Biosignals-Based Social Support

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ABSTRACT

This paper documents the design process and implementation of a Biosignals-based Social Support Android Application. The application enables people to share and respond to each other's biosignals. Users are encouraged to communicate with each other through gesture-based. We hope to develop, explore, and evaluate the system's ability to encourage lightweight gestures as a means of social support.

CCS CONCEPTS

• **Human-centered computing → Empirical studies in ubiquitous and mobile computing**.

KEYWORDS

biosignals, heart rate, interpersonal communication, social support

ACM Reference Format:
Emily Lo, Fannie Liu, and Laura Dabbish. 2019. Biosignals-Based Social Support. In . ACM, New York, NY, USA, 5 pages.

1 INTRODUCTION

This research extends on the field of exploring how biosignals can be expressive and taken as social cues in order to increase interpersonal communication.

Biosignals are patterns exhibited by the human body that we can monitor, such as heart rate, sin conductivity, and brain activity based on region. There have been many physiological studies [2] that correlate these biosignals to the intensity of an emotion.

The results from these papers have led to research experimenting with displaying these biosignals to others to see how effective it is as a secondary social cue [1]. Current research focuses on the social meaning of displaying biosignals, and how others interact with these expressive biosignals in a natural and intuitive way. For example, researchers have played with displaying different colors, which correlate to detected levels of emotion [7]. Animo [3] is a smartwatch app that enables people to share and view each other's biosignals.

Previous research targets one direction in the conversation between the detected user and the observing participant. We have seen many ways of displaying these biosignals and researched the kinds of social implications and privacy concerns that may arise from these interactions. Thus, we aim to explore how these biosignals could be more actionable for observers. This research will attempt to help make biosignals more approachable by creating fixed actions associated with biosignal readings, making the conversation flow in both directions.

15-400 Final Paper, May 12, 2019, Pittsburgh, PA

2 RELATED WORK

2.1 Sharing Biosignals

Most prior work related to biosignals are catered to the individual, such as providing information about fitness, well-being, or social skills. However, recent research has explored biosignals as it relates to interpersonal communication, focusing on how they affect our emotions. For example, Janssen and her colleagues demonstrated the sound of a heartbeat can increase feelings of intimacy and closeness [6]. Sharing heart rate can increase social connectedness, where it can become an emotional expression, a means to gain awareness about another person's context, or simply a playful way to interact and feel present with another person [5].

Research shows users that share heart rate through a smartwatch app communicated in new ways to each other, as it was a lightweight "poke" and a conversation starter. Participants felt that they became more aware of other users' presence of state. At the same time, the simplicity of the smartwatch application lead to a shortage of context around the biosignal. We addressed this by giving the shared moment more real estate—the mobile application will allow for users to customize their own messages in addition to sharing their biosignals.

3 DESIGN PROCESS

This portion of the paper documents the steps that were taken along the way this semester, and is only for reporting purposes of 15-400.

I met regularly with Fannie Liu, the Ph.D student that leads this project to sync up on the project and ensure that we were moving on the right track. Fannie also worked with two other Masters HCI students Gillis Bernhard and Tiffany Yang, who were in charge of pilot user studies and determining the frontend structure of the application.

3.1 Competitive Analysis

The first couple of weeks, I looked into different kinds of outlets students had for social support currently. These ranged from mobile applications that focused on mental health to in-person services like CMU's own CAPs. For each of the systems, I looked at:

- Main type of social support
- Use cases
- Target audience and how users interact

Table 1: Summary of Competitive Analysis - Applications

Service	Keywords	Type of support
Circle of Six	Physical safety, existing friends	Safety
Reachout	Forum, Strangers	Emotional
Supportiv	Group chat-based, Strangers	Emotional
What's Up	Journal, self-help	None
Whisper	Anonymous, Forum	Relief
Yik Yak	Anonymous, Chat-based	Relief

- Metrics/how successful it is

The summarized findings are in Table 1. The only application that was specifically for support and worked off of existing relationships was Circle of Six—with the many ways of interacting with people we already know, not needing an extra application specifically for emotional support may explain the lack of applications with these kinds of interactions. Circle of Six focused more on physical safety, allowing families and close friends to keep tabs on how everyone else is physically.

We noted that the rest of the applications can be broken down into two types: self-help, and group-based empathy. We want to focus on emotional support, which is found in all of the group-based empathy. However, it seemed that people were more comfortable seeking support only when interacting with strangers. Our application hopes to explore relationships between strangers and already-existing close friendships: people within the same social context (i.e. college program or age range) but have not met the person physically yet.

In tangent to this, I looked at the types of ways CMU students could share with each other or seek support: a Facebook page called "Overheard at CMU", and the counseling and psychological services that CMU provides, mostly known as CAPs. Overhead at CMU is almost entirely for entertainment purposes, but sometimes it does bring students together when a student publicly quotes an emotionally vulnerable moment.

The competitive analysis emphasizes that our application will likely draw from social support and would likely be most effective in scenes where users can relate in some social context, but are not already friends.

3.2 Chatting System

We knew the base of the application would require some kind of chatting system, one where users are updated live-time of messages that are sent directly to that one person. We also knew that we had to perform calculations with streamed heartrate data. This lead to some comparisons for types of data platforms that we would host the information on, and possibly some backend options to run the stress-detection code on.

The options were quickly researched and weighed, it made the most sense to use Firebase since it had extensive documentation and had reasonable prices for both storage amount and requests per minute.

3.3 Gesture Detection

Our initial idea for the flow would be to allow users to perform any gesture while in the chat with another user. The application would then have to be able to correctly identify a fixed set of gestures that users could perform.

I attempted to train a TensorFlow model locally and upload to the mobile application, which would use the consolidated decision tree to determine which gesture was being performed. Through this process, I made an application (code here) that records the data for one single movement, which is then exported to a csv file of just numbers. See Figures 1-3 for snapshots of the kind of data that was taken for each kind of motion.

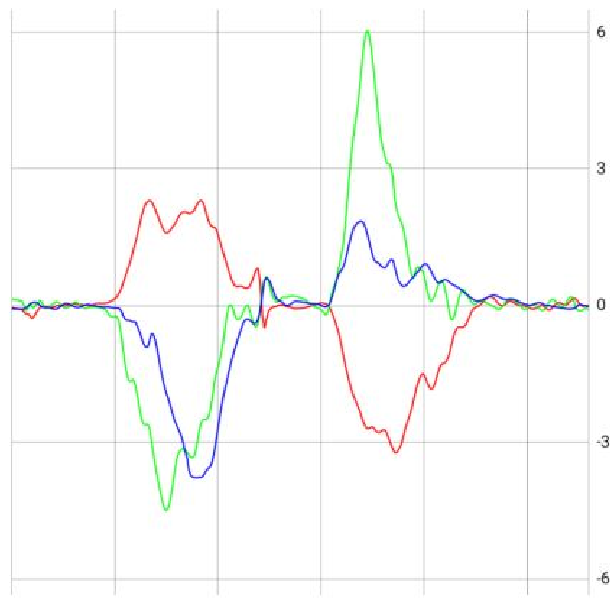

Figure 1: Gyroscope data for gesture putting hands on temples

After collecting data, training the data came up fruitless. However, we came to the conclusion that users would be choosing their gestures before the gesture detection would occur, so not using TensorFlow would be suitable for this application.

Instead, I used this same app to visually inspect the kinds of differences that would help me distinguish which gestures users were making. For example, hands out had a particular pattern where all three directions (x in red, y in blue, z in green) would peak negatively. After all gestures were decided, I went through and wrote code that detects whether the chosen gesture is performed by looking at how the x, y, and z axis vary according to movement type.

3.4 Stress Detection

This portion of the semester, I focused on connecting the application to the chosen HRV sensor, which was the Polar H10. I also read through resources Fannie pointed me to in terms of calculating

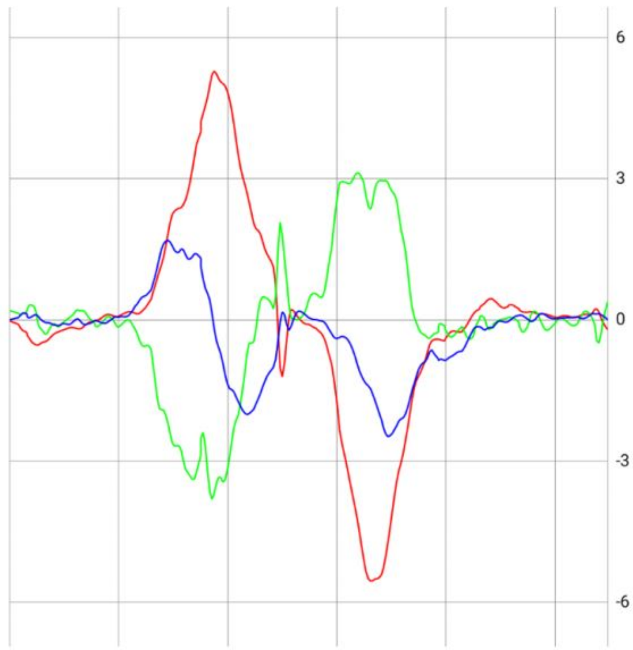

Figure 2: Gyroscope data for gesture bringing phone in for a self-hug.

stressful moments. We considered three different methods that were explained in two papers:

- Option 1. [4] Stress detection based on time-domain HRV features. Uses a combination of mean HR, pNN50, and RMSSD features in a sliding window, which can be seen in Figure 4.
- Option 2.[6] Activity-aware mental stress detection scheme that involves Electrocardiogram (ECG), which includes HRV with RMSSD and pNN50, galvanic skin response (GSR), and accelerometer data.

The first option was more straightforward in terms of implementation, and our chestband supported all of the parameters necessary to replicate their procedure. The second option noted that their results were relatively similar with just heartrate compared to adding in all information, but still boiled down to a decision tree that was generated from training data.

Thus, I implemented the first option as part of our stress detection and documented it here. I also found a way to push an hour's worth of heartrate data to the database at a time, rather than streaming data into Firebase as the Polar H10 recorded data.

3.5 Android Application

Throughout the entire semester, each of these smaller parts were made with minimal Android screens to show functionality. In the last two weeks, as mid-fi prototypes became finalized, I managed to plug in some of the backend features to a more presentable frontend.

All screens that were completed at the end of the semester can be seen here. Below is the summarized version of all of the finished screens:

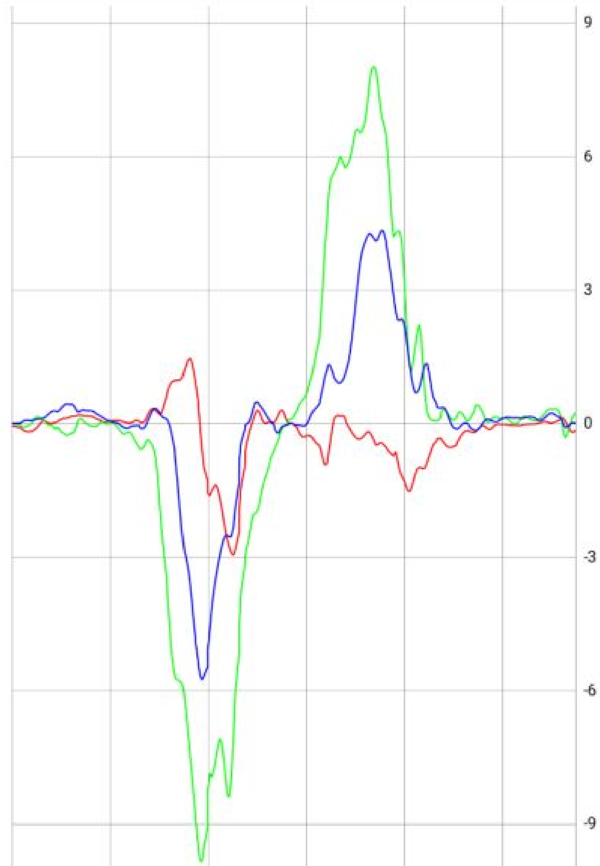

Figure 3: Gyroscope data for gesture waving palms outwards.

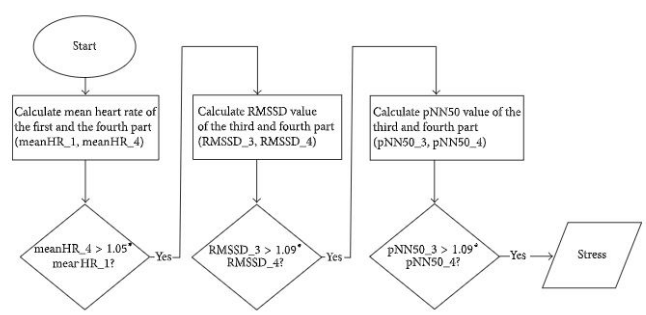

Figure 4: Stress Detection Algorithm. Photograph by Mario Salai et al, via Journal of Healthcare Engineering.

- Login page, done through Firebase Authentication
- Home page, which displays current partner and all most recent messages
- Onboarding flow, which brings user through series of onboarding questions concerning potentially stressful events that upcoming week–stores results in Firebase

- Messaging page, allows users to see navigate to sent gesture-minigames and all past messages. Messaging prompts other user and pushes to Firebase.
- Notifications for:
  - Stress detection, prompts user for whether or not they were stressed and the option to nudge select friends
  - Friend sending them a gesture, allows user to open to a specific chat and a minigame
  - Nudge message from a stressed friend, allows user to choose and send a minigame
- Profile page, allows users to see what kinds of charms they've received from other users, and for them to modify their stressors for that week

Notifications to users were also achieved by the Android system.

4 APPLICATION SYSTEM

4.1 Design

This Android application allows people to send each other messages or small gesture-based games in response to detected stress.

4.1.1 Onboarding Process. At the beginning of the week, users are prompted to fill out an onboarding survey that records the potentially stressful events they have coming up. At the end of the process, they are assigned to one other user who will be their main partner for that week.

4.1.2 Sharing. While the application is running in the background of the phone, it will be connected via Bluetooth to a Polar H10, a heartrate monitor that is strapped around the user's chest. The application uses the stream of heartrate data to determine whether there is a possible moment of stress, at which the app sends the user a notification. The user first confirms whether or not they feel stressed—if they do not, parameters that determine the sensitivity of our stress detection are adjusted and the notification is dismissed.

If they do feel stressed, they have the option to nudge users in their assigned friend group. They optionally are allowed to describe their current emotions, or add any kind of contextual message with the nudge notification to their supporter.

4.1.3 Content from Supporter. When users receive a notification that their assigned partner is stressed, they have the opportunity to send a gesture-based game. We separated these games based on the kinds of gestures that are detected within each oneâĂŤin total, we have six total gestures that were chosen based on feedback from pilot user studies and its ease of detection using just Android motion sensors.

Within each gesture, users are allowed to choose from a few variations of games—these display a different animations and allow users to exchange different kinds of "tokens“. Along with each game, users are allowed to send text messages through the application.

4.2 Implementation

We implemented the application by connecting Firebase with the application itself, which is hosted on an Android phone. The heartrate monitor chosen for this research was the Polar H10, mainly for its compatibility with Android and its reliable Bluetooth connection, since we planned to stream the heartrate data. Gesture detection is done solely on the Android application, based on the motion sensors built into the phone. Since the game is contained in its own activity, we only had to detect for one gesture at a time.

User data, messages, and heartrate data is stored in Firebase. The game animations are stored and displayed on the Android device. The application requires users to have the application running in the background, have Bluetooth and coarse location permissions and data connection on.

5 METHODS

To test the application, we plan to deploy the app in a two-week field study, allowing participants to freely use the app in order to observe patterns of usage that naturally emerge.

5.1 Participants

We plan to recruit first-year undergraduate females in computer science at Carnegie Mellon. We chose this population because we expect the students to be making a large transition in their academic careers, which will inevitably lead to possibly more stressful moments.

5.2 Procedure

Analytics for the usage of the application are built into the Firebase. The database contains the information:

- Stressed/Not stressed in response to stress detection: Test accuracy of stress detection system
- Total number of nudges to supporters, number of times users declined to nudge supporters: Compare distribution of people who actually nudged other users within the application
- Total number of nudges to main supporter vs. rest of the support group: Compare distribution of having one-on-one interaction with main supporter
- Number of times each game is sent to someone: Compare distribution of gestures being sent, and which games were most popular within each gesture

6 CONCLUSION AND FUTURE WORK

This paper documents the design process and implementation of a mobile application that will allow users to share stressful moments with others through gesture-based minigames. With the backend framework mostly complete, Fannie will be using the designs that Gillis and Tiffany produce by the end of the semester to complete the frontend. If more screens are availalbe and functionality of the application changes, I will continue to develop the application over summer.

We hope to be able to deploy the application to users in a field study the next fall semester.

ACKNOWLEDGMENTS

I would like to thank my patient and kind mentor Fannie Liu and her advisors Laura Dabbish and Geoff Kaufman. I would also like to thank my teammates Gillis Bernhard and Tiffany Yang, and my 15-400 advisor Jonathan Aldrich for supporting me through my first semester of research!

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