Boiling Mind - A Dataset of Physiological Signals during an Exploratory Dance Performance

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ABSTRACT

The relationship between audience and performers is crucial to what makes live events so special. The aim of this work is to develop a new approach amplifying the link between audiences and performers. Specifically, we explore the use of wearable sensors in gathering real-time audience data to augment the visuals of a live dance performance. We used the J!NS MEME, smart glasses with integrated electrodes enabling eye movement analysis (e.g. blink detection) and inertial motion sensing of the head (e.g. nodding recognition). This data is streamed from the audience and visualised live on stage during a performance, alongside we also collected heart rate and eye gaze of selected audience. In this paper we present the recorded dataset, including accelerometer, electrooculography(EOG), and gyroscope data from 23 audience members.

CCS CONCEPTS

• **Human-centered computing** → **Interaction design**; **Interaction design process and methods**.

KEYWORDS

Physiological Signals, Visualization, Audience Engagement

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Figure 1: Visualizations while performers were dancing

1 INTRODUCTION

Each live performance is unique, even when following the same choreography, or script. Reactions between audiences and performers can have noticeable effects on the overall experience. This work attempts to understand and amplify these effects by integrating real-time audience physical and physiological data directly into the performance itself.

We present an exploratory performance to integrate various physical and physiological audience signals, obtained using wearable sensors, into the visual effects of a live dance performance. Specifically, the work shows: (1) the technical feasibility of streaming multiple sensors using electrooculography (EOG) and head movement with smart eyewear, Blood Volume Pulse (BVP), and a gaze tracker (2) an integrated wearable system that consists of a smart eyewear, back-end processing and output visualization (3) a multi-person, multi-modal audience dataset (available here).

Connecting performers and audience via sensing technology is not new. Previously, researchers have attempted to develop an interactive system where sound and visual changes were manipulated by dancers' movement [10, 12]. However, even though tracking performers movement can enrich the stage design, that work does not involve the audience directly. Some works explore audience participation by using linguistic feedback [3, 6], collective heart rate [15], electroencephalography (EEG) [8], and galvanic skin response (GSR) [17, 20]. Here we build on these ideas by integrating EOG and head movement signals obtained using commercial eyewear with heart rate and gaze.

Eyewear-recorded EOG has been used to recognize activity, concentration, and potential social interaction [4, 7, 9, 13, 19]. Heart rate (HR) and heart rate variability (HRV) have also been used to track affect and mental state [5, 14]. By using multi-modal sensors like these on audience, we hope to pave the way for systems that can characterise audience mental states like engagement and enjoyment both cheaply and in real-time.

2 PERFORMANCE AND HARDWARE SETUP

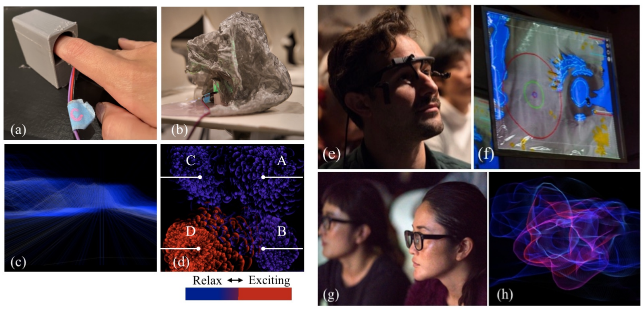

Figure 2: Audience Wearing Blood Volume Pulse Sensor (a), Pupil Core (e) and Jins Meme (g), EOG-enabled Smart Eyewear. (c), (f), and (h) Visualization of the physiological data collected from the audience.

A 20 minute experimental public dance performance titled "Her Chair", was performed on November 4th 2019, at the Session House Theater (Tokyo, Japan), in collaboration with a contemporary dance group Mademoiselle Cinema.

The audience were aware that their signals would be visualised and projected onto a screen as part of the performance, and we have informed consent from everyone whose data is included in the anonymized dataset. The setup and performance were conducted with the full approval of the ethics board of our university.

In order to measure the response of the audience to the dancers' motion we use a combination of audience EOG, eye tracking and BVP. EOG was used to calculate audience blinks [9], and BVP was used to calculate HR and HRV.

Audience data was visualized in real time using TouchDesigner software and projected on the stage. When three audience members blink simultaneously, the visuals were changed from blue to red as shown in Fig.2 (h). To abstractly express the audience's interest to the stage, the eye movement streamed from the Pupil Core was visualized as shown in Fig.2 (f). HR data was presented as a planar image flowing horizontally as shown in Fig.2 (c). The ratio of low frequency band (LF) and high frequency (HF) band of HRV signal (LF/HF) was used to set the display coloring. As an example of how this translated into the visuals,an LF/HF ratio of 0.0 to 2.0 was assumed to be in a relaxed state and was visualised as blue. Conversely, a ratio of 2.0-5.0 and beyond was interpreted as audience excitement, and was represented by red colors.

3 DATASET DESCRIPTION

The dataset mainly consists of MEME recordings including 3-axis accelerometer data, 2-side EOG data, and three gyroscopes data (sampled with 50Hz). We also include audience HR data from BVP sensor (20Hz) and eye movement data from the Pupil Core (120 Hz sampling binocular) as well as dancers' motion data in our dataset for more comprehensive information.

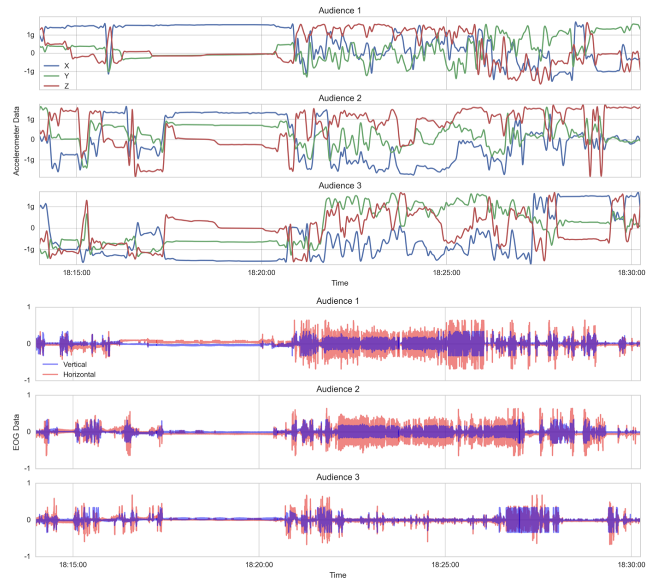

Figure 3: Example x,y,z accelerometer (above) and EOG (below) data from three audience members during the performance

We present an initial exploration of the 3-axis accelerometer to show the quality of the data recorded. Fig. 3 (above) depicts accelerometer data from three audience members' glasses recordings. The accelerometer data looks usable and some patterns between the audience members can be seen, e.g. potential head nods and hand clap timings. To further quantify the synchrony among physiological signals, we will apply various techniques such as windowed cross-lagged correlation (WCLC) [2] and dynamic time warping (DTW) [1, 11].

We also investigate the EOG data recorded from MEME. Fig. 3 (below) shows an example of EOG taken from three audience members. The data seems usable and not more or less noisy then similar data we collected in the laboratory before. With the feasibility to reflect people's cognitive state [4, 18], EOG data could also provide us with implicit engagement information. From initial observations, we found that audiences blinked less as the performance went on, which potentially suggests growing visual attention [16].

4 DISCUSSION AND FUTURE WORKS

We present an approach at collecting and streaming multi-person, multi-modal sensor data using commercial eyewear. We give a brief analysis of of the recorded data and provide a full dataset for download. Future work includes 1) building the feedback loop from the audience to the dancers, by visualizing physiological data to the stage and enable dancers to adjust their performance according to the audience status, 2) applying more intuitive methods of human cognition analysis including combining blink frequency, blink strength, and head gesture to make precise rating on engagement.

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