BEDA: Visual analytics for behavioral and physiological data

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Abstract— **We present BEDA, a tool to help researchers synchronize, visualize, and analyze data sources for single or multiple sessions of behavioral and physiological data. We developed this tool to assist in a study exploring the efficacy of sensory integration (SI) therapy in a school setting. The tool integrates human-coded behavioral data and sensor-generated physiological data from therapy sessions in a 12-week longitudinal study. SI, as a specialty area of occupational therapy, has been widely used to help individuals with developmental disabilities that have difficulties regulating sensory input and modulating arousal levels. There is a lack of research supporting the use of SI; we chose to explore SI further using physiological measures in addition to traditional measures. Conducting studies that rely on many modes of data (video, audio, human-coded behavioral data, physiological measures, etc.) becomes an organizational challenge, especially over a period of several months. Some of these challenges arise in the synchronization, visualization, and analysis of the multiple data sources. BEDA aims to facilitate easier data analysis. Early feedback suggests this tool has potential in clinical and research settings. To date, we have not found evidence that pressure vests increase engagement or decrease undesired behaviors in our school setting. We have also not found correlations between pressure vest use and our physiological measures.**

Keywords—Visual analytics; behavioral coding; physiological data analysis; sensory integration therapy; single-subject research design; longitudinal data analysis

I. Introduction

Children with autism and other developmental disabilities often have difficulties in regulating sensory input and modulating behavior [1]. An individual who has difficulty regulating sensory input may also have difficulty fully participating in all aspects of their communities. Occupational therapists have tried to address issues with sensory regulation through the use of sensory integration (SI) therapy [2]. Few studies, however, explore the cause and effect relationship between the use of SI therapy and behavioral and physiological data concurrently with rigorous analysis [3]. One example of a physiological measure, electrodermal activity (EDA), measures change in electrical skin conductance produced by changes in sweat production. The sweat glands are controlled by the sympathetic nervous system, and researchers have suggested that changes in EDA may, therefore, reflect changes in arousal [4]. Analyzing an individual's EDA data along with behavioral data may help researchers identify how SI therapy affects both internal states and external behaviors. However, there are numerous challenges when analyzing longitudinal data with multiple data sources (video, sensor data, human-coded behaviors, and sensor data analysis results). Researchers may have to use manual techniques to synchronize several data streams (e.g., a software package to annotate videos, a statistical package to analyze results, etc.). With data streams residing in different software environments, it can be cumbersome to move between analysis results and actual data streams. BEDA is designed to mitigate these difficulties. It supports (1) synchronization, visualization, and navigation of different sources of data, (2) visual analysis of both outwardly observable behaviors and internal physiological data, and (3) record-keeping activity.

II. Related Work

Several existing tools support the visualization and analysis of different sources of data (video and time-coded sensor data) [5], [6], [7]. A video annotation tool, Vcode/Vdata, optimizes the video annotation workflow and supports convenient annotations by allowing users to define behaviors and insert them into the video timeline [5]. In addition to supporting annotation, another software application, Elan, provides synchronization between video and time series data and visualization of both video streams and time series data [6]. BEDA is most similar to Chronoviz, which aids in annotation, visualization, navigation, and analysis of multimodal time-coded data [7]. None of these tools, however, support record keeping and analysis of multiple data sessions in a longitudinal study. Below we describe the use of BEDA in a case study exploring SI therapy in a school setting over a 12-week period. BEDA was designed in collaboration with special education researchers to support an ongoing longitudinal study.

III. Case Study

Sensory integration (SI) techniques, such as the application of pressure vests, are common practice in educational and therapeutic settings for individuals who have difficulty regulating sensory input. However, we lack rigorous research showing cause and effect relationships between these techniques and changes in either arousal level or behavior of the individual receiving the intervention [1], [3]. A pressure vest is a commonly used SI intervention that gives the wearer the sensation of receiving a hug but can be worn with little inconvenience in any setting [1]. An interdisciplinary team of professionals from Special Education and Computer Science conducted a case study with a 9-year-old child, Eddy,

diagnosed with a developmental disability in a school setting. The child's occupational therapist (OT) specifically recommended pressure vests for his therapy. One purpose of this study is to explore whether wearing a pressure vest would produce predictable and measurable changes in EDA levels and, if it did, how these changes related to observable changes in behavior. In this paper, we will present how BEDA can support researchers to investigate more rigorous data analysis in longitudinal studies.

We conducted a controlled study in a public school in collaboration with the child's teacher and OT. We identified undesired behaviors and observed their occurrence when the pressure vest was worn. These behaviors included yelling, hitting the table, and other disruptive and potentially sensory-based observable behaviors. We also identified behaviors that indicated Eddy was engaged in the educational activity at hand, such as manipulating materials and looking at the teacher. We then recorded the occurrence of both undesired and engaged behaviors during intervention sessions across different conditions to determine if the pressure vest produced the hypothesized effect on undesired and engaged behaviors. EDA data was also collected through a sensor attached to Eddy's ankle.

We used a single-subject reversal experiment design to evaluate the effect of the pressure vest on Eddy's behavior and EDA levels [8]. We analyzed 20 sessions of data for this study across the following four different conditions: (1) structured teaching while wearing the vest without pressure, (2) unstructured teaching while wearing the vest without pressure, (3) unstructured teaching while wearing the vest with pressure, and (4) structured teaching while wearing the vest with pressure. We discovered that the structure we imposed on the context produced improvement in Eddy's behavior, so in the second condition, we simulated a context similar to that existing in the classroom. When Eddy's behavior worsened, a rationale for the use of the pressure vest existed. When his behavior remained stable (i.e., no improvement) with the pressure vest, we re-introduced the structured teaching to assess whether we could produce a reversal to improved levels of behavior. In the following section, we illustrate the functionality of BEDA and demonstrate how we used the tool to support the data analysis for our case study.

IV. SYSTEM DESIGN AND DATA ANALYSIS WORKFLOW

Through discussions with researchers, clinicians, and Eddy's teachers, we iteratively designed BEDA to support this study. We highlight the features of BEDA in this section.

A. Visualization, synchronization, and navigation

The users first load video and sensor data into BEDA. Figure 1 shows the BEDA interface after loading a video and EDA sensor data. In Figure 1(e), BEDA visualizes the entire sensor data stream in a line graph in a single view, which gives users an overview of the data. Users can zoom in and out as needed using the buttons in Figure 1(b). Users can change the color and the range of the graph. Synchronization is the next problem people encounter when using multiple streams of data. Because researchers often collect behavioral data of

participants through video recording and physiological data through external sensors, these data need to be synchronized or aligned on the same timeline for analysis. BEDA allows for one-click synchronization by providing both a navigation and a synchronization mode; users can easily change modes by clicking the button in Figure 1(a). In synchronization mode, users can navigate the video timeline using a playhead located below the video (see Figure 1(c)) and the sensor timeline using the orange playhead (see Figure 1(d)). After users put each playhead at the time point that aligns the two data streams, they synchronize the individual streams by switching to navigation mode (Figure 1(a)). In navigation mode, users can navigate the synchronized video and sensor data together.
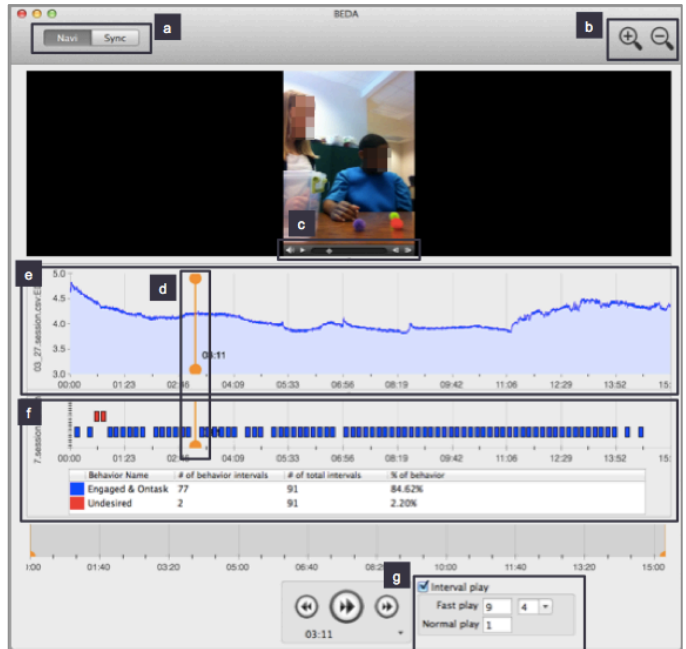

Fig. 1. BEDA interface with a video, EDA sensor data, and human-coded behaviors.

B. Behavioral coding (analysis of outward behaviors)

Behavior coding from video can be time consuming and organizationally challenging. Researchers typically code behavioral data by hand on paper. In our case study, we coded two behaviors, undesired and engaged (on-task) behaviors, using momentary-time sampling (see Figure 2). That is, we recorded whether the identified behaviors occurred during the last 1 second of every 10-second interval in the video. If, for example, the engaged behavior occurred in the 1-second interval, users entered '+' in the corresponding square on the sheet shown in Figure 2. In some cases, researchers were independently moving through video files every 10 seconds by hand, using a media player such as QuickTime[1]. Using this approach, two independent coders attempting to code the same interval would often code different time intervals. Tools for consistent indexing of video were needed.

BEDA supports behavioral coding via keystroke. Users define intervals of video play (see Figure 1(g)). In this case

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[1] http://www.apple.com/quicktime/

study, the interval was set to a fast play speed for 9 seconds and a normal speed for 1 second. These rates are reconfigurable by the users. This automated approach ensures consistent indexing of video because researchers no longer have to move a playhead by hand. BEDA also allows users to define the name, color, and hot key for targeted behaviors. In our case study, we coded undesired and engaged (on-task) behaviors using the hot keys "u" and "e" in red and blue respectively on the annotation timeline. Figure 1(f) shows many annotations of engaged behavior (blue rectangles), and few cases of undesired behaviors (red rectangles) in this session. During the behavior coding, the tool automatically calculates the percentage of the annotated behaviors by calculating the number of coded behaviors out of total number of intervals in the video. This was previously done by hand and labeled on the score sheets (see bottom of Figure 2).

Fig. 2. Behavioral data coding sheet.

C. Analysis of physiological data (analysis of internal state)

EDA signals can be separated into phasic skin conductance response (SCR) and tonic skin conductance level (SCL) components [4]. The changes in SCR, often appearing as peaks in the signal, are associated with short-term stimuli or non-specific stimuli. In contrast to SCR, SCL responses denote gradual changes in EDA. SCR and SCL features are often used as proxies to infer arousal and engagement. Common extracted features from SCR and SCL are peaks per minute (PPM) and area under the curve (AUC), and others [9].

Figure 3 shows the Data Analysis interface. Users can select a pre-programmed analysis script (see Figure 3(b)) and click the 'Analyze Now' button; analysis results appear in the data analysis window (see Figure 3(a)).
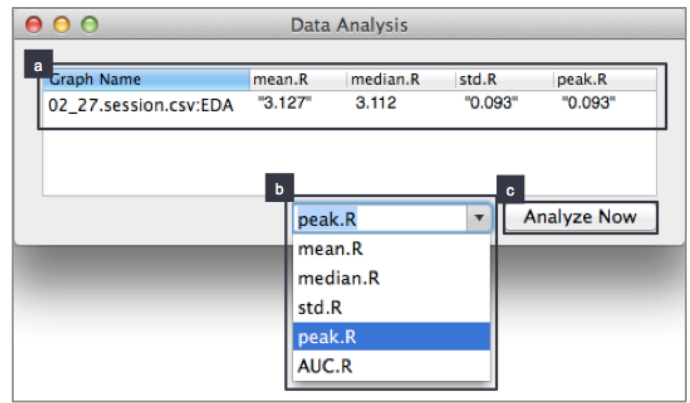

Fig. 3. Physiological (e.g., EDA) data analysis interface.

For users who are familiar with signal processing and want to conduct more specialized analysis, BEDA allows users to write their own scripts using MATLAB[2] and R[3]. After they import the scripts into BEDA, the name of the script appears in the combo box shown in Figure 3(b). Users can then select the script name and run it. This allows users to extend functionality by importing scripts. This also supports rapid iteration of algorithms in the same environment. The user can extract new features from EDA and compare them to existing measures.

D. Switching between the summary-graph view and the multi-sessions view

Researchers studying individuals' behavior in applied settings (e.g., school, home) often use single-subject study designs; they collect data for multiple sessions across different conditions to test the effectiveness of interventions [8]. In our case study, we had four conditions. Continuous data collection and coding are crucial when using this methodology, because the decision to change conditions is made based on the incoming data [8]. For example, if we identified consistent behavioral or physiological patterns within a condition (e.g., wearing a pressure vest), we then can make a decision to change the condition to, for example, not wearing the pressure vest. Thus, simultaneously visualizing both behavioral and EDA analysis across different conditions helps researchers identify patterns within a condition and across different conditions. This also helps researchers identify whether a condition (e.g., wearing a pressure vest) produced changes in the individual's behavioral and EDA data. After looking at the summary-graph view (see Figure 4), researchers often want to return to the actual video and sensor data streams to investigate sessions in more detail. Currently, this process is cumbersome because researchers must manually find the video and sensor data and load the data. BEDA allows users to switch between the summary-graph view and actual data streams with a click.

A) Summary-graph view

With BEDA, users can mange multiple sessions from diverse data sources in one environment. Users create conditions and label session data with the corresponding condition (e.g., wearing a pressure vest). When a user loads several conditions in the summary-graph view list box (see Figure 4(a)), BEDA includes the sessions in those conditions in the summary-graph view visualization (see Figure 4(b) and (c)). In the graph in Figure 4(b), different coded behaviors are represented as different colors. Data points in the same condition are connected to each other, and there is a gap between conditions. In Figure 4(c), we see the EDA analysis results, PPM and AUC, visualized as a bar graph. Users can compare relationships between coded behaviors and EDA analysis results across different conditions.
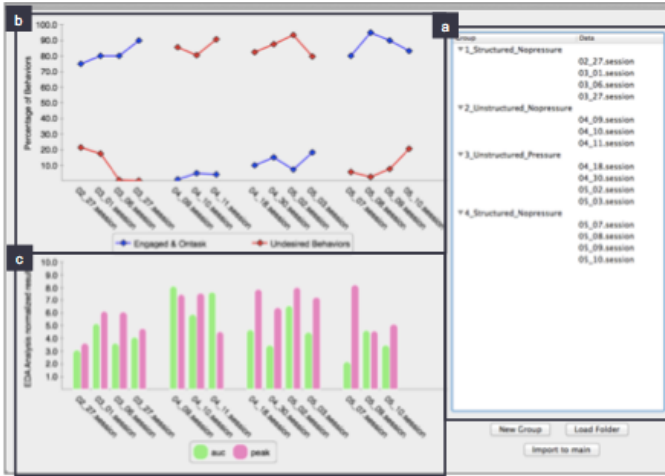

Fig. 4. Summary-graph view: visualizing behavioral and EDA data analysis results of multiple sessions across different conditions. (a) List box of conditions and corresponding sessions. (b) Line graphs showing coded behaviors. The x-axis lists the sessions in chronological order. The blue graph represents percentage of engaged behaviors and the red graph represents percentage of undesired behaviors. Data points in the same condition are connected to each other and a space appears between conditions. (c) Aggregate EDA results for PPM (pink graph) and AUC (green graph).

B) Multi-sessions view

In the summary-graph view, users can find patterns or outliers to investigate in more detail. For example, while both sessions on May 7 and May 9 show higher engagement behaviors and fewer undesired behaviors, the EDA analysis of these two sessions is very different. Clicking the names of these sessions via the list box in Figure 4(a) opens them in the multi-sessions view (see Figure 5). From this multi-sessions view, users can probe sessions and see specific video, sensor data, and human-coded behavioral data. If users drag one of the orange playheads (see Figure 5(a-2)), the video, sensor, and human-coded behavioral data related to this session (see Figure 5(a-1) and (a-2)) move together. Users can navigate each session separately and compare one session with others. Finally, the users can configure the size and order of the graphs.
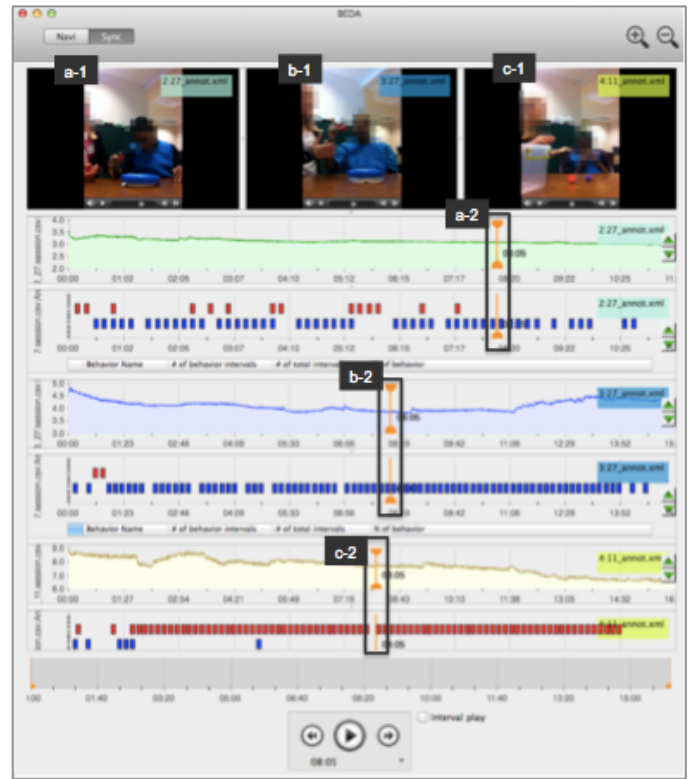

Fig. 5. Multi-sessions view: navigating multiple sessions of original data. If users drag the orange playhead in the Figure 5 (a-2), the video (Figure 5 (a-1)) and data for this session (Figure 5 (a-2)) move together.

V. CONCLUSION AND FUTRUE WORK

We presented a tool, BEDA, that supports analysis of longitudinal data from different sources of data, such as video and sensors. We used this tool to support research that examined the efficacy of SI therapy with a rigorous concurrent analysis of behavioral and physiological data. While closely working with special education researchers, we identified the challenges encountered in this style of studies and developed a tool to mitigate them. This tool supports visualization, synchronization, and analysis of diverse data sources (video and physiological data (e.g., EDA)). The tool further supports annotation of behavior from video and sensor signal analysis in the same environment. Finally, the tool permits users to analyze multiple sessions by interactively switching views between the summary-graph view and the multi-sessions view of multiple study sessions.

We have not found evidence that pressure vests increase engagement or decrease undesired behaviors. To date, we have also not found correlations between pressure vest use and EDA with the default EDA measures shown in Figure 3(b). The next step is to explore variations on these measures.

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