Having a Heart Time? A Wearable-based Biofeedback System

Chao Ying Qin
Imperial College London, UK
chaoying.qin@network.rca.ac.uk

Jun-Ho Choi
Yonsei University, Seoul, Korea
idearibosome@yonsei.ac.kr

Marios Constantinides
Nokia Bell Labs, Cambridge, UK
marios.constantinides@nokia-bell-labs.com

Luca Maria Aiello
Nokia Bell Labs, Cambridge, UK
luca.aiello@nokia-bell-labs.com

Daniele Quercia
Nokia Bell Labs, Cambridge, UK
daniele.quercia@nokia-bell-labs.com

ABSTRACT

Biosignal sharing is a way to convey our emotional states, internal experiences, and activities, which could potentially make us not only individually more aware, but also enhance our ability to understanding collective emotions. While wearable research has advanced on the techniques for processing and acquisition of biosignals, it is unclear how such systems could work in real-life scenarios, unobtrusively, and at scale. We present a wearable-based biofeedback system for processing physiological indicators from consumer-grade devices, and visualizing the emotional state of a group of people in an abstract and playful way.

CCS CONCEPTS

• **Human-centered computing → Computer supported cooperative work**; **Ubiquitous and mobile devices**; *Visualization application domains.*

KEYWORDS

Biosignals; Emotions; Wearables; Affective sharing; Biofeedback

ACM Reference Format:

Chao Ying Qin, Jun-Ho Choi, Marios Constantinides, Luca Maria Aiello, and Daniele Quercia. 2020. Having a Heart Time? A Wearable-based Biofeedback System. In *22nd International Conference on Human-Computer Interaction with Mobile Devices and Services (MobileHCI '20 Extended Abstracts), October 5–8, 2020, Oldenburg, Germany*. ACM, New York, NY, USA, 4 pages. https://doi.org/10.1145/3406324.3410539

1 INTRODUCTION

Expressive biosignals, like our heartbeat, are known to be affected by our emotional states and internal experiences. In turn, monitoring biosignals can increase the emotional of individuals as well as groups. The ability of understanding other people emotions is often referred to as *emotional intelligence*—a skill that helps to overcome stressful situations, communicate in effective ways, and empathize [18]. For this reason, HCI and Ubicomp research has attempted to designing systems to support and augment our emotional intelligence in multiple contexts. More recently, researchers argue for interactive systems that make physiology accessible for the design [20]; a prerequisite towards building tools for emotional intelligence. They envision systems that provide a path into the body's systems by aligning the inbodied to better support the embodied interaction. With the advancements of wearable technologies, these systems can support users to get insights from their own and others' bodily signals, and provide interventions aimed at improving performance and well-being [20]. The system we propose adopts the paradigms of Inbodied Interaction.

To realize this vision, researchers often face one main challenge: to measure emotional states unobtrusively, and at scale. While current wearable sensing systems, to a great extent, can estimate feelings or psychological conditions, they do so mostly on specific constructs like stress and anxiety [2, 4], targeting individuals. To overcome this challenge, we aim at translating physiological indicators gathered through consumer-grade wearable devices into a multi-dimensional emotion model (e.g., Plutchik's model [16]), and visualize them in an abstract and playful way to increase the collective awareness of psycho-physiological state of a group of people. In so doing, we present an end-to-end wearable-based biosignals sharing system, and we made two contributions: (a) collecting and analyzing physiological indicators in real-time, and (b) visualizing these indicators into an abstract and playful way that conveys the emotional state of a group of people. For example, a group of people wearing watches could share their physiological signals, which, in turn, are displayed in a screen as the collective emotional state.

2 RELATED WORK

Affective Computing and Wearables: We frame our work within the broader area in computing that deals with the recognition, interpretation, and understanding of human affects [15], with a particular focus on wearable sensing. Wearable-based consumer products such as Feel[1], Oura[2], and Moodmetric[3], Empatica[4], capture and process physiological indicators (e.g., heart rate, skin conductance) to produce quantitative representations of emotional states. Today's widespread adoption and technological advancements of wearable devices facilitate monitoring of people's biosignals unobtrusively, and at scale [1, 6, 14, 19]. For example, Gjoreski et al. [4] used Empatica devices to detect stress by combining heart rate variability (HRV) and electrodermal activity (EDA) analysis, while Gloor

MobileHCI '20 Extended Abstracts, October 5–8, 2020, Oldenburg, Germany

ACM ISBN 978-1-4503-8052-2/20/10.
https://doi.org/10.1145/3406324.3410539

[1] https://www.myfeel.co/
[2] https://ouraring.com/
[3] https://moodmetric.com/
[4] https://www.empatica.com/

Figure 1: Our watch application, implemented using the Tizen platform. It runs on Samsung watches and continuously records physiological readings through the device's optical PPG sensor.

et al. [5] showed that happiness is strongly linked with intense activity.

Biosignals Sharing: Most prior work in biosignals target individuals by providing feedback on fitness and well-being [3, 13]. At collective level, prototypes like HeartChat [7] and EmpaTalk [11] allow online chat partners to communicate their emotions through the use of visual indicators of heart rate changes. In a similar vein, sharing changes in heart rate, skin conductance, and breathing [3] has also been demonstrated to alleviate stress in workers collaboration settings [22]. A potential application of our system. Sharing biosignals among groups have not only been demonstrated to increase awareness, but also to boost social and interpersonal interactions. For example, Janssen et al. [8] showed that heartbeats sounds can increase intimacy and closeness, while others demonstrated that biosignals sharing can increase awareness of another person's context by feeling them present [12, 21].

3 WEARABLE BIOSIGNAL SHARING SYSTEM

3.1 Watch Application and Physiological data corpus

We developed an application for Samsung watches using the Tizen platform[5] (Figure 1). The application continuously records people's heart rate from the device's optical PPG (Photoplethysmography) sensor at 10Hz, and nudges them into submitting self-reports about their emotional state via notifications at random times. Specifically, users can report how *happy* they are and how *relaxed* they feel, on a scale from 1 to 5. We deployed the watch application with 12 subjects for a period of three weeks, and collected 1,121 hours of raw PPG signals and 1,032 self-reports, which we used to validate our mapping of physiological indicators to emotional states.

3.2 Mapping HR/HRV to emotions

The collected raw signals are then processed using off-the-shelf signal processing tools [23] to conduct HRV analysis. Usually, HRV —the variation in time between heartbeats— is measured through a family of parameters that are defined in the time domain (e.g., RMSSD), in the frequency domain (e.g., LF/HF), and as non-linear indices (e.g., SD1, SD2) [10]. In particular, we focus on two parameters, i.e., RMSSD and LF/HF, as well as the instantaneous HR. *RMSSD* is a widely used parameter across studies as a proxy to an HRV score [10]. It is defined as the root mean square of successive differences of consecutive RR intervals, and reflects activity in the vagal tone. Additionally, the ratio of low and high frequencies *LF/HF* is another widely parameter that captures both sympathetic and vagal activity, thus providing a way of assessing the state of our Autonomic Nervous System, and broadly our emotional states [9]. To map biosignals to emotional states, we resorted to a literature-driven mapping approach. In particular, we reviewed previous findings presented in [9], and we identified that a combination of HR, RMSSD, and LF/HF parameters distinguish quite effectively different emotional states in Plutchik's emotion model [16]. For example, joy is characterized by a unique footprint of high/low levels of these three parameters.

To further validate our mapping approach, we analyzed the data collected during the three-week deployment study. Particularly, we analyzed the HR and the two HRV parameters in relation to the self-reported emotion labels. To do so, we computed each user's baseline HR and HRV parameters by averaging all values for each of the three features across the whole duration of the trial. We then computed a metric that captures each user's daily deviations from their baseline values. To explore their relationship to the self-reported data, we computed the probability for each emotional state for each day as $P(E) = \frac{|EL|}{|L|}$, where L is the set of all the self-reports across all days, EL is a subset of L computed as $EL = \{l \in L \mid l \geq \bar{M}L\}$, where l is a self-report, and $\bar{M}L$ the median value of all the self-reports. Using the median value of the self-reports allowed us to partition these self-reports as being either positive or negative. When comparing the low and high groups of HR and HRV parameters in relation to the probabilities for each emotional state, we observed consistent results that matched theoretical expectations [9]. For example, people who reported higher levels of positive emotional states such as joy had, on average, 14.7% higher HR and 4.8% lower HRV parameters, than those who reported lower levels of joy.

3.3 Collective Emotional States Display

To visualize the collective emotional states, we resorted to an abstract, behavior model that simulates the coordinated behavior in human society. The visualization display of collective emotional states (Figure 2 (c)) is based on the Boids model, which is a type of behavior model that offers a simple way to depict group dynamics. It also resonates with the human instinctive interpretation of collective behavior [20]. The Boids model originates from Craig Reynolds, who described it as an approach to simulate the aggregate motion of a flock of birds, a herd of land animals, or a school of fish through a distributed behavioral model [17]. By design, it also preserves users' anonymity in sharing their own physiological data as it visualizes them in a collective way.

We developed a web-based visualization using HTML5/JavaScript and D3 that simulates a collection of independent particles moving on a canvas. These particles, called 'boids', depict the collective emotional state of a group of people. Reynold's model [17] defines three forces that control the behavior of boids; (a) separation, (b) alignment, (c) cohesion. Separation controls collisions with nearby

[5]https://www.tizen.org/

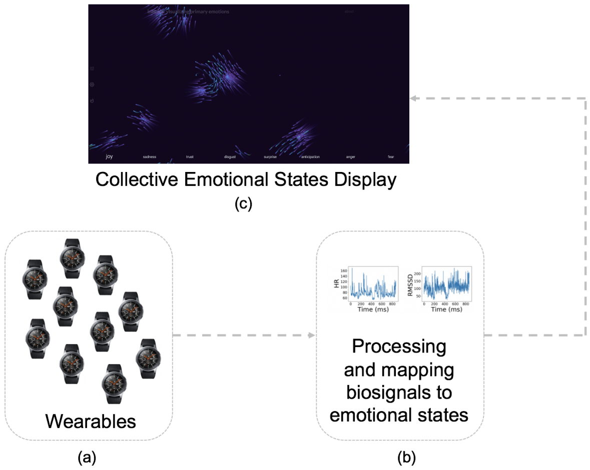

Figure 2: Schematic architecture overview. (a) Data obtained from multiple watches are (b) processed and aggregated, and (c) visualized in a playful way. The visualization display conveys the collective emotional state of a group of people.

boids, alignment matches a boid's velocity with that of neighbors, and cohesion allows boids to stay closer to each other. By varying these parameters, real-time physiological indicators could be translated into eight different emotional states. For example, Figure 3a illustrates a scenario in which a group of people experience a positive emotion (i.e., joy), while Figure 3g depicts a negative one (i.e., angry).

4 DISCUSSION AND CONCLUSION

We present a wearable-based biosignal sharing system for groups. Our end-to-end system measures physiological indicators of a group of people, translates these indicators into emotional states, and visualizes them in an abstract and playful way. Aligned with the Inbodied Interaction paradigm [20], our system aims to better align with how our body internally works, and create emotional awareness between a group of people.

Practically, our system could be deployed in a number of settings. We foresee potential applications at the workplace, in small or large teams, or even at larger audiences such as theater rooms during lectures, or crowd events. For example, team members could wear watches that obtain their heart rate in real-time, and through our system's visualization they get an immediate feedback of the team's mood. In turn, they can act upon this feedback to handle stressful situations, or embrace joyful ones. While the current visualization is served via a web browser, the same approach could be adapted to large interactive installations and integration in physical spaces.

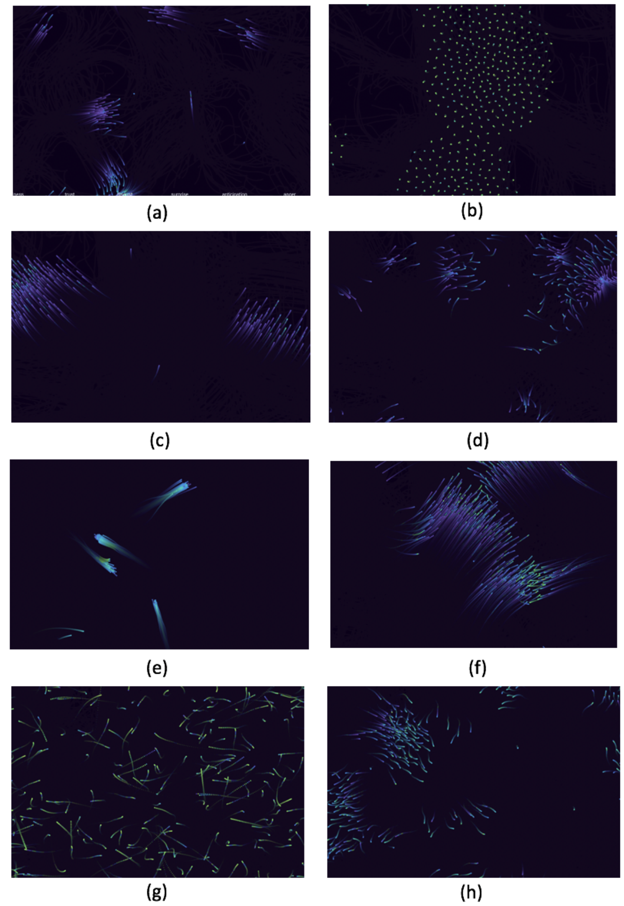

Figure 3: The eight visualizations represent: (a) joy, (b) sadness, (c) trust, (d) disgust, (e) surprise, (f) anticipation, (g) anger, and (h) fear.

REFERENCES

[1] Luca Maria Aiello, Daniele Quercia, and Eva Roitmann. 2018. Hearts and Politics: Metrics for Tracking Biorhythm Changes during Brexit and Trump. In *Proceedings of the 2018 International Conference on Digital Health*. 111–115. https://doi.org/10.1145/3194658.3194678
[2] Jean Costa, Alexander T Adams, Malte F Jung, François Guimbretière, and Tanzeem Choudhury. 2016. EmotionCheck: Leveraging Bodily Signals and False Feedback to Regulate our Emotions. In *Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing*. 758–769. https://doi.org/10.1145/2971648.2971752
[3] Jérémy Frey, May Grabli, Ronit Slyper, and Jessica R Cauchard. 2018. Breeze: Sharing Biofeedback Through Wearable Technologies. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*. 1–12.
[4] Martin Gjoreski, Mitja Luštrek, Matjaž Gams, and Hristijan Gjoreski. 2017. Monitoring Stress with a Wrist Device Using Context. *Journal of Biomedical Informatics* 73 (2017), 159–170. https://doi.org/10.1016/j.jbi.2017.08.006
[5] Peter A Gloor, Andrea Fronzetti Colladon, Francesca Grippa, Pascal Budner, and Joscha Eirich. 2018. Aristotle said "Happiness is a State of Activity"—Predicting Mood Through Body Sensing with Smartwatches. *Journal of Systems Science and Systems Engineering* 27, 5 (2018), 586–612. https://doi.org/10.1007/s11518-018-5383-7
[6] Katrin Hänsel, Akram Alomainy, and Hamed Haddadi. 2016. Large Scale Mood and Stress Self-assessments on a Smartwatch. In *Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing: Adjunct*. ACM, 1180–1184. https://doi.org/10.1145/2968219.2968305
[7] Mariam Hassib, Daniel Buschek, Paweł W Wozniak, and Florian Alt. 2017. HeartChat: Heart Rate Augmented Mobile Chat to Support Empathy and Awareness. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems*. 2239–2251.
[8] Joris H Janssen, Jeremy N Bailenson, Wijnand A IJsselsteijn, and Joyce HDM Westerink. 2010. Intimate Heartbeats: Opportunities for Affective Communication Technology. *IEEE Transactions on Affective Computing* 1, 2 (2010), 72–80.
[9] Sylvia D Kreibig. 2010. Autonomic Nervous System Activity in Emotion: A Review. *Biological psychology* 84, 3 (2010), 394–421.

[10] Sylvain Laborde, Emma Mosley, and Julian F Thayer. 2017. Heart Rate Variability and Cardiac Vagal Tone in Psychophysiological research–recommendations for experiment planning, data analysis, and data reporting. *Frontiers in psychology* 8 (2017), 213.

[11] Myungho Lee, Kangsoo Kim, Hyunghwan Rho, and Si Jung Kim. 2014. Empatalk: A Physiological Data Incorporated Human-Computer Interactions. In *CHI'14 Extended Abstracts on Human Factors in Computing Systems*. 1897–1902.

[12] Fannie Liu, Laura Dabbish, and Geoff Kaufman. 2017. Supporting Social Interactions With An Expressive Heart Rate Sharing Application. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 1, 3 (2017), 1–26.

[13] Pablo Pancardo, José Adán Hernández-Nolasco, Francisco D Acosta, and Miguel A Wister. 2016. Personalizing Physical Effort Estimation in Workplaces Using A Wearable Heart Rate Sensor. In *Ubiquitous Computing and Ambient Intelligence*. Springer, 111–122.

[14] Sungkyu Park, Marios Constantinides, Luca Maria Aiello, Daniele Quercia, and Paul Van Gent. 2020. WellBeat: A Framework for Tracking Daily Well-being Using Smartwatches. *IEEE Internet Computing* (2020).

[15] Rosalind W Picard. 2000. *Affective computing*. MIT press.

[16] Robert Plutchik. 1984. Emotions: A General Psychoevolutionary theory. *Approaches to emotion* 1984 (1984), 197–219.

[17] Craig W Reynolds. 1987. *Flocks, Herds and Schools: A Distributed Behavioral Model*. Vol. 21. ACM. https://doi.org/10.1145/37402.37406

[18] Peter Salovey and John D Mayer. 1990. Emotional Intelligence. *Imagination, Cognition and Personality* 9, 3 (1990), 185–211.

[19] Philip Schmidt, Robert Dürichen, Attila Reiss, Kristof Van Laerhoven, and Thomas Plötz. 2019. Multi-target Affect Detection in the Wild: An Exploratory Study. In *Proceedings of the 23rd International Symposium on Wearable Computers*. 211–219. https://doi.org/10.1145/3341163.3347741

[20] mc schraefel. 2019. in5: a Model for Inbodied Interaction. In *Extended Abstracts of the 2019 CHI Conference on Human Factors in Computing Systems*. 1–6.

[21] Petr Slovák, Joris Janssen, and Geraldine Fitzpatrick. 2012. Understanding Heart Rate Sharing: Towards Unpacking Physiosocial Space. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. 859–868.

[22] 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*. 71–80.

[23] Paul van Gent, Haneen Farah, Nicole van Nes, and Bart van Arem. 2019. Analysing Noisy Driver Physiology Real-time Using Off-the-shelf Sensors: Heart Rate Analysis Software From the Taking the Fast Lane Project. *Journal of Open Research Software* 7, 1 (2019).