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Introduction

A “stress response” can be defined as:

“A physiological reaction caused by the perception of aversive or threatening situations” [1]

Humanity’s problems can always be related to stress. If any one person is stressed, they experience “stress responses” – that is, they are feeling a consequence of some form of burden that has been placed upon them physically or mentally. Stress is inevitable in a person’s life, and the amount that people experience can only be minimized through the choices we make – simply because they do not enjoy the stresses that result from risky decisions as an example.

Nevertheless no matter whom you are the human body can react badly to the stress which you experience: whether it is directly from the stressor, or the stress response. A common example to relate to is an elderly person suffering a heart attack due to an emotional stress. Whilst the stressor is not actually stressing the person through physical means, a physical stress response is still triggered – and a dangerous one at that. On a larger scale, it has been found that physiological responses have significant adverse long-term effects on our health when dealing with continuous stressors, as opposed to episodic stressors. [1]

Bearing this in mind, we have a strong reason to understand what stress responses we experience, and what we can do to minimise them. Currently, whilst there are technologies to determine significant stressors and stress responses in our lives, we cannot say it is to a point that it is readily accessible. Furthermore, people do not make conscious efforts to assess their stress, especially during their times of stress. If people were more aware of what stressors and stress responses were doing to them both mentally and physically, the problems that people experience would be reduced or eliminated. In particular, this would be most effective if people were made aware of dangerous physiological reactions at the time they are experiencing it.

For something as important as what has been discussed, and with the new and ever-changing technological world we live in, the issue can now start to be addressed effectively. There are current technologies that we use on a day-to-day basis that can have a further enhanced capability to detect stress responses and, essentially, assess levels of stress.

One particular technology that fits this category is a mobile smartphone (“phone”). Those who associate with current technology will be well aware that phones are capable of doing more than making a voice call. Phones have evolved from simply making vocal communication to messaging, and now have progressed to completely different user experiences and interactions with touch screens replacing buttons. What people are less aware of is the hardware that is contained within a standard phone. Phones are now equipped with hardware that provides us with more information than older phones. This allows applications to interact with the physical world we live in and, in particular, the user. The

hardware can be utilised to interact with the user and gain information regarding the onset of stress through the user's stress responses.

Hence, we have a probable solution to the problem. This path of research is valid for a problem of such significance. The knowledge we can gain from a valid solution can result in many benefits: a key benefit being a reduction in dangerous stress responses from conscious effort due to awareness. This path of research will further open up avenues to deal with stress. Ultimately, especially with further technological advancement, we will be able to minimise stress responses from a person, and the knowledge regarding our own stress responses is a good first step and foundation towards the solution.

Background

Aim

Detecting the onset of stress using a mobile phone involves capitalising on stress responses from the user, measuring their intensity and making a judgement. As mentioned before, we are in need of a method of stress detection that acts dynamically, and responds to stress immediately as opposed to only upon user request.

A key thing that defines people as different is what we respond to in a stressful manner, and what the physiological and mental reactions are. With the many different personalities everyone has, there are many responses. However, there are stress responses people experience are involuntary, and common amongst the majority of people. Hence, stress responses, which are a unique combination of physiological reactions, can be detected and identified strictly as stress. We are, of course, familiar with common stress responses. Whilst there is a large variety, examples of some common symptoms include:

- Changes in vocal pitch and amplitude
- Pacing up and down a certain distance
- Increased heart rate
- Perspiration via palms
-

Comment [HV2]: Need to put more all, rather than just what I am using

Current methodologies that are successful account for specific symptoms. The aim of the next part of the chapter is to explain the current solutions to the problem at hand, what they offer for the detecting the onset of stress, and what each of the latest resolutions are lacking from the perfect solution.

Literature Review

There are many attempts at implementations that can be noted both using and not using a mobile phone. Such successful implementations include “AutoSense” [2], “Sociophone” [3], “MoodScope” [4] and “Mood Meter” [5], as well as a methodology to remotely manage hypertension [6]. As seen here, a majority of successful implementations to address the larger problem uses external hardware to work with the mobile phone.

In studying these methodologies, we can identify accurate procedures used to determine the onset of stress. We can also note dangerous physiological reactions from these implementations, which address the big picture of a key benefit in identifying the onset of stress. On the other hand, with the restricting aspect of measuring stress using a specific means, there is a hole in the accuracy of these applications. It also does not cater for everybody’s personal reactions, but rather defines stress at a certain point and determines the onset of stress according to that definition.

Measuring hypertension (high blood pressure) is an extremely important for stress management [1, 6]. Hypertension is a prime danger, and has a strong association to stress, hence being one of the leading significant stress responses. As a result, methods in [6] to remotely manage it can prove rather helpful

as a key element of stress management as a whole. This particular application also specifically applies to concerns for diabetic patients, however is not restricted to that. Using a blood pressure monitor with an active Bluetooth connection, a mobile phone can interact with the hardware to process the data and send it to the respective physician(s). This particular application, however, does not use the mobile phone for direct methods of input – rather it takes care of everything else.

AutoSense ([2]) uses “an unobtrusively wearable wireless sensor suite that can collect continuous measurements” [2]. This external hardware communicates with a phone via an application to collect data regarding stress. The solution “focuses on physiological measures monitoring cardiovascular, respiratory, and thermoregulatory systems.” [2]. This allows detection of physiological reactions from the hardware, which is then sent to the phone through a low-frequency radio signal. An algorithm is used to collate the data and, ultimately, provide a judgement of stress.

Mood Meter ([5]) was not a mobile-phone based application, but still uses technology that mobile phones are currently able to use today. A camera is used to detect people’s “smiles”, and rate them on a scale according to the “Shore framework” [7] – a geometric algorithm that detects a smile, and its intensity, with a high degree of accuracy even from a distance [5]. The data is then processed and sent to a central server for collating and further processing.

Sociophone ([3]) is an application which monitors face-to-face conversations at the core to investigate social interaction. It is classified as an “interaction-aware application” [3]. Whilst the focus is not around stress, human interaction often leads to the revealing of other stress responses in the event the person is stressed [1, 3]. The symptoms of different characteristics that the application checks for are also similar to those that can be analysed to detect the onset of stress, namely: “sound signals, online turn segmentation¹ and meta linguistic feature extraction²” [3].

MoodScope ([4]) is a sensor that measures the mental state of a user that does not use physical properties. Rather, the aim of the project is to detect the mood of a user to provide a context as an input for other applications which, in turn, enables “context-aware computing” [4] – something that is highly important in creating a successful application, since it allows the application to act dynamically and enhance human-computer interaction, as opposed to acting statically [8]. MoodScope does not use physiological signals as most do, but rather uses the activity a user has with their phone to determine what mood they are in. MoodScope further uses customised data sets for each user to gradually improve the accuracy of the application for each user. Whilst it starts off inaccurate, it uses a 2-month training period to increase the accuracy of the application in its inferences, raising the accuracy from 66% to 93%, when analysing 32 participants [4]

We can draw a number of parallels between each of the applications, whilst also noting key differences in achieving certain elements of our common goal. We can see in [2], [3], [4] and [6], phones are used for the collecting and processing of data to generate information regarding human interaction. In

¹ A “turn” is a continuous speech segment where a person starts and ends her speech [3]

² Meta-linguistic features include characteristics of speech that are not classified as the “language”. Examples include pace of speech, and whether the type of speech used is assertive or dominant

particular, [2], [3] and [6] collect physiological information, with [2] and [3] specifically using this to calculate one's mood, which we can directly infer one's level of stress. [6], on the other hand, collects physiological data to specifically respond to a dangerous, and very key, stress response. [4] does not utilise physiological reactions, yet still manages to detect stress through other interesting means. [5] is very different, since it uses other technologies to collect useful data, analyse the data and produce results based off one parameter to scale what mood the person is in.

The methodology used in [2] and [3] are one of the most advanced, despite [2] being a relatively older use of phone applications for this purpose. In [2], the hardware itself is very intricate – it has the capacity to collate many parameters within a very small device that is “comfortable to wear for long hours in the field” [2]. However, we can agree that not having hardware attached to us is, in itself, a superior advantage. [3] further inspires the idea of collecting data using the phone's hardware, which is, of course, a much more comfortable option for the user. It also results in the user being much less conscious of the analysis, since the phone simply runs in the background and causes less disruption with the user's activities whilst collecting and analysing data.

As such, [3] inspires the idea of utilising the phone's hardware. We can note that the physiological reactions sensed in [2] can now be sensed using current mobile phone technology. There are methods to calculate one's heart rate, such as in the application “Stress Check” [9]. This application uses the phone's camera and flashlight to detect one's heart rate. We can detect respiratory function using the phone's inbuilt accelerometer to detect a rate of displacement on one's lung area, hence allowing us to accurately calculate changes in volume of air within one's lungs [10]. [2] also detects skin temperature, which can be found using the phone's thermometer. All these inbuilt hardware render the external hardware used by [2] as redundant. The advantage that the external hardware offers, however, is that people still claim accuracy, however [2], despite using dated technology, still determines one of the highest accuracies out of all the solutions. This can be attributed to many factors, with the inaccurate nature of using the internal hardware of a phone being one of them.

Whilst both [2] and [3] uses static information for its inferences, [2] has a 90% accuracy rate for 20+ participants, and [3] has an overall accuracy of 60%, with variations of $\pm 5\%$ due to different phones. A phone's internal hardware can cause inaccuracies specifically due to its physical placement upon collecting of data, as well as the design of the hardware itself. [2] conveniently places the hardware on the person's chest. Whilst this is possible to achieve using internal hardware, it is highly inconvenient for one to place their phone on their chest – this would take the element of convenience by using a mobile phone's internal hardware to create less interference with their daily activity. [3] only uses the common camera and microphone hardware in a phone. Depending on where it is positioned, it can be used conveniently for analysis. However, at the same time, there is a degree of inaccuracy, depending on at what distance the phone is placed at during its inaccuracies. Whilst the hardware is of relatively good quality, it is found that dedicated hardware to these purposes are still of better quality.

One significant advantage that each of the solutions offer is the use multiple parameters to determine its results. These use algorithms that can weigh the importance of each of the parameters and make a decision from there. This is highly advantageous, as it allows us to hone in on the specific reasoning

behind the physiological reactions. We must remember that physiological reactions can apply to more than one type of response [1]. The use of multiple parameters offers a distinguished combination of symptoms which can be more accurately associated with stress. However one disadvantage of these applications is that these are static algorithms that do not account for differences in human nature from user to user. These algorithms can be improved so as to cater for users more accurately.

[4] has a contrasting aspect to its ability to cater for multiple users. It uses aspects of machine learning over a period of time to increase the accuracy of the application. Using only static inferences, the application offers a very low accuracy (66%), whilst post-training, the application was able to provide an accuracy of 93% to the two users [4]. This is a highly significant change attributed solely to concepts of machine learning, and hence a large factor to consider in achieving our own personal goal. The application actually uses less reliable methods of detecting moods than as per previously mentioned, but achieves the same degree of accuracy as those applications.

The application uses a supervised learning algorithm referred to as Sequential Forward Selection (SFS). SFS involves machine learning via regression. Unknown data inputs estimate and produce an inference using regression techniques. The algorithm is used hand-in-hand with a personalised data model to create an even more accurate data model on a case-by-case basis. Whilst the personalised data model can be used by itself to create inferences, it also involves a much longer time-frame for the model to reach its potential. This issue is solved by complementing with the SFS algorithm, which acts as a “one-size-fits-all” model to give the application a starting idea of how to process the information, as opposed to developing it from scratch [4]. The following graph gives us the best idea of how the application evolves over the 60-day learning period.

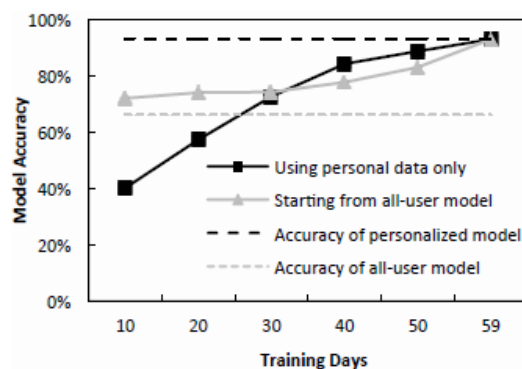


Figure 1: Improvement in accuracy over a 60-day period due to machine learning

The initial concept of how to detect mood, however, is not as superior for the purposes of detecting stress. The application is not reliant on physiological stress responses, but rather stress responses based on direct phone activity. This, of course, leads to a low degree of accuracy; as such activity widely differs from person to person, with very little overlap of common activities for all potential users. This is let alone how people’s activities vary upon the onset of stress. We can directly conclude from [1].

Comment [HV3]: Find more sources

As such, the main aspect of the application to take as inspiration is the concept of supervised machine learning to create an accurate model. Whilst the methods of collecting data are respectable, other applications have more accurate results from methods of collecting physiological data to detect the onset of stress.

[6] is another old application which has still proven to be very resourceful. The big picture of our aim involves the dangers that stressors and stress responses bring to an individual, and the technology used in [6] can be used to address this issue directly. We can also use these methods to determine levels of stress. This methodology still uses external hardware to obtain the raw data regarding blood pressure. However, the application is used for the processing of this data, after it is received from the external hardware. The information is then sent to a central server for notification using mobile technology.

The application uses one of the most direct symptoms of stress responses possible, however is currently not very feasible to achieve only using a phone's hardware. Whilst there have been developments, such as [1], none have progressed past the stage being restricted to using external hardware to determine this parameter accurately. As such, it is currently infeasible to achieve our goal until the necessary hardware is incorporated into mobile phones.

The application, however, inspires the idea of further refinement of the application, by sending the data to relevant places. Being a problem that has only been brought to attention as of recent, we do not have much data that is collated and sourced from using such means. This application, however, takes this data. Hence, this solution proves useful for the collection of data, as well as the benefits of alerting the appropriate people, for monitoring purposes, in a non-invasive manner.

Comment [HV4]: Add the other sources

Proposal

The aim of this chapter is to show a plan of how to fill the voids of the problem through other means. We have discussed where the current applications and solutions stand, and so from here we can utilise the benefits to fulfil the ultimate objective. We can combine these benefits, with slight additions, to form a long-term project. The current goal is to lay down a strong framework that can be built upon for future generations of research. The overall goal is to minimise stress responses and the dangers associated with stressors and stress responses.

From our previous analysis, we can deduce requirements of the following:

- We are in need of a system that detects the onset of stress in a convenient manner
- A mobile phone has been deemed the most appropriate equipment. It is portable, and allows easier detection of the onset of stress with less conscious effort. Mobile phones are also equipped with a lot of helpful hardware, and are equipped with more as time passes due to technological advancement. Due to the capabilities of a mobile phone, we will eliminate the need for external hardware, as most are used to detect stress responses are now integrated into the latest phones.
- Machine learning algorithms are a key part of the project, in order to ensure accuracy for all users – there is no one size fits all, and there is always room for improvement due to the varying nature of stress responses from different users.
- Mobile phones also have abilities to communicate, not only with the user, but globally by utilising data connections such as Wi-Fi and mobile data networks. Hence, we will require a form of persistence to collect data that can easily be sent by users of the application. This data can assist with the machine learning process and, combined with the initial data provided, allows a unique form of semi-supervised learning that has not been used in any state-of-the-art applications to date

As explained before, a person experiencing stress responses is not necessarily acting rationally. We require a solution that will collect our data through natural means. This include when the phone is on standby next to us or in our pocket, when we are using our phone for remote video or vocal communication, or simply through interactions when using other applications such as games, the Internet, video viewing, etc.

A mobile phone is a convenient gadget to use, with over two thirds of Australians owning a smart phone . In particular, we will initially target specific stress responses and expand on these further. Stress responses to analyse include heart rate, vocal communication, and use of sweaty palms and a person's rate of pacing. Each of these have been determined as stress responses by [1]. It is a unique combination of physiological activity that is most often related to mental stress. These are also feasible symptoms to measure using the latest mobile phone technology. The associated hardware with each of

Comment [HV5]: Insert article here
<http://www.smartcompany.com.au/technology/online/32768-australians-go-local-with-smartphones----and-three-other-trends-from-google-s-latest-research.html#>

Comment [HV6]: Insert references

these responses is the camera and flash, microphone, hygrometer³ and accelerometer respectively. With technological advancement and time, the project will be able to expand further and detect other stress responses, such as detecting blood pressure using only the phone's internal hardware.

Concepts of machine learning are sure to be adopted to increase accuracy. Initially, the application prototype will consider binary classification of experiencing an onset of stress or not. Future developments will involve a non-binary classification of how much stress is experienced by the user, on a scale involving more than two options. In considering binary classification, we will start with a simple Bayesian model, and change the model according to what results we start to obtain, as well as what algorithm will be used. The model could be SFS, as mentioned in [4], or random forest decision tree, as discussed in [5]. The application will also be fed test data, to provide a supervised environment which the application can learn around using the appropriate algorithms. This will ensure a more acceptable degree of accuracy, whilst improving to perfection over time. As we will discuss next, we will actually adopt semi-supervised learning techniques to ensure efficient learning processes with maximal accuracy.

Comment [HV7]: Insert machine learning book

We are also well aware of the communication abilities that a phone has. Being able to send data globally allows global users to send their data regarding physiological stress signals, as well as whether the determined result was correct or not. We can thus use the concept of a persistence model to collate useful data sourced solely from a mobile phone, and use this in future research. Furthermore, whilst the initial process of supervised machine learning involves having a set of test-data, we can also collect more initial data for future users by collecting from the current application users themselves. In having more data, we are adopting a semi-supervised learning process - we are using data that is sent without interference from the developer. Whilst we run the risk of false data being sent for use, the risk of corrupted test data is minimised using the original test data, and giving it more weighting when used in modelling.

Comment [HV8]: Insert machine learning book

Thus, upon research, we have determined a seemingly perfect solution that has not been exercised yet. A proof of concept has been partially developed, where we are testing the hardware and the degrees of accuracy to which the hardware holds true.

With the progression that stands as is, as well as a partial proof of concept that has been developed, we now have the following to consider over our time period of Tuesday May 27th 2014 – Friday 3rd October 2014, which is described in Figure 2.

Comment [HV9]: TODO: Insert GANTT chart

³ Hygrometer is defined as “a device for determining the humidity of the atmosphere”

<http://science.howstuffworks.com/nature/climate-weather/meteorological-instruments/hygrometer-info.htm> It can also be used to measure the moisture of the

Conclusion

Comment [HV10]: TODO

Bibliography

- [1] N. R. Carlson, *Physiology of Behavior*, Amherst, USA: Pearson, 2007.
- [2] E. Ertin, N. Stohs, S. Kumar, A. Raij, M. al'Absi and S. Shah, "AutoSense: Unobtrusively Wearable Sensor Suite for Inferring the Onset, Causality, and Consequences of Stress in the Field Onset, Causality, and Consequences of Stress in the Field," *SenSys*, Seattle, WA, USA, 2011.
- [3] Y. Lee, C. Min, C. Hwang, J. Kee, I. Hwang, Y. Ju, C. Yoo, M. Moon, U. Lee and J. Song, "SocioPhone: Everyday Face-to-Face Interaction Monitoring Platform Using Multi-Phone Sensor Fusion," *MobiSys*, Taipei, Taiwan, 2013.
- [4] R. LiKamWa, Y. Liu, N. D. Lane and L. Zhong, "MoodScope: Building a Mood Sensor from Smartphone Usage Patterns," *MobiSys*, Beijing, China, 2013.
- [5] J. Hernandez, W. Drevo, R. W. Picard and M. E. Hoque, "Mood Meter: Counting Smiles in the Wild," *UbiComp*, Cambridge, MA, USA, 2012.
- [6] A. G. Logan, W. J. McIsaac, A. Tisler, M. J. Irvine, A. Saunders, A. Dunai, C. A. Rizo, D. S. Feig, M. Hamill, M. Trudel and J. A. Cafazzo, "Mobile Phone-Based Remote Patient Monitoring System for Management of Hypertension in Diabetic Patients," *American Journal of Hypertension, Ltd*, vol. 2007, no. 20, p. 7, 2007.
- [7] C. Küblbeck and A. Ernst, "Face detection and tracking in video sequences using the modified census transformation," *Journal of Image Vision Computing*, vol. 24, no. 6, p. 9, 2006.
- [8] A. K. Dey and G. D. Abowd, "Context-Awareness, Towards a Better Understanding of Context and Context Awareness," *Graphics, Visualization and Usability Center and College of Computing*, Georgia Institute of Technology, Atlanta, GA, USA, 1999.
- [9] Azumio, "Stress Check | Azumio," Azumio, 2012. [Online]. Available: <http://www.azumio.com/apps/stress-check/>. [Accessed 3 April 2014].
- [10] V. Chandrasekeran, "Measuring Vital Signs Using Smart Phones," *University of North Texas*, Denton, TX, USA, 2010.