A Wearable and Mobile Intervention Delivery System for Individuals with Panic Disorder

Luis Cruz
PARC, A Xerox Company
Luis.Cruz@parc.com

Jonathan Rubin
PARC, A Xerox Company
Jonathan.Rubin@parc.com

Rui Abreu
PARC, A Xerox Company
rui@parc.com

Shane Ahern
PARC, A Xerox Company
Shane.Ahern@parc.com

Hoda Eldardiry
PARC, A Xerox Company
Hoda.Eldardiry@parc.com

Daniel G. Bobrow
PARC, A Xerox Company
bobrow@parc.com

ABSTRACT
Panic disorder is a serious condition that affects approximately six million adults in the United States per year. Reducing the severity of panic attack symptoms would allow a better quality of life for panic attack sufferers. This paper presents steps towards a mobile and wearable system that aims to help reduce the severity of symptoms experienced by individuals with this condition. The system provides a way to continuously monitor the physiological data of an individual via a wearable device. Users are able to report when panic attacks take place, along with a rating of the severity of symptoms experienced. Reported episodes provide ground truth data to build panic prediction models. The eventual goal of the system is to make predictions about approaching panic attacks and to deliver interventions that help the individual to cope with the approaching episode. We describe a mobile-based intervention that has been developed, which instructs the individual to perform breathing and relaxation exercises. Presently, the system has been utilized in a small pilot study where 10 individuals who suffer from panic disorder reported 29 panic attacks while collecting physiological data, along with the severity of symptoms. We found that out of 15 symptoms the ones with high severity reported were anxiety, worry and shortness of breath. Furthermore, physiological differences were observed between panic and non-panic intervals.

CCS Concepts
•**Applied computing** → **Health care information systems; Health informatics;** •**Information systems** → *Data analytics; Mobile information processing systems;*

Author Keywords
Physiological monitoring, wearables, mobile applications, mHealth, ubiquitous computing

MUM '15, November 30-December 02, 2015, Linz, Austria

ISBN 978-1-4503-3605-5/15/11...$15.00
DOI: http://dx.doi.org/10.1145/2836041.2836058

INTRODUCTION
Panic disorder is a condition that affects a large portion of the population: in the United States alone, 6 million adults are reported to suffer from panic disorder [13]. Individuals that suffer from panic disorder can have their lives constrained and, depending on the severity of their condition, symptoms can become debilitating. During a panic attack individuals may experience shortness of breath, increased heart rate, dizziness, chest pain, sweating, hot flashes, trembling, choking, nausea and numbness, as well as feelings of unreality, fear of losing control and fear of dying. The majority of these symptoms are physiological, and hence detectable through measurements such as heart rate, respiration rate, perspiration and skin temperature.

Wearable devices can provide an unobtrusive option for collecting physiological data while people proceed with their daily activity. Moreover, mobile and wearables technology is increasingly being utilized in health-monitoring systems [15]. This paper presents progress towards a wearable health monitoring system for patients with panic disorder. The long-term goal is to have patients wear a device to monitor panic symptoms and, whenever a panic attack is predicted, deliver interventions that help reduce the severity of the symptoms experienced, such as breathing and relaxation exercises. Figure 1 depicts a high-level overview of the mobile and wearable system.

In order to develop panic attack prediction models, it is necessary to first collect ground truth information about panic attack occurrences. The mobile and wearable system we describe in this paper was used within a data collection study to obtain this necessary ground truth data.

The remainder of this paper is organized as follows. First, related work in the field is presented. Next, the architecture of the mobile and wearable system is described. Following, the experimental setup, data collection study and the respective results are presented. Finally, discussion and conclusions about the work are outlined.

RELATED WORK

Physiological monitoring for Panic Disorder
Physiological responses to both spontaneous [8, 19] and in vitro [2] panic attacks have been studied in-the-lab.

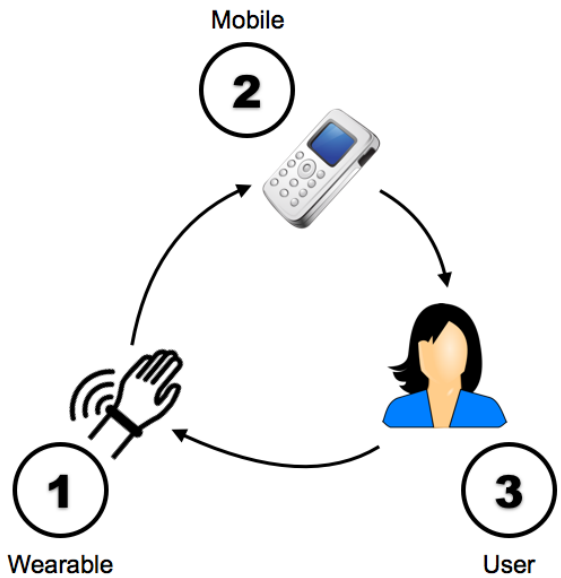


Figure 1: The system uses a wireless wearable sensor to collect physiological data, which is automatically analyzed via a smartphone application to detect approaching panic attacks. After detection, an intervention is delivered directly to a user's mobile phone. An example of an intervention is to begin breathing and relaxation exercises using a biofeedback mobile application.

In-the-lab

Some in vitro studies have artificially induced panic attacks by intravenously administering sodium lactate to an individual. Sodium lactate is an anxiogenic substance that is known to induce panic attacks in individuals who suffer from panic disorder [9]. The study discussed in [2] compared the physiological responses associated with panic attacks between groups of individuals who were administered sodium lactate and groups who were given a placebo. The authors found significant increases in heart rate and minute ventilation immediately preceding the onset of a panic attack.

In-the-lab studies that involve either induced or spontaneously occurring panic attacks are limited in the amount of time they are able to monitor the physiological signals of a subject – typically short amounts of time preceding and directly after episodes occur. In our work we have captured spontaneously occurring panic attacks by continuously monitoring subjects within an ambulatory in-the-wild environment.

In-the-wild

There have been relatively few ambulatory studies conducted where the physiological signals of individuals who suffer with panic disorder were monitored continuously in a real-world setting. One such study, conducted by Meuret *et al.* [11], showed that a series of physiological changes occurred up to one hour before an individual experienced any symptoms related to a panic episode. During this period subjects were not aware of any symptoms until the moment they experienced an 'out-of-the-blue' panic attack. Rosenfield *et al.* [16] used change-point analysis [14] to show that vital sign measurements such as heart rate, the amount of carbon dioxide in the blood (PCO2), tidal volume (the volume of air moved into or out of the lungs), and respiration rate and heart rate variability, exhibited one or more change points in the hour preceding a reported panic episode. When compared with regular measurements, where a panic episode was not reported, none or relatively few change points were exhibited. The findings prompted the authors of [16] to state that:

> *"The results from both change point analyses (single and multiple) seem to indicate that, before panic attack onset, various physiological systems exhibit deviations from a set point. These deviations may be a part of a cascade of systemic dysregulation escalating into a panic attack".*

Our work extends the work of [11, 16]. The goal of our work is to utilize a prediction algorithm within a mobile and wearable system in order to allow users of the system to respond to approaching panic episodes via interventions delivered direct to mobile devices. Previously, we have detailed the construction of panic prediction models in [17]. In this current work, we describe a complete mobile and wearable system for panic attack detection and intervention delivery and further present results from a data collection study in which the system was utilized to collect ground truth data.

Stress and Emotion Detection

Physiological monitoring has also been used within stress detection systems, as well as emotion detection. Healey conducted both in the lab [6] and out of the lab [4] experiments to classify emotional states such as anger, hate, grief, platonic love, romantic love, joy and reverence. Healey also investigated the problem of stress detection during driving tasks [5, 6]. By constraining the problem of stress recognition to this setting, challenges associated with accounting for physical activity were able to be minimized.

Hong *et al.* [7] focused on understanding the role physical activity has on stress detection. They present the results of an in-the-lab study where stressors were introduced while subjects performed various types of physical activities such as sitting still, walking and cycling. Separate stress recognition models were constructed for each activity type. The importance of building personalized models was also emphasized, given individual differences in physiological responses. Other efforts in stress detection have used less intrusive, speech based signals in order to classify stress [10].

Detecting panic episodes can be considered an extreme form of stress detection. While our work has similarities to research efforts in stress detection, it differs in that we seek to detect approaching panic episodes – before they take place – in order to deliver in-the-moment mobile-based interventions, which can be used to help individuals respond to and cope with panic episode symptoms.

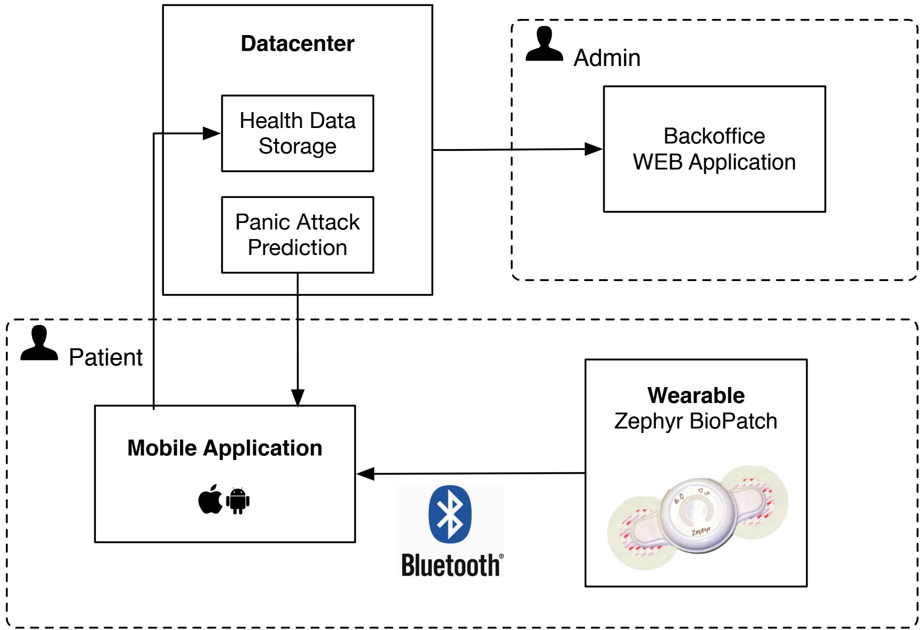


Figure 2: Wearable and Mobile Intervention Delivery System Architecture.

SYSTEM OVERVIEW

To predict approaching panic episodes it is important that data is continuously analyzed in order to prevent missing a time frame in which a user may experience an attack. Physiological changes can begin to take place up to one hour before a panic attack [11, 16]. Therefore, the system must process the preceding hour of data in real time to detect changes. As smartphones and wearable devices have limited processing and energy resources we've directed data to a central server that deals with storage and analysis of data.

The architecture used to implement this mobile and wearable system is depicted in Figure 2. Each component of the system is explained in detail below.

Wearable

Many different wearables are currently available, including devices such as Fitbit[1] or Jawbone[2] trackers. Wearable devices have been used for activity tracking, diet management and health care. They are predominantly worn on the wrist or chest and can also be embedded within clothing (e.g., Heddoko[3]), shoes (e.g., Lechal[4]) and glasses (e.g., Google Glass[5]). The following parameters are relevant to detect panic attacks [17]:

- Heart rate (HR)
- Breathing rate (BR)
- Heart rate variability (HRV)
- Core temperature (Temp)
- Activity, as measured by accelerometers

Consequently, to be suitable for this system the wearable has to provide accurate measurements for the listed parameters. Wrist-worn wearables are common because they are easy to use and are often worn as an accessory (e.g., watch). However, wrist-worn wearables are not currently able to provide all the required parameters listed above, such as heart rate variability. As such, we chose to use the chest-worn Zephyr BioPatch™ (see Figure 3) for physiological data collection. The Zephyr BioPatch provides a reasonable tradeoff between intrusiveness and accuracy [3]. It is worn on a patient's chest by attaching to ECG electrodes or an ECG strap.

The data read by the wearable is transmitted to the user's smartphone by Bluetooth using our mobile application (discussed next). Physiological information is summarized at a frequency of 1Hz.

Figure 3: Wearable device – Zephyr BioPatch™.

[1] http://www.fitbit.com/
[2] http://jawbone.com
[3] http://www.heddoko.com
[4] http://www.lechal.com
[5] https://www.google.com/glass

Mobile Application

The mobile application plays an important role in the system:

- **It authenticates the user in the datacenter.** This is an important step since we are dealing with sensitive data. Health care data is private and personal so care must be taken to make sure that collected data is securely transferred and stored.

- **It collects data from the wearable and uploads it to the datacenter using an internet connection.** Since we cannot connect the wearable directly to the server, it provides a bridge between the wearable and our datacenter. Because there is a chance of a user being temporarily without internet connection, the application provides a buffer that stores up to 1 hour of wearable data locally on the smartphone.

- **It reports current physiological parameters to the user.** The main view provides the current values for heart rate, breathing rate and core temperature (see Figure 4a). This view intends to help users get familiar with their regular vital sign information.

- **It provides a graphical interface for the breathing exercise intervention (see Figure 4b).** In this intervention, a user is instructed to breath at a particular rate. The current respiration rate is provided as feedback to the user, as well as a message stating whether the user has to speed up or slow down. The view also allows the user to pause and resume the intervention.

- **It allows users to report panic episodes.** This is useful to collect ground truth data. The application provides a widget with a *Start* and *Stop* button as depicted in Figures 5a and 5b. The widget is easily accessible through the notification screen to allow accurate reporting of episode timestamps. Whenever the patient starts feeling panic attack symptoms he or she hits *Start* and when he or she feels the panic attack has ended he or she hits *Stop*. After recording the episode they will be presented with a view to report the severity of 15 symptoms using a scale corresponding to *None (0), Mild (1), Moderate (2), Strong (3), Extreme(4)*, as shown in Figure 5c. Table 1 shows the complete list of symptoms, which is derived from the DSM-IV (Diagnostic and Statistical Manual of Mental Disorders) [1] and the Panic Disorder Severity Scale standard instrument [18].

Intervention Delivery

When a patient experiences symptoms that might be related to a panic attack, the mobile application suggests/notifies the user to perform breathing and relaxation exercises. This intervention is based on [12] and involves asking the patient to maintain a *breaths per minute* goal for a specified duration.

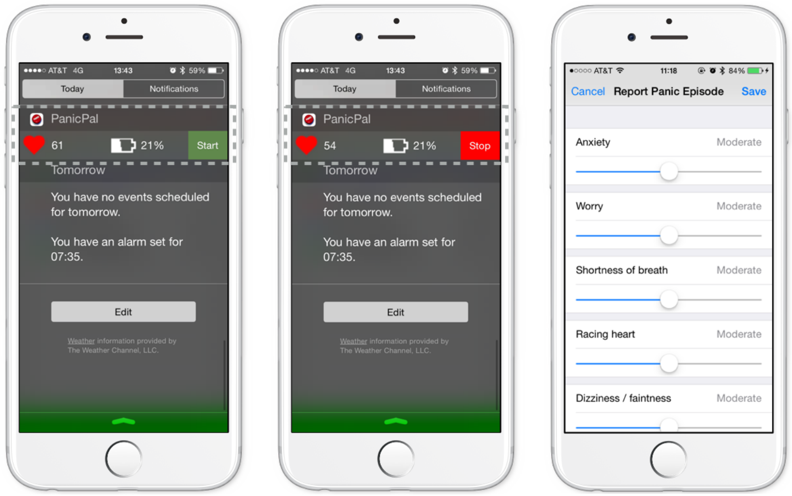
In order to guide the user to breathe at the given goal rate there is a graphical feedback view that shows the current breathing rate of the individual. There is also textual information prompting the user to "speed up" or "slow down" in case of lower or higher respiration rate, respectively. Sound prompts can also be toggled on or off, which indicate when the user should be breathing in or breathing out. A screenshot of the

Panic Symptoms and Emotions	
1.	Anxiety
2.	Worry
3.	Shortness of breath
4.	Racing / pounding heart
5.	Dizziness / faintness
6.	Chest pain / discomfort
7.	Feelings of unreality
8.	Sweating
9.	Hot flashes / cold flashes
10.	Fear of losing control / sanity
11.	Trembling / shaking
12.	Choking sensations
13.	Nausea
14.	Numbness / tingling
15.	Fear of dying

Table 1: Complete list of panic episode symptoms

(a) (b)

Figure 4: Screenshot of a) the main view and b) the breathing exercise view in the mobile application.



(a) (b) (c)

Figure 5: Views that user experiences when reporting a panic attack. a) widget with start button; b) widget with stop button; c) view to report the severity of the symptoms.

mobile-based breathing exercise intervention is provided in Figure 4b.

Datacenter

The datacenter is responsible for storing all the data and predicting panic attacks. Whenever the datacenter detects that the user is about to have a panic attack, it sends a push notification to the mobile application running on the patient's smartphone. Panic prediction models utilize change point analysis to build feature vectors and anomaly detection algorithms to distinguish between pre-panic and non-panic intervals. The change point analysis identifies locations where significant changes have occurred in the time series data [14]. Further details about panic attack prediction models can be found in [17].

EXPERIMENTAL SETUP

To develop a panic prediction model it is necessary to collect data from patients that suffer from panic disorder. Data collection also served as a validation of the mobile and wearable system we propose. This section describes the experiment conducted for collecting data. This study was approved by Palo Alto Research Center's Institutional Review Board and all subjects signed informed consent forms.

Data Collection

Subjects were recruited from local Meetup groups for people coping with panic and anxiety, as well as advertisements placed using Google Adwords and Craigslist (a classifieds website). In total, 10 volunteers participated in the study. Each one was given a wearable device and was asked to wear it as often as possible for 3 weeks. Physiological data from each subject was collected during the study. Additionally, subjects were asked to use the mobile application to manually report panic episodes as described earlier in this document. Subjects were provided with instruction guides for the initial setup of the mobile and wearable system.

From the 10 subjects in this experiment, 7 recorded physiological data and 6 of those subjects reported panic attacks occurring.

RESULTS

In total, 29 panic attacks were reported. The severity of symptoms during panic episodes for each subject is reported in Table 2. This table presents the mean values grouped by individual for number of reports submitted, duration of attack and the reported severity of 15 symptoms listed in Table 1. Recall that 0.0 represents no symptom and 4.0 represents extreme symptom severity. One of the panic episodes was removed from the results because Subject 2 had reported the beginning of a panic episode, but forgot to report its end and the severity of its symptoms.

In order to have an overall idea of the values manually reported by users, Table 3 presents descriptive statistics of collected values, i.e., *minimum, maximum, median, mean,* and *standard deviation* for number of reports submitted, duration of attack and the reported severity of the 15 symptoms listed in Table 1.

Given the reported panic episode information, we are able to label physiological data collected from the wearable device as either relating to a panic interval or a non-panic interval. Figure 6 shows representative plots from Subject 4 for data collected preceding a reported panic episode (left side) compared with a corresponding interval of non-panic data (right side). The measurements shown are for heart rate, breathing rate, heart rate variability and core temperature as a function of time. Note that the left and right plots use different axis scales. The values shown have been adjusted to factor out the effects physical activity had on the physiological parameters, see [17] for further details. Zero represents approximately average values for the individual, negative values represent measurements that were greater than expected and positive values represent measurements that were lower than expected.

Subject	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**Avg**
Number of reports	1	4	2	19	0	2	1	4.1
Average duration (seconds)	636.0	125.3	14.0	233.2	–	167.0	2.0	196.2
Anxiety	2.0	2.8	1.5	2.8	–	2.5	2.0	2.3
Worry	3.0	2.3	2.5	2.8	–	0.5	2.0	2.2
Shortness of breath	1.0	2.5	1.0	3.2	–	1.5	2.0	1.9
Racing heart	1.0	2.8	2.0	2.3	–	2.0	2.0	2.0
Dizziness faintness	0.0	2.3	0.5	0.2	–	1.0	2.0	1.0
Chest pain discomfort	2.0	2.3	0.5	2.3	–	1.0	2.0	1.7
Unreality	0.0	2.0	1.0	0.5	–	1.5	2.0	1.2
Sweating	0.0	2.0	0.5	0.0	–	0.0	2.0	0.8
Hot cold flashes	0.0	2.0	0.0	0.3	–	0.0	2.0	0.7
Losing control going crazy	0.0	2.0	0.0	1.4	–	2.5	2.0	1.3
Trembling shaking	0.0	2.0	0.0	0.1	–	3.0	2.0	1.2
Choking sensations	0.0	2.0	1.0	2.5	–	0.0	2.0	1.2
Nausea abdominal distress	0.0	2.0	1.0	0.0	–	0.0	2.0	0.8
Numbness tingling	0.0	2.0	0.0	0.1	–	1.0	2.0	0.8
Fear of dying	0.0	2.0	0.0	0.0	–	0.0	2.0	0.7

Table 2: Average panic episodes and symptom severity reported per subject

	Min.	**Max.**	**Median**	**Mean**	**Std. Dev.**
Number of reports	0.0	19.0	2.0	4.1	6.7
Duration	0.0	896.0	144.5	211.3	193.4
Anxiety	0.0	4.0	3.0	2.7	1.1
Worry	0.0	4.0	2.0	2.5	1.2
Shortness of breath	1.0	4.0	3.0	2.7	1.1
Racing heart	0.0	4.0	3.0	2.2	1.1
Dizziness faintness	0.0	3.0	0.0	0.6	0.9
Chest pain discomfort	0.0	4.0	2.0	2.1	1.0
Unreality	0.0	3.0	0.0	0.9	1.0
Sweating	0.0	2.0	0.0	0.4	0.8
Hot cold flashes	0.0	4.0	0.0	0.6	1.0
Losing control going crazy	0.0	4.0	2.0	1.4	1.2
Trembling shaking	0.0	4.0	0.0	0.6	1.1
Choking sensations	0.0	4.0	2.0	2.0	1.3
Nausea abdominal distress	0.0	2.0	0.0	0.4	0.8
Numbness tingling	0.0	2.0	0.0	0.4	0.8
Fear of dying	0.0	2.0	0.0	0.3	0.8

Table 3: Summary statistics of panic episodes

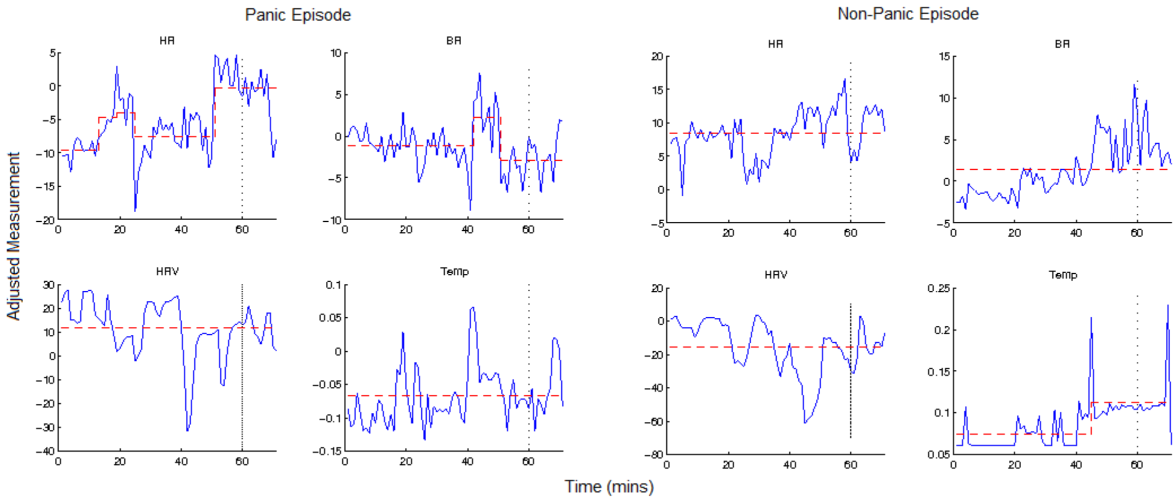


Figure 6: Physiological data collected during panic episode and non-panic episode for Subject 4. Solid blue line: values read from the sensor. Dashed red line: change point analysis.

The results of running change point analysis on this data are also plotted (dashed red line).

DISCUSSION

The results presented show that panic attacks can vary according to the severity of symptoms and they are experienced differently among individuals. For example, data presented in Table 2 shows that the number of episodes reported by individuals varied substantially. Subject 5 didn't report any panic episode during the 3 weeks while Subject 4 reported 19. Subject 1 experienced longer panic attacks, with an average of 636 seconds. Subject 7 only reported one panic attack, which had a duration of 2 seconds and all parameters had the default severity value of 2 (moderate). It is very likely that this panic episode was reported by mistake. It is also interesting to note that some symptoms have less impact then others. *Hot cold flashes* and *fear of dying* were the symptoms that patients were affected by the least on average.

From Table 3 we conclude that symptoms with higher severity on average were *anxiety*, *worry* and *shortness of breath*. *Sweating, Nausea abdominal distress, numbness tingling,* and *fear of dying* were never reported as higher than *moderate* (2) and had the lowest standard deviations (0.8). Table 3 also shows that the average duration of panic attacks is approximately 211 seconds with a standard deviation of 193, meaning that the duration of the episodes experienced also varied greatly.

The main difference that we observed between pre-panic and non-panic intervals was the magnitude of the recorded measurements. Figure 6 shows that there was some fluctuation in heart rate and overall heart rate and temperature were higher than expected in the hour preceding a panic attack compared to the non-panic period. The value for heart rate variability was lower in the pre-panic period, compared with the non-panic period. There were also some slight fluctuations in breathing rate in the pre-panic period and in general breathing rate was higher than expected before a panic episode compared to a non-panic interval. This suggests that features that capture these changes can be incorporated in a classifier for panic attack detection.

CONCLUSION

This work proposes a mobile and wearable system for individuals with panic disorder. For 3 weeks the system successfully collected data from 7 individuals. In order to label panic attack occurrences, subjects were asked to manually report them using the mobile application. The system was also able to monitor individuals and collect their physiological data.

As part of our future work, we plan to continue to evaluate the complete system. In particular, we plan to run further studies to evaluate the efficacy of the mobile-based breathing and relaxation exercise intervention for individuals who suffer from panic disorder. In addition, it would be interesting to explore personalized interventions for each individual to gauge whether this has a beneficial effect. Collecting contextual data surrounding panic episode reports could also provide further useful information.

REFERENCES

1. American Psychiatric Association. 1994. *Diagnostic and statistical manual of mental disorders : DSM-IV* (4th ed. ed.). American Psychiatric Association Washington, DC. xxvii, 886 p. ; pages.

2. Raymond R Goetz, Donald F Klein, Robert Gully, Jeffrey Kahn, Michael R Liebowitz, Abby J Fyer, and Jack M Gorman. 1993. Panic attacks during placebo procedures in the laboratory: physiology and symptomatology. *Archives of general psychiatry* 50, 4 (1993), 280–285.

3. Jono Hailstone and Andrew E Kilding. 2011. Reliability and validity of the Zephyr™ BioHarness™ to measure respiratory responses to exercise. *Measurement in Physical Education and Exercise Science* 15, 4 (2011), 293–300.

4. Jennifer Healey, Lama Nachman, Sushmita Subramanian, Junaith Shahabdeen, and Margaret E. Morris. 2010. Out of the Lab and into the Fray: Towards Modeling Emotion in Everyday Life. In *Pervasive Computing, 8th International Conference, Pervasive 2010, Helsinki, Finland, May 17-20, 2010. Proceedings*. 156–173. DOI: http://dx.doi.org/10.1007/978-3-642-12654-3_10
5. Jennifer Healey and Rosalind W. Picard. 2005. Detecting stress during real-world driving tasks using physiological sensors. *IEEE Transactions on Intelligent Transportation Systems* 6, 2 (2005), 156–166. DOI: http://dx.doi.org/10.1109/TITS.2005.848368
6. Jennifer A. Healey. 2000. *Wearable and automotive systems for affect recognition from physiology*. Ph.D. Dissertation. Massachusetts Institute of Technology.
7. Jin-Hyuk Hong, Julian Ramos, and Anind K. Dey. 2012. Understanding physiological responses to stressors during physical activity. In *The 2012 ACM Conference on Ubiquitous Computing, Ubicomp '12, Pittsburgh, PA, USA, September 5-8, 2012*. 270–279. DOI: http://dx.doi.org/10.1145/2370216.2370260
8. Malcolm Lader and Andrew Mathews. 1970. Physiological changes during spontaneous panic attacks. *Journal of Psychosomatic Research* 14, 4 (1970), 377–382.
9. Michael R Liebowitz, Abby J Fyer, Jack M Gorman, Donald Dillon, Ilana L Appleby, Gail Levy, Samuel Anderson, Morton Levitt, Michael Palij, Sharon O Davies, and others. 1984. Lactate provocation of panic attacks: I. Clinical and behavioral findings. *Archives of General Psychiatry* 41, 8 (1984), 764–770.
10. Hong Lu, Denise Frauendorfer, Mashfiqui Rabbi, Marianne Schmid Mast, Gokul Chittaranjan, Andrew T. Campbell, Daniel Gatica-Perez, and Tanzeem Choudhury. 2012. StressSense: detecting stress in unconstrained acoustic environments using smartphones. In *The 2012 ACM Conference on Ubiquitous Computing, Ubicomp '12, Pittsburgh, PA, USA, September 5-8, 2012*. 351–360. DOI:http://dx.doi.org/10.1145/2370216.2370270
11. Alicia E. Meuret, David Rosenfield, Frank H. Wilhelm, Enlu Zhou, Ansgar Conrad, Thomas Ritz, and Walton T. Roth. 2011. Do unexpected panic attacks occur spontaneously? *Biological psychiatry* 70, 10 (2011), 985–991.
12. Alicia E Meuret, Frank H Wilhelm, and Walton T Roth. 2001. Respiratory biofeedback-assisted therapy in panic disorder. *Behavior Modification* 25, 4 (2001), 584–605.
13. National Institute of Mental Health. 2015. Panic Disorder. Available at http://www.nimh.nih.gov/health/topics/panic-disorder/index.shtml. (2015).
14. E. S. Page. 1957. On problems in which a change in a parameter occurs at an unknown point. *Biometrika* (1957), 248–252.
15. Alexandros Pantelopoulos and Nikolaos G Bourbakis. 2010. A survey on wearable sensor-based systems for health monitoring and prognosis. *Systems, Man, and Cybernetics, Part C: Applications and Reviews, IEEE Transactions on* 40, 1 (2010), 1–12.
16. David Rosenfield, Enlu Zhou, Frank H. Wilhelm, Ansgar Conrad, Walton T. Roth, and Alicia E. Meuret. 2010. Change point analysis for longitudinal physiological data: detection of cardio-respiratory changes preceding panic attacks. *Biological psychology* 84, 1 (2010), 112–120.
17. Jonathan Rubin, Hoda Eldardiry, Rui Abreu, Shane Ahern, Honglu Du, Ashish Pattekar, and Daniel G. Bobrow. 2015. Towards a mobile and wearable system for predicting panic attacks. In *Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing, UbiComp 2015, Osaka, Japan, September 7-11, 2015*. 529–533. DOI: http://dx.doi.org/10.1145/2750858.2805834
18. M Katherine Shear, Timothy A Brown, David H Barlow, Roy Money, Diane E Sholomskas, Scott W Woods, Jack M Gorman, and Laszlo A Papp. 1997. Multicenter collaborative panic disorder severity scale. *American Journal of Psychiatry* 154, 11 (1997), 1571–1575.
19. Dominic JC Wilkinson, Jane M Thompson, Gavin W Lambert, Garry L Jennings, Rosemary G Schwarz, Don Jefferys, Andrea G Turner, and Murray D Esler. 1998. Sympathetic activity in patients with panic disorder at rest, under laboratory mental stress, and during panic attacks. *Archives of General Psychiatry* 55, 6 (1998), 511–520.