPortrait. Finally, analysts can communicate to SubjectBook statistical tests on the study's variables, for producing the StudyPortrait - a grid visualization of the study's significant outcomes across subjects. All three visualization levels are automatically created, and a pyramidal software architecture (Fig. 1) is used to navigate between them.

SubjectBook is presented via a case study, where vehicle drivers were subjected to different distracting stressors, while multimodal data were being collected for behavioral analysis.

Related Work

Over the years, several tools have been proposed to visualize multimodal affective datasets [1, 2, 6, 13]. To the best of our knowledge, no tool abstracts data/results at the subject and study levels, mirroring the scientific method. Also, data sharing among researchers is either not supported by these tools or is not straightforward.

Kim et al. [2] proposed BEDA, a tool for synchronizing, visualizing, and navigating behavioral and physiological data in longitudinal studies. It creates a visual summary to help identify interesting patterns within a single experimental session or across different experimental sessions. BEDA resembles to some degree the SessionPortrait level of SubjectBook. However, no visual abstractions are provided at the subject or study levels; thus, BEDA cannot qualitatively support hypothesis-driven research that traverses these levels quantitatively. Also, it does not accomodate biographic and psychometric information.

ChronoViz [1] is another tool that supports annotation, visualization, navigation, and analysis of multimodal timecoded data. Similar to ChronoViz, ELAN [13] provides visualization and synchronization but only between audio and video data. Neither ChronoViz nor ELAN, however, support record keeping and analysis of multiple sessions in longitudinal studies.

Oefinger et al. [6] developed a web-based tool for visualizing and manipulating multi-scale physiological data. Unfortunately, this tool does not support any other data type.

Design

SubjectBook was designed to visualize longitudinal affective studies where numerous human subjects are involved. In this type of studies, baseline measurements are initially collected for subjects under normal conditions. These measurements are then compared with corresponding measurements taken under interventional conditions. The analysts' aim is to identify any significant changes in the response variables and associate them with any significant changes in the explanatory variables. For example, significant increase in sympathetic arousal (explanatory variable) due to driving distractions may negatively influence driving performance, resulting in significant increase of lane deviations (response variable).

The analysts' investigation takes place either at the intrasubject level or at the inter-subject level, using data from the experimental sessions. Accordingly, we designed a three-level visualization scheme: SessionPortrait, Subject-Portrait, and StudyPortrait.

SessionPortrait

SessionPortrait is the grassroots visualization level, where data collected during each experimental session, including surveys, signals, and videos, are combined into a visual report. As illustrated in Fig. 2, SubjectBook puts sessionspecific data under a tab dedicated to that session. Specifically, the session's temporal signals are synchronized and presented in the form of stacked line charts. This arrangement brings to the fore relationships among physiological (explanatory) and performance (response) channels in a particular session. Analysts can switch from one session to the other by simply clicking the appropriate tab.

Session-independent data (i.e., covariates), such as trend psychometrics and biographic information, are placed above the session tabs, providing constant access to such information. Trend psychometric scores are visualized within the corresponding scales. Biographic information is presented in a separate panel, next to trend psychometrics.

One important feature of SessionPortrait is stimulus annotation. This annotation boils down to a colored region on the chart, marking the duration of an intervention. For example, the two colored regions in Fig. 2 mark two similar events -



Figure 2: SessionPortrait: tab view.



Figure 3: Synchronization between a physiological signal and observational streams.



Figure 4: SessionPortrait: multi-session view.

texting distractions. Different events are assigned different colors.

In order to establish association between the subjects' internal and external states, synchronization between physiological signals and observational data (e.g., facial videos) is needed. SessionPortrait provides a convenient way for analysts to perform such a task. By clicking at any data point in a line chart, the associated videos will appear, and start playing from that point onward in sync with a scanning playline in the line chart (Fig. 3).

The tab view supports qualitative analysis within each experimental session. However, comparing measurements across different sessions is also desirable. To address this problem, we provide a view that brings together corresponding measurements from all sessions. In this view, each session is represented by a radar graph, where each axis represents one variable and takes values between 0 and 1. For each variable, we compute the mean values in all sessions and normalize them with respect to the largest mean obtained. The range of values each variable assumes determines the extent of coloring. Figure 4 gives an example of a multi-session view. It is easily noticeable that the highest heart rate variability (HRV) was reached in session S2. This figure also shows that there were no significant differences in palmar electrodermal activity (EDA) among sessions.

SubjectPortrait

SubjectPortrait is the second level of visualization; it enables analysts to identify intra-subject patterns, by condensing subject data into its essence, showcased in a single figure. For each subject, summary information for the explanatory variable is juxtaposed to summary information for the response variable, framed by context (covariates), in a construct reminiscent of an ID card. Specifically, the key explanatory variable in each session is represented by a horizontal colored bar, with the proportion of red color reflecting the proportion of time during which the subject's level of affect rose above her/his mean baseline. Next to the affect bars, there are disks with different filling levels, representing the key response variable (typically performance) in each session. Filling levels are: empty, lightly-filled, heavily-filled, and fully-filled, corresponding to the first, second, third, and fourth quartile with respect to the proportion of time during which the subject's performance dipped below her/his mean baseline.

Finally, subjective feedback collected from subjects at the end of each session is represented with color-coded semicircles that appear between the affect bars and the performance disks. Quartiles are used again to encode the intensity of the perceived affect, mapping to four color shades: green, yellow, orange, and red, corresponding to the first, second, third, and fourth quartile with respect to the maximum range of the psychometric scale.

Figure 5 provides a SubjectPortrait example. This abstraction illuminates how the subject's affect changes in each session, and how his performance appears to be influenced by it. As the sessions progress from top to bottom, it is apparent that the interventions have a stronger catholic effect on the subject's physiological state. In sync, his performance seems to deteriorate, as indicated by the increasingly filled disks. His perceived affect, represented by the increasingly redder semicircles, is in agreement with the objective (physiological) measurements represented by the bars. The subject is male, as indicated by the contextual icon. Analysts can click on the subject's icon to bring up his SessionPortrait, thus accessing the grassroots visualization level. This is often needed to perform quality control, confirm patterns, or disambiguate unexpected observations.

StudyPortrait



Figure 5: A SubjectPortrait example.



Figure 6: The StudyPortrait of a study on driving behaviors under distractions.

StudyPortrait is the third level of visualization, aiming to communicate the study's outcome in a nutshell. It provides a high-level visual summary, illustrating whether the explanatory and response variables during each phase of an interventional session are significantly different with respect to baseline or not.

For the subject set, we compute the distributions of paired differences between:

1. The mean of the key explanatory variable E in S_j (interventional session) and S_{ϕ} (baseline session) in phase P_i ,

$$\Delta \overline{E}(.,j,P_i) = \overline{E}(.,S_j,P_i) - \overline{E}(.,S_{\phi},P_i).$$
(1)

2. The mean of the key response variable in S_j and S_{ϕ} using an equation similar to (1).

Paired t-tests are then used to determine whether the mean of each distribution is different than 0 or not at a significance level chosen by the analyst. If the difference is significant, the corresponding phase is represented by a red rectangle. Otherwise, the rectangle is left blank. Figure 6 shows the outcome of a study featuring three interventional sessions.

Case Study

We used SubjectBook in a study of driving behaviors under distracting stressors. A central goal of this study was to understand how driver-based and vehicle-based data might be used in tandem to detect high risk driving scenarios. In a sample of 59 drivers, balanced in terms of age and gender, the effects of cognitive, emotional, sensorimotor, and mixed stressors on driver affect and performance with respect to baseline was studied in a simulation experiment. Each subject was asked to perform five simulator drives: Loaded Drive - no Stressor (LD1), Loaded Drive with Cognitive Stressor (LD2), Loaded Drive with Emotional Stressor (LD3), Loaded Drive with Sensorimotor Stressor (LD4), and Failure Drive (FD). The instantaneous perspiration at the perinasal area was used as proxy of the subject's affective state, thus forming the study's explanatory variable. The instantaneous steering angle was used as proxy of the subject's driving performance, thus forming the study's response variable. To ascertain that the experiment's challenging drives were perceived as such, we asked subjects to complete the NASA Task Load Index (TLX) after each drive.

Figure 6 shows the case's StudyPortrait. LD1 is the baseline session and is not represented in the StudyPortrait's grid, because it is absorbed in the paired comparisons. LD4 is a special session that has no across session baseline (only within session) and for this reason cannot be displayed at the StudyPortrait level. Emotional, cognitive, and sensorimotor stressors were used in LD2, LD3, and LD4, respectively. These standard interventional sessions are represented in the grid by two rows each - one for the explanatory variable, and the other for the response variable. Each row is split into 5 columns (i.e., phases), depending if a stressor was present or not: P1 (no stressor), P2 (with stressor), P3 (no stressor), P4 (with stressor), and P5 (no stressor). The results show that all stressors incurred significant increases (p < 0.001) in mean sympathetic arousal accompanied by significant deterioration in mean absolute steering.

Analysts can delve into the next visualization level (SubjectPortrait) by clicking at "Browse this Study". Figure 7 shows a snapshot of the case's SubjectPortrait level. Remember that erratic steering performance is represented by a fully-filled disk, while the best steering performance is represented by an empty disk. This view helps identifying subjects with high levels of physiological arousal, such as subject T025. Additionally, the subjective feedback after each session can be used to explain unexpected behaviors. For example, the green semicircle in session LD3 of subject T024 means that she did not perceive the intervention as challenging, thus, explaining the low arousal indicated by the short color bar.

To gain a deeper insight as to how a particular subject responded to stimuli in the experiment, analysts can click at the subject icon to delve into the next visualization level the SessionPortrait. Data collected during session LD4 for subject T029 is presented in Fig. 8. The line chart at the upper portion of the screen represents the explanatory variable (i.e., arousal), while the line chart to the bottom represents the response variable (i.e., steering). The two yellow backgrounds in each chart mark the interventional phases, that is, texting. It is evident from the line charts that as soon as the subject starts texting ,the physiological arousal increases, and steering performance deteriorates.

Conclusion and Future Work

We presented a novel approach to visualizing multimodal affective datasets. Three levels of data abstraction mirror the scientific method. First, data from different sources are combined and presented in a way that supports cause and effect association within context. Second, information for each subject is abstracted into a figure reminiscent of an ID card, enabling analysts to appreciate within subject phenomena. Third, the inter-subject outcomes of the study are represented through a grid visualization. Importantly, SubjectBook is a web-based tool that enables researchers to share data with other collaborators or with the research community.



Figure 7: SubjectPortraits for the driving study.



Figure 8: The SessionPortrait for subject T029 in session LD4.

In the future, we plan to link this tool with R, in order to more firmly connect qualitative with quantitative data analysis.

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