Design Considerations for Expressive Biofeedback in Social Interactions

Fannie Liu
Carnegie Mellon University
5000 Forbes Ave.
Pittsburgh, PA 15213, USA
ffl@cs.cmu.edu

Geoff Kaufman
Carnegie Mellon University
5000 Forbes Ave.
Pittsburgh, PA 15213, USA
gfk@cs.cmu.edu

Laura Dabbish
Carnegie Mellon University
5000 Forbes Ave.
Pittsburgh, PA 15213, USA
dabbish@cs.cmu.edu

Copyright is held by the author/owner(s).

Abstract
We are exploring the concept of *expressive biofeedback*, leveraging state-of-the-art wearable technologies to introduce a host of new social cues into communication contexts using sensed physiological data. While we traditionally attune and adjust our behaviors and perceptions during social interactions according to behavioral cues such as body language and facial expressions, physiological data can help us achieve a deeper understanding of each other by presenting the underlying meaning and processes of our interactions. Heart rate, skin conductance, and brain activity, which are typically unobservable, can now be unobtrusively sensed and displayed to interaction partners in a variety of ways at different times before, during, or after communication. This position paper discusses the design considerations, challenges, and opportunities that arise in developing an expressive biofeedback system that incorporates sensed physiological data to improve social interactions.

Author Keywords
biofeedback; physiological sensing; face-to-face interaction

ACM Classification Keywords
H.5.m [Information interfaces and presentation (e.g., HCI)]: Miscellaneous

Introduction
Our bodies react automatically as we interact with other people. Our heart rate can rise and fall with fluctuations in

our emotional and cognitive states, our skin can become more conductive as our engagement levels increase, and our brain activity changes with our cognitive processing [5, 6]. However, these physiological changes are not readily observable to the human eye. Instead, as we interact, we must rely on behavioral cues that we can observe in others, such as body language, facial expressions, and voice tone and pitch. If we were made aware of physiological changes in addition to behavioral changes that occur in ourselves and others, we may be able to better sense the feelings, engagement, and mutual understanding experienced by one another during an interaction. As more and more people integrate mobile and wearable technologies into their everyday lives, we have the opportunity to enrich our interactions by bringing to light physiological changes using these technologies, which we can then gauge and display as new social cues.

Wearable devices, such as smartwatches and headsets, now have the ability to sense our physiological states. Smartwatches like the Apple Watch and Moto 360 are able to monitor heart rate. The Embrace Watch and E4 Wristband from empatica include heart rate monitoring as well as electrodermal activity (EDA) sensors. Brain activity can also be measured in electroencephalogram (EEG) headsets, which are now available in consumer-grade products such as the NeuroSky MindWave, Muse, and Emotiv EPOC headbands. These devices allow for the physiological sensing that can be used to deliver feedback in everyday interactions.

We propose designing an expressive biofeedback system for improving social interactions in face-to-face situations using the aforementioned sensing devices. This system will gather heart rate, skin conductance, and EEG data and present visualizations of those data to users to allow them to follow the physiological changes occurring in themselves and others throughout their interactions, and engage in behaviors that improve their interactions accordingly. This position paper highlights related work in this domain and describes some of the design considerations that we will explore in creating an expressive biofeedback system.

Related Work

Physiological sensing has been used extensively for individual monitoring, such as for physical health, stress, and well-being [1, 10]. In a technique called biofeedback, the sensed data is displayed in a visualization for users to track their physiological state and, over time, learn to control it [7]. For example, biofeedback has been used to help users control their heart rate through breathing techniques and has shown potential for treating disorders such as clinical depression and posttraumatic stress disorder [12].

More recently, biofeedback has been applied to social situations. Synder and colleagues (2015), for example, explored biofeedback in the form of an ambient display called MoodLight [8]. The MoodLight system changes the color and intensity of the lights in a room according to the level of arousal and synchrony in the changes in arousal of the occupants of the room, respectively. Participants can experiment with the system by coordinating with each other and controlling their stress levels. Tan and colleagues (2014) developed a biofeedback system to support collaborative work via video conferencing [9]. This system, which displayed the skin conductance, blood pressure, and respiratory rates of a worker receiving instructions for building a K'Nex device (a toy construction system) was effective in reducing the stress and perceived workload for both the worker and an instructor who saw the feedback.

Neurofeedback, or biofeedback for controlling brain activity, may also have the potential to impact social interactions. Neurofeedback has been used to treat those with disorders associated with impairment in social interaction, including autism and Asperger's syndrome. As a treatment for these disorders, neurofeedback training focuses on helping patients control EEG frequency band activity, where bands include delta, theta, alpha, beta, and gamma waves. Neurofeedback training for autism and Asperger's focus on decreasing theta band activity and increasing beta band activity [2, 3, 11]. While the underlying mechanisms for the effectiveness of this type of training are unknown, Kouijzer and colleagues (2009) suggest that they may lie in the theta/beta changes possibly increasing activation in the default mode network (DMN) [4]. The DMN has been related to Theory of Mind, the ability to attribute mental states to the self and to others; therefore, increased activation in the DMN may improve social interaction. Neurofeedback has not yet been used in social contexts, but by making interaction partners aware of their EEG band activity, especially in the theta and beta frequencies, we may be able to see improvements in social interactions between healthy adults as well.

Designing Biofeedback for Social Interactions

We are currently building a system to display biofeedback to conversation partners as they converse. Our goal for this system is to enhance and improve social interactions by introducing physiological data as a new way in which people can express themselves and understand each other. With expressive biofeedback, we aim to have users reflect on one another's behaviors by recognizing their underlying emotional and cognitive states, and by suggesting positive social behaviors. In creating and testing an expressive biofeedback system, there are several design considerations to explore:

Presenting the Data

First, we need to determine how to present the data such that it can be most useful as new social cues. That is, users should be able to properly understand, trust, and act according to the data in social interactions. For instance, displaying frequencies from brain activity in a graph format may appear more scientific and therefore more trustworthy to users than an abstract format like the intensity of a light, which users might dismiss. On the other hand, a concrete visualization such as a line or bar graph shown on a screen may reframe the experience for the users–that is, the interaction may become too formal and obtrusive. An abstract representation, such as light intensity, color, sounds, or smells in the room, could offer a less jarring interaction experience. We will explore and develop different concrete and abstract ways of representing the physiological data.

Types of Data

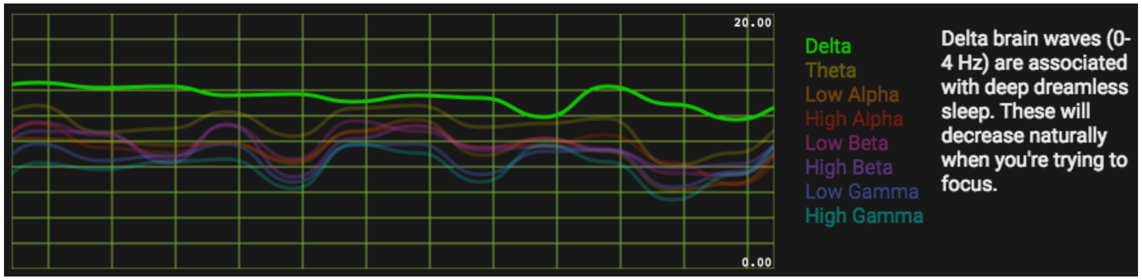
While we can obtain raw physiological data from our sensing instruments, we need to determine whether it is the right type of data to present to users. Raw physiological data, such as EEG band activity, may be harder to interpret than higher level information inferred from the data, such as the apparent emotional state or level of attention. Displaying emoticons according to meanings associated with activity in each EEG band may be more recognizable to users. Users may be more receptive when they see "sleepy" emoticons representing high theta activity, which is associated with drowsiness, and "thinking" emoticons for beta activity, which is associated with active thinking and attention. We will compare the effects of displaying the raw sensor data (e.g., raw EEG data) and inferred data from the sensors (e.g., attention) on the interaction. Figure 1 shows example visualizations for comparing types of data from sensed brain activity.

Cognitive Load

We also need to consider the cognitive load that comes with processing new social cues in addition to existing ones. Brain activity, in particular, can be difficult to follow due to its complexity. EEG data can come from several frequency bands, including delta, theta, alpha, beta and gamma bands. Having to interpret each of these different bands, when EEG data is already a novel and unfamiliar element in typical social situations, may end up being more

Design Issues	Parameters
Presenting the data	concrete vs. abstract format
Types of data	raw sensor data vs. inferred data from sensors
Cognitive load	continuous vs. intermittent feedback
Data interpretations	subjective interpretations vs. actual meaning
Types of tasks	conversational vs collaborative tasks
Privacy	public vs. private feedback
Feedback and reinforcement	direct vs. subtle feedback

Table 1: Design parameters for social biofeedback



(a) Line graph visualization of EEG data, where all of the different frequency bands are displayed with a description when highlighted.

(b) Emoticon visualization, where emoticons are associated with activity in various EEG bands. In this case, the “thinking” emoticon is highlighted, meaning a user would have high activity in either low beta bands or gamma bands, which are involved in active thinking and cognitive processing.

Figure 1: Example visualizations for brain activity according to types of data (raw EEG data or inferred emotional state).

distracting than supportive. In addition to pre-interaction training for the biofeedback and how it is presented, we need to consider when and how often to deliver the feedback. We will compare the effects of continuous, real-time feedback and intermittent feedback (as well as the effects of concrete versus abstract data presentations) on inhibiting or encouraging the quality and “flow” of the interaction.

Data Interpretations

We need to understand what people’s subjective interpretations are for the different types of sensed data, and how those interpretations align (or fail to align) with the actual meaning of the data. For example, though both heart rate and brain activity can be used to sense engagement, participants may view their own or interaction partners’ level of engagement differently according to the different sources of data. Since the heart is often metaphorically and symbolically associated with feelings of love and caring, while the brain is associated with thinking, participants may perceive engagement as more emotional when based on heart rate variability, but as more cognitive when based on brain activity data. In actuality, emotional and cognitive processing can be determined from either sensors. After users interact with each other supported by our biofeedback system, we will rely on surveys and interviews to gauge their understanding of what the physiological data they saw mean to them.

Types of Tasks

Different types of biofeedback may be suited for different types of social situations. Biofeedback related to stress and emotions may be more useful in tasks like advice giving, where one must consider the state of the person they are giving advice to or receiving advice from. Cognitive processing may be more useful in job interviews or cooperative work, where participants are probably more interested in each other’s thought processes than emotional states. We plan on testing biofeedback given during a variety of tasks. These will include conversational tasks, such as unstructured conversations and job interviews, as well as collaborative tasks such as decision making and negotiation.

Privacy

Since biofeedback involves displaying personal information that is not typically public, we need to consider who should have access to the feedback. Participants may not be comfortable showing each other their level of arousal from skin conductance, or their level of focus from brain activity, especially if they are not familiar with how to control these physiological states. Participants may also be more self-reflective when they only see personal feedback, as they will not have to consider another person’s biofeedback. However, publicly displaying the information may allow for participants to better synchronize with and understand each other. We will investigate the effects of biofeedback that is only visible to oneself with biofeedback that is visible to each other in an interaction. These empirical studies will compare the impact of biofeedback displayed on personal screens or devices, as compared to shared screens or devices, as well as the effects of individual versus aggregated biofeedback.

Feedback and Reinforcement

The goal of our expressive biofeedback system is to improve social interactions. Therefore, we need to consider how to suggest positive social behavior to users according to their physiology. For example, users may not be responsive when directly told on a screen to pay attention because sensors have detected that their beta band activity is too low. Users might be more receptive to a more subtle felt vibration as a less condescending reminder. At the same time, a vibration may not be as effective in encouraging behavioral change as a clearly stated message. We also need to consider how to reinforce positive social behavior. For instance, users could playfully interact with the MoodLight system to change the color of the room [8]. Patients in neurofeedback therapy would be able to advance a video forward as long as they stayed focused [2]. For our expressive biofeedback system, we might consider having the system "intervene" when users are not paying attention–for example, by sounding an alarm, dimming or closing the lights, or publicly displaying an inattentive user's physiological data–and testing users' reception of and responses to such "nudges" to re-engage.

Conclusion

Expressive biofeedback may have the potential to enrich our interactions by providing new social cues. Using new wearable technologies, we are now able to sense and display our physiological states in our everyday conversations. We have already started building our proposed expressive biofeedback system, in which we will incorporate heart rate, skin conductance, and brain activity. In designing and testing this system, we will explore how biosignals might support our social interactions by helping us understand each other better through the communication and display of our physiological states.

References

[1] Yadid Ayzenberg, Javier Hernandez Rivera, and Rosalind Picard. 2012. FEEL: frequent EDA and event logging–a mobile social interaction stress monitoring system. In *CHI'12 Extended Abstracts on Human Factors in Computing Systems*. ACM, 2357–2362.

[2] Robert Coben, Michael Linden, and Thomas E Myers. 2010. Neurofeedback for autistic spectrum disorder: a review of the literature. *Applied psychophysiology and biofeedback* 35, 1 (2010), 83–105.

[3] Hartmut Heinrich, Holger Gevensleben, and Ute Strehl. 2007. Annotation: Neurofeedback–train your brain to train behaviour. *Journal of Child Psychology and Psychiatry* 48, 1 (2007), 3–16.

[4] Mirjam EJ Kouijzer, Jan MH de Moor, Berrie JL Gerrits, Jan K Buitelaar, and Hein T van Schie. 2009. Long-term effects of neurofeedback treatment in autism. *Research in Autism Spectrum Disorders* 3, 2 (2009), 496–501.

[5] Robert W Levenson and Anna M Ruef. 1997. Physiological aspects of emotional knowledge and rapport. (1997).

[6] Giacomo Rizzolatti and Laila Craighero. 2004. The mirror-neuron system. *Annu. Rev. Neurosci.* 27 (2004), 169–192.

[7] Mark S Schwartz and Frank Ed Andrasik. 2003. *Biofeedback: A practitioner's guide* . Guilford Press.

[8] Jaime Snyder, Mark Matthews, Jacqueline Chien, Pamara F Chang, Emily Sun, Saeed Abdullah, and Geri Gay. 2015. MoodLight: Exploring Personal and Social Implications of Ambient Display of Biosensor Data. In *Proceedings of the 18th ACM Conference on Computer Supported Cooperative Work & Social Computing*. ACM, 143–153.

[9] Chiew Seng Sean Tan, Johannes Schöning, Kris Luyten, and Karin Coninx. 2014. Investigating the effects of using biofeedback as visual stress indicator during video-mediated collaboration. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. ACM, 71–80.

[10] Kristin Taraldsen, Sebastien FM Chastin, Ingrid I Riphagen, Beatrix Vereijken, and Jorunn L Helbostad. 2012. Physical activity monitoring by use of accelerometer-based body-worn sensors in older adults: a systematic literature review of current knowledge and applications. *Maturitas* 71, 1 (2012), 13–19.

[11] Lynda Thompson, Michael Thompson, and Andrea Reid. 2010. Neurofeedback outcomes in clients with Asperger's syndrome. *Applied psychophysiology and biofeedback* 35, 1 (2010), 63–81.

[12] Amanda L Wheat and Kevin T Larkin. 2010. Biofeedback of heart rate variability and related physiology: A critical review. *Applied psychophysiology and biofeedback* 35, 3 (2010), 229–242.