Benjamin Harris, Chelsea Dobbins, Stephen Fairclough and Paulo Lisboa, "Exploring Wearable Devices for Unobtrusive Stress Monitoring" in the *Second International Conference on Internet of Things, Data and Cloud Computing (ICC'17)*, Cambridge, UK, 22 – 23 March, 2017 (Accepted Version)

Exploring Wearable Devices for Unobtrusive Stress Monitoring

Ben Harris, Chelsea Dobbins
Department of Computer Science
Liverpool John Moores University
Byrom Street, Liverpool, L3 3AF,
United Kingdom
+44 (0) 151 231 2284
B.A.Harris@2012.ljmu.ac.uk
C.M.Dobbins@ljmu.ac.uk

Stephen Fairclough
School of Natural Sciences & Psychology
Liverpool John Moores University
Byrom Street, Liverpool, L3 3AF,
United Kingdom
+44 (0) 151 904 6311
S.Fairclough@ljmu.ac.uk

Paulo Lisboa
Department of Applied Mathematics
Liverpool John Moores University
Byrom Street, Liverpool, L3 3AF
United Kingdom
+44 (0) 151 231 2225
P.J.Lisboa@ljmu.ac.uk

ABSTRACT
Recent advances in modern technology have seen the proliferation of low-cost commercial sensors which are capable of unobtrusively obtaining diverse physiological datasets to identify the presence of psychological stress. In particular, sensor-orientated smartwatches have the potential to assist a person in multiple facets of their daily life. These devices may be used as a tool for collecting physiological and contextual datasets in the wild. This paper explores the current literature on application of machine-learning techniques in stress system studies. This informs the selection of appropriate methodologies for data intensive research to support accurate inferences of the presence of stress.

CCS Concepts
• **Applied computing~Consumer health** • *Applied computing~Health informatics.*

Keywords
Stress; classification, physiological computing; sensor technology; wearable devices.

1. INTRODUCTION
Stress is an umbrella term that is commonly used to describe the bodily response when homeostasis is faced with a real or perceived threat. Two forms of this biochemical response exist, (1) acute stress, otherwise known as the 'fight-or-flight' phenomena, which represents a myriad of stress-responses that deal with emergences. Then there is (2) chronic stress, which is considered to be much more harmful to long-term health. These episodes take place over an extended period of time and are often triggered by long-standing stressors. Failure to discern chronic episodes has become a widespread problem as they can cause and exacerbate numerous stress-related diseases, such as, diabetes and coronary heart disease [1]. Furthermore, overuse of the stress response systems can produce a compromised immunocompetence [2], increasing the risk of developing various afflictions. Over recent years, there has been a growing body of research focusing on the problem of stress detection using smart technologies and sensors to extract physiological and contextual data. These datasets are then pre-processed and used as input for building machine-learning models that can identify the occurrence of stress.

Context-aware computing is a paradigm that describes applications that can capture and use contextual data to improve performance. This concept has recently been investigated by the physiological computing (PC) research field. Additionally, there have been other areas of research that have explored the possibility of implementing a context-awareness element. For example, aside from physiological computing systems, recommender systems (RSs) have benefitted enormously from its inclusion. This has been demonstrated by the formation of the Context-Aware Recommender Systems (CARS) research field. Context as an element is absent from traditional recommender algorithms, instead they only refer to *users* and *items* as computational variables. Verbert et al. [3] label context as an aggregation of various datasets that help describe the setting in which a recommendation is executed. Video and music systems, such as Netflix and Spotify, would benefit from utilising contextual components in their algorithmic schemes. For example, if these services were to utilise GPS data as a contextual component they could identify suitable music/movies for a user's environment. In the case for Spotify and recommending suitable music, if the systems could confirm a persons' location was in a library, it could then recommend music that aids concentration.

In the physiological computing realm, the concept of providing recommendations in the form of lifestyle and dietary advice has only just begun. Past efforts have focused on using physiological data to detect the onset of many unfavourable states including, anxiety [4], anger and depression. The performance of a system is dependent on its ability to make accurate inferences based on the parameters set by developers. Typically, developers follow standardised guidelines, in the case of heart rate (HR), a reading exceeding 100 beats per minutes (bpm) could be symptomatic of stress, anything below 60 bpm may be considered as a sign of bradycardia [5]. However, physiological readings are ambiguous by nature, thus, there may be another explanation for an exceedingly high heart rate. For this reason, it is important to collect contextual data when determining what an appropriate response would be. For example, consider a person relaying HR data that is consistently above 100 bpm as a result of physical activity. Without contextual data, a system would not be able to identify whether this is a concerning behaviour (stress or anxiety) or routine (exercising).

There has been an abundance of research focusing on stress detection and classification across different scenarios, this includes, acoustic [6] and office [7] environments, on-road scenarios whilst driving [8], human-computer interaction [9], and even when undergoing laser eye surgery [10]. A common ingredient throughout these studies is the utilisation of a smartphone. The pervasive nature of these devices, coupled with their multi-functional capabilities marks them as a viable platform for stress detection. The infrastructure for a smartphone-led solution to combat this widespread issue is already in place, with approximately 33% of the world's population expected to own a smartphone by 2017 [11]. The ubiquity of modern smartphones allows researchers to collect data that can be generalised to real-life settings. This is in contrast to traditional experimental settings that are artificial, meaning that the stimuli and subject responses are unlike those that would occur in the real world [12]. Nevertheless, using the aforementioned infrastructure to conduct observational studies overcomes this limitation and provides a platform for collecting more accurate and reliable data over a longer period of time. As the capability of smart technologies continue to improve, we can expect finer granularity and greater variety from our data. For this reason, Cohn et al. believe that is it imperative for researchers to place more emphasis on the intervention process, with specific focus being addressed to behavioural data that occurs in the moment [13]. This concept exists at the core of our work, using innovative technologies to capture ecologically valid data to make accurate inferences and distinctions between the different types of stress. This work carries the additional objective of using a recommender approach as a means to deliver interventions that recommend coping strategies, which are personalised to the individual and sensitive to geographical location.

The structure of this paper is as follows. Section 2 presents the related background that places this work within the space of both physiological systems and context-awareness. Section 3 illustrates the different methodologies that have been used or proposed in the development of context-aware stress monitoring systems. The paper is then concluded in section 4 and future directions of this work are presented.

2. BACKGROUND

This section provides an introduction to the concept of using physiological signals as a mode of input for computer systems, an overview of the past work that has been accomplished in stress identification systems, and an exploration of how contextual data can enhance the intelligence of physiological systems when making inferences.

2.1 The Concept of Physiological Computing

Physiological computing (PC) is concerned with the creation of adaptable systems that can accurately adjust to a user's covert psycho-physiological cues [14]. The biocybernetic loop is responsible for managing data at all levels of a physiological system [15]. This concept can be considered as the backbone to all physiological systems, as it is specifically concerned with the real-time data processing stages of collection, analysis and translation that produces a form of computer input. The primary intention is to withdraw the use of keyboard or mouse as a form of input, and instead use physiological signals that can manipulate a system. Recent technological advancements have seen the creation of smart sensors, which are capable of accurately reading various physiological signals, such as heart rate (HR) and heart rate variability (HRV), electrodermal activity (EDA), cortisol levels, muscle activity and much more. The diversity of sensor technology has created many opportunities in the physiological computing research field. For example, Postolache et al. [16] have used electrocardiogram readings from sensors to extract HR and HRV values as part of a feedback system for wheelchair users. This system used multiple sensors in its approach, including, e-textiles electrodes, a 3D MEMS accelerometer and flexible force sensors, conditioning circuits and a microcontroller platform. Furthermore, transforming physiological readings into an input for a game is also a growing research area. Nacke et al. [17] have developed a biofeedback game that requires physiological input in the form of electrocardiogram and electromyogram readings. This work explored several mechanics of a game that utilised direct and indirect physiological control. Through the utilisation of multiple sensors, the game was able to adapt specific in-game features based on the player's physiological readings. For example, the character's model size of an enemy was dictated by the player's respiration rate. Moreover, the consensus from the gathered feedback showed that people preferred the game with physiological input relative to a game with no physiological input.

Affective computing (AC) is a subfield of PC, and is primarily concerned with "*creating technologies that can monitor and appropriately respond to the affective states of the user in an attempt to bridge the communicative gap between the emotionally expressive human and the emotionally deficit computer"* (D'Mello and Calvo 2013, p. 2288) [18]. A small part of the AC research has explored the efficacy of emotionally-aware applications that can recognise, interpret and process human emotions. To simplify the myriad of emotions, researchers have categorised emotions into two planes: basic and non-basic [18]. Basic emotions include states such as anger and happiness, whereas non-basic emotions include states such as boredom and curiosity. Of the work done in this field so far, little attention has been directed to non-basic emotions, instead basic emotions have been the primary focus. A large body of the work has used the valence-arousal scale to identify a person's emotional state. For instance, Soleymani et al. [19] recorded facial expression and other physiological features such as, EDA, skin temperature and blood pressure to determine a person's physiological response using the aforementioned arousal-valence scale whilst they watched a scene from a movie. Other work has focused on enhancing the reflection process to promote instances of self-learning within the individual. Mcduff et al. [20] presented an affective application entitled 'AffectAura' that uses numerous features to create a visualisation of a user's estimated affective states. Participants from the study found that was helpful in aiding the reflection process. Another variation of AC research has focused on utilising methods to enhance the meditative experience of a user. An example of this exists in the form of virtual reality tool, RelaWorld [21], a brain-computer interface (BCI) application that uses electroencephalograph (EEG) technology to aid the meditative experience. The results from this study were positive and supported the applications efficacy as a meditative aid. These findings also support the role of virtual reality technology in eliciting presence and enhancing the overall meditative experience.

There is much promise in using covert physiological signals as a form of computational input. It is necessary for application developers to understand the complex relationships between physiological measurements and the bodily state. With this knowledge we can take a more informed approach of selecting appropriate classifiers. This is in contrast to past attempts which have assumed that the more modalities used simultaneously, the more accurate the classifier will be.

2.2 Using Physiological Markers to Identify Episodes of Stress and Anxiety

Using smart technologies to identify moments of stress and anxiety has been at the centre of attention in many research domains for several years [22]. A wide variety of physiological sensors have been used to measure anxiety and stress. For instance, Miranda et al. [4] focused on anxiety detection using a combination of sensor technologies, specifically the Google Glass and Zephyr HxM band. This specific study focused on capturing a person's spontaneous blink rate from the eyewear and HR from the band. Interestingly, the researchers found that individuals with social-anxiety disorder (SAD) tended to have a higher HR after a period of anxiety. This suggests that those with SAD endure a longer recovery time before their HR returns to a normal range. Bakker et al. [23] focus on detecting stress patterns from EDA data collected during a real-world study. The authors comment on the subjective factors that determine the quality and accuracy of the collected data, and emphasise that the continuity of contact between the skin and EDA sensor device is extremely important for robust data collection. However, failure to acquire physiological data that is a true representative of a person's psychological state may lead to inaccurate inferences and predictions. Sano et al. [25] collected skin conductance amongst other types of data (including accelerometer, technology usage and caffeine intake to name a few) using a wearable sensor and smartphone to create a model that recognised moments of stress. A more unorthodox method was described in [8], where stress was managed by using a steering wheel to collect; EDA, skin temperature and hand pressure, and a camera that collected; facial expressions, HR and respiration rate. This work is still at the prototype stage, though interestingly the researchers note that it is important to consider the implications of creating such a system, and that it is entirely possible that using these methods may exacerbate a person's stress. This emphasises the importance of obtaining high inference accuracy, the inclusion of contextual data is necessary to limit the occurrence of false positive outcomes.

2.3 Using Contextual Data to Improve Inference Accuracy

Context in computing has received much attention since it was discovered as an essential component in recommender systems [26]. Context can be defined as, "*any information that can be used to characterize the situation of an entity. An entity is a person, place, or object that is considered relevant to the interaction between a user and an application including the user and applications themselves"* (Dey and Abowd, p. 307) [27]. This definition can be considered as quite broad, covering the inclusion of both implicit and explicit data. The powerful sensors embedded in modern-day smartphones enables a large portion of contextual data acquisition to be implicit. Regarding the issue of stress detection, data derived from the GPS or accelerometer of a smartphone can be used to characterize the fluctuations within a physiological dataset. Thus, by utilising contextual data, physiological systems are more informed and sufficiently equipped to draw inferences. Moreover, the concept of context-awareness has seen the development of systems that can adapt and change their behaviour based on various pieces of data that describe the user's situation [28]. It is now commonplace for these built-in sensors to collectively produce these heterogeneous datasets that can potentially yield valuable insight on an individual's wellbeing. These datasets contain four core components that can work in synergy, however, it is possible for the smallest contextual detail from a specific module to provide an explanation for a specific behaviour. These datatypes can be identified as:

- **Environmental Context.** This data can be taken from a GPS sensor and can provide information as to where an activity or physiological development has taken place. For example, should a system detect an abnormal heart rate (HR), a GPS could reveal that the user is in gym. Upon discovering this information, it is logical to assume that physical exercise has caused a HR spike, rather than a stress response in the form of a hormonal cascade [29].
- **Personal and Temporal Context.** This is different in that it does not require the utilisation of a sensor, but access to the calendar application or student timetable. Using the scenario of a student completing coursework, on the day of the deadline, it is likely for this person to demonstrate unequivocal symptoms of stress, anxiety and even depression. Upon confirmation of this occurrence, it is important for the system to respond appropriately, for example, reminding the student to take timely breaks and to stay hydrated.
- **Physical Context.** This can be extracted from sensors such as accelerometers and gyroscopes to identify whether a person is ascending/descending, which

suggests that a person is walking up/down a set of stairs. Furthermore, they can be used to identify the user's locomotion, i.e. whether the person is walking or running, which will dramatically effect a person's physiological signals.

Allowing applications to process contextual data in the decision-making process increases the probability of an adequate response being generated. Additionally, it is important for the end-user to have an element of control in the ultimate action that is taken [30]. Extra functionality can be attained from the inclusion of an option to provide user feedback on the recommended coping strategy, e.g. 'the suggestion that was provided helped me cope with the situation', or 'the suggestion did not help me cope with the situation'. This allows the user to shape the application to suit their personal preferences, thus, the user is controlling how the application interacts with them. Literature in this research area supports the importance of user control. For example, Barkhuus et al. [31] argue that to maintain the perception of user control there must be a degree of personalisation involved on the HCI level, and that when using a passive or active context-aware application it is lost. Furthermore, the authors state that despite personalised context-awareness requiring a higher interaction cost, the consensus that users prefer this type of context-aware computing (CAC) system remains.

It has been proven that contextual data can be used to enhance the accuracy of a physiological system. We want to investigate the usage of physiological features with multiple contextual sources that are relevant for the purpose of stress identification. Furthermore, we hope to obtain an understanding of which contextual sources have the most impact when making a stress inference.

3. METHODOLOGY AND MATERIALS

We plan to do experiments that focus on the effect of coursework deadlines and subjective stress levels.

3.1 Overview

Recent technological advancements have seen the development of unobtrusive wrist bands equipped with multiple pervasive sensors. This has seen an increase in the number of studies using these commercial sensors as a data collection tool. Our study adopts a similar approach; as we decided to utilise the Microsoft Band 2 (see Figure 1) to extract HR, EDA and accelerometer values. The Band is composed of a thermoplastic elastomer silicone vulcanite with an adjustable clasp, this ensures that the device can be worn by a wide range of people. Furthermore, this sensor device contains an embedded li-polymer battery that can last up to 48 hours depending on its usage. This is a significant benefit, as a common bottleneck for past real-world studies is the longevity of the data collection tool being used. To extract these values and store them on the smartphone, we have developed an application that writes to a .csv file. The Band communicates with a smartphone via Bluetooth and Microsoft's Health app, which is responsible for synchronising the two devices. Additionally, we have created an Android application that continuously writes a person's GPS coordinates to a .csv files along with a timestamp. This approach uses the GPS sensor from a smartphone to find the users current location, this is frequently refreshed and changed by determining whether the last known location is different to the current known location.

Figure 1. The Microsoft Band 2 Interface

During the study we also aim to conduct four questionnaires; Cope Scale, Penn State Worry Scale, Social Readjustment Scale (SRC) and the Perceived Stress Scale (PSS). We believe that the answers obtained from these questionnaires will provide insight to the mentality of the participants whilst taking part in our study. Furthermore, it is possible to use some of the questionnaire answers as markers in the acute-chronic stress identification problem. For example, the SRC looks at events that occurred over the past 12 months, the results of this particular survey could provide data that can be used to detect the occurrence of chronic stress.

4. METHODS FOR DEVELOPING SENSOR BASED CONTEXT-AWARE STRESS MONITORING SYSTEMS

Miniaturisation of sensor technology has enabled manufacturers to develop a series of unobtrusive devices, which contain considerable processing power and are capable of extracting multiple physiological and contextual features that are suitable for the purpose of stress monitoring. However, the collected data must go through the multiple processes involved in a machine-learning model, before an inference can be made. There is a trade-off between the sensitivity of a measure (its sensitivity to changes in stress) and intrusiveness of the sensor apparatus required to capture the measure. For this reason, sensitive measures may not be used in the field because the apparatus is too cumbersome or uncomfortable.

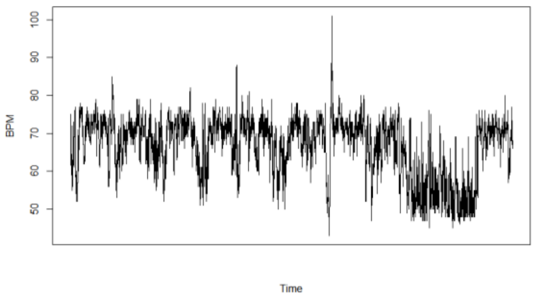
4.1 Data Acquisition

To determine the occurrence of stress it is necessary to collect physiological signals that can provide insight to a person's internal state. For this reason, there have been many attempts to identify stress using physiological signals such as HR, HRV, EDA, electroencephalogram (EEG), electrocardiogram (ECG) and skin temperature (ST) amongst others.

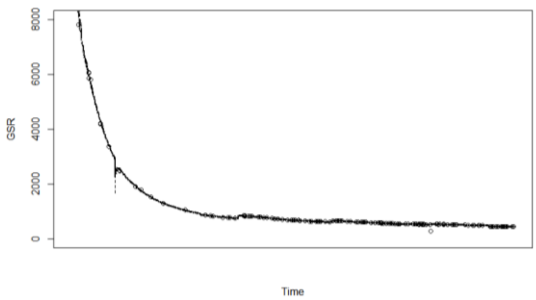
The acquisition of contextual data can be defined as being either; implicit, explicit or inferred. Verbert et al. [3] produced a categorisation of the sources that can provide contextual insight. Included in this list are several data types that can provide rich insight to the mental and physical state of the user. For example, location context can be collected implicitly via the GPS sensor of a smartphone. Cross-referencing data that places a person in a university lecture with higher heart rate readings suggests that a user is suffering from a type of stress and/or anxiety. Moreover, we can use activity context when the GPS is unavailable, this is usually acquired explicitly through QR or RFID scanning or text input. A further contextual data source that is not discussed in this study is the accelerometer and/or gyroscope of a smartphone. It is possible to use the X, Y, Z coordinates of a smartphone to determine the physical activity of a user, for example, they could be used to identify if a person is running or walking. This piece of information may explain why a user has accelerated ECG signals as without this context, physiological datasets can be ambiguous and difficult to dissect.

4.2 Pre-processing

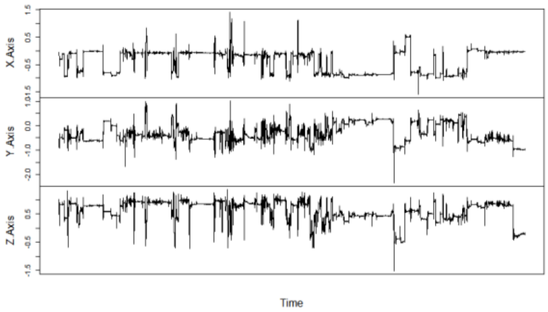
Raw physiological data extracted from wearable sensors is not suitable as a direct input because of existing artefacts, errors and missing pieces of data. For this reason, it is important to prepare the data in such a way that increases the likelihood of a machine-learning algorithm solving the problem. This includes implementing either an automated or manual cleaning method that removes any unnecessary chunks of data. Furthermore, most researchers prefer to define the data granularity, this is commonly achieved by applying filtering techniques to create a refined dataset.



(a)



(b)



(c)

Figure 2. Three examples of the raw data collected from our pilot tests of (a) heart rate, (b) galvanic skin response and (c) accelerometer signals in original form before undergoing several iterations of preprocessing.

A combination of high-pass [33], low-pass [16] and band-pass [34] based filters have been used on physiological signals, the selection of a particular method is usually dependent on the signal quality as stated in [35]. Alberdi et al. [7] utilise a spatial-spectral filter in numerous frequency bands to compute spatial-spectral EEG components. Additionally, many studies have investigated the efficacy of implementing k-nearest neighbour (K-NN) based methods for handling artefacts, specifically HRV analysis [36].

4.3 Feature Extraction

Feature extraction is the process of converting raw signals into usable datasets that can be used as feature inputs for ML algorithms. The selection of appropriate features is an important task that can have a great impact on the overall success of a classifier. Multiple signal processing techniques have been used to extract features from physiological datasets (HR, HRV and GSR). Fourier Transformation (FT) is a popular technique for transforming physiological signals from a time to frequency domain. Liu et al. [24] utilised a variation of FT known as the Lomb periodogram, to generate frequency-based HRV features such as, total spectral power of all RR intervals up to 0.04 Hz and total spectral power of all RR intervals in discrete bands (0-0.003 Hz and 0.003-0.04 Hz etc.). Wavelet Transformation (WT) is another method that has been used to transform physiological signals from time to frequency domains. Chęć et al. [37] used a wavelet-based peak detector that was originally developed by [38] that obtained 91.4% accuracy and 95.9% precision for detecting peaks in ECG signals. Principal Component Analysis (PCA) is a technique used to identify variables from large datasets and has been referred to as a *dimensionality reducer* [39]. PCA methods have been used in numerous studies, specifically, in fall detection when determining the direction of the main axis of the human body [40] and in reducing the number of EEG features when modelling the stress of people in the scenario of playing computer games [41]. Independent Component Analysis (ICA) is another feature extraction technique that has used for reducing unwanted features. Past studies have used this approach to remove eye movement artefacts from EEG data [41] and to identify underlying amplitude waveform of blood volume pulse signals [42].

4.4 Classification

In stress monitoring systems the classifier is built using a combination of physiological and contextual data to determine the mental state of the user. A large body of past work has adopted a binary classification approach with the output either identifying a person as (0) not stressed or (1) stressed. However, there has been a plethora of work that has investigated the efficacy of ML techniques with numerous features as reliable biomarkers of stress. For example, Muaremi et al. [43] use HRV features to build general and user-specific logit models, obtaining accuracies of 52% and 59% respectively. Additionally, a classifier was built using the HRV features alongside several smartphone features such as, no. of calls, audio length and mean call length. The addition of smartphone features saw a slight increase in the classifiers performance achieving accuracies of 53% and 61%, respectively. Support vector machines (SVMs) have been the go-to method for identifying stress with varying degrees of accuracy, which is ultimately dependent on the features used. The SVM method is a discriminative classifier that transforms data to a higher representation, and is then separated by a hyperplane. A linear SVM approach was used in [25] to recognise stress using features such as, mobile phone usage, survey results, accelerometer and distance travelled. After conducting several tests, the system achieved an average accuracy of 75% using data derived from phone usage and ambulatory sensors. Zhai et al. [44] use a linear SVM to perform a classification between "relaxed" and "stressed" states using features generated from cardiac and electrodermal activity datasets. Interestingly, when pupil diameter (PD) was removed from the model the classification accuracy fell by circa 30%, whereas, when removing features such as GSR and BVP the accuracy fell by only 1-2%. This is surprising as there has been little work that has followed on from this and further investigated the efficacy of PD as a marker of stress. It may be because of the unobtrusive methods that are required to obtain this data. However, as technology advances, devices such as Google Glass will create more opportunities for researchers to unobtrusively acquire features such as, PD and spontaneous blink rate (SBR).

Other methods such as Fuzzy Logic (FL) and Artificial Neural Networks (ANN) have shown promise, but have not yet received a great detail of attention. Sierra et al. [45] developed a FL model using HR and GSR features, achieving 99.5% accuracy for *true stress detection* and 97.4% for *true nonstress detection* using HR and GSR features. The proposed system relies on two temporal parameters; template time and acquisition time. Allowing a longer period of time for these two parameters to be acquired increases the accuracy of a system. However, real-life application of this system requires the production of a classification result in a timely manner. Other areas of the research domain have looked at using ANNs for the purpose of stress classification and prediction. Hosseini et al. [46] developed an emotional stress recognition system that used a two-layer back propagation neural network with features derived from EEG signals. The researchers focused on several classification problems, but for the issue of emotional stress an accuracy of 79.2% was achieved using a five-fold cross validation method. Further investigative work into the different modelling techniques for the purpose of stress monitoring and detection is required. Additionally, there must be comparisons between the performances of stress models using various features to determine the most suitable.

Past efforts in modelling stress have used ad-hoc methods for both, the determination of metrics and performance. Despite using different metrics, the results have suggested that it is possible to create somewhat reliable models of stress. However, there is room for improvement and with further research the realisation of a low-cost, unobtrusive and highly-accurate stress monitoring system will be met.

4.5 Discussion

Our pilot testing has revealed the great potential for using commercial sensors in uncontrolled environments. However, there are several obstacles that must be addressed before we proceed to begin our data collection study. Firstly, we have discovered the commercial sensor can easily lose contact with the skin and quality of data suffers as a result, this can have detrimental impact on the sensor readings (see the GSR graph in Figure 2). Considering this, we believe that it is necessary to inform participants on how to fit the sensor correctly and the study protocol. Additionally, these sensors have limited battery life (the band has an average duration of 48 hours) and require the participants to actively place the device on charge at a suitable time and in a swiftly manner. Upon analysis of the physiological data it is clear to see that there is ambiguity that can prevent accurate observations of patterns that may correspond to stress. Thus, additional data sources are required to improve the potential of stress identification inferences. We believe that data sources such as, accelerometer and GPS, are sufficient choices that can elevate the accuracy of a stress model. In the case of accelerometers, we can use the recorded coordinates to determine the physical activity of a user. This information can be used to allow a system to isolate the contribution of movement to a physiological record.

5. SUMMARY AND FUTURE WORK

This review is the starting point for future work and is concerned with the collaboration of context-awareness and physiological computing. Early results suggest that it is possible for low-cost commercial smart sensors, such as the Microsoft Band, to operate as data collection tools. There are many benefits from the development of an autonomous and unobtrusive stress monitoring and classification system. For example, it can have a direct positive impact in working and educational environments. As sensor technologies continue to advance the reliability of physiological data will continue to improve, potentially enhancing the classification accuracy of future stress detection systems. As it stands, collecting these datasets in real-life settings is difficult as the data can be unreliable as it can be difficult to determine the existence of noise and artefacts.

It is not possible to directly identify stress; but we can make inferences of stress by using psychophysiological measurements. In order to identify stress, traditional systems require the completion of subjective questionnaires and hormonal extraction techniques, which is often disruptive. However, modern smartphone-orientated stress systems can make informed decisions using unobtrusively collected physiological data to provide a just-in-time intervention. Nevertheless, there are further considerations when determining the underlying cause of a physiological change as often these signals can be ambiguous. For this reason, we require the acquisition of contextual data to build a model that understands the underlying motives behind a physiological dataset. Contextual data can exist in many forms, the most discussed in the literature are derived from, GPS, accelerometer and temporal data features.

We believe that the multiple datatypes that we are able to collect from future commercial devices will translate too many ML adaptations. Ultimately, we will be able to determine the efficacy of different feature combinations with different ML approaches. Future work aims to build on the work presented in this paper by undertaking a full data collection study to examine stress in the everyday lives of undergraduate university students. This will be used to identify patterns that represent a person's emotional stress state with reference to specific markers that could induce stress, such as coursework deadlines. Furthermore, it may be possible for this system to explore the different psychological effects that specific markers have on an individual and the reasoning behind this state.

References

[1] B. S. McEwen, "Stress, adaptation, and disease. Allostasis and allostatic load.," *Ann. N. Y. Acad. Sci.*, vol. 840, pp. 33–44, 1998.

[2] B. L. Ganzel and E. Wethington, "Allostasis and the human brain: Integrating models of stress from the social and life sciences," *Hum. Dev.*, vol. 117, no. 1, pp. 134–174, 2011.

[3] K. Verbert, N. Manouselis, X. Ochoa, M. Wolpers, H. Drachsler, I. Bosnic, and E. Duval, "Context-aware recommender systems for learning: A survey and future challenges," *IEEE Trans. Learn. Technol.*, vol. 5, no. 4, pp. 318–335, 2012.

[4] D. Miranda, M. Calderón, and J. Favela, "Anxiety detection using wearable monitoring," *Proc. 5th Mex. Conf. Human-Computer Interact. - MexIHC '14*, pp. 34–41, 2014.

[5] H. Liu, J. Hu, and M. Rauterberg, "iHeartrate: a heart rate controlled in-flight music recommendation system," *Proc. Meas. Behav. 2010*, pp. 256–268, 2010.

[6] H. Lu, D. Frauendorfer, M. Rabbi, M. S. Mast, G. T. Chittaranjan, A. T. Campbell, D. Gatica-Perez, and T. Choudhury, "StressSense: Detecting Stress in Unconstrained Acoustic Environments using Smartphones," *Proc. 2012 ACM Conf. Ubiquitous Comput. - UbiComp '12*, p. 351, 2012.

[7] A. Alberdi, A. Aztiria, and A. Basarab, "Towards an automatic early stress recognition system for office environments based on multimodal measurements : A review," *J. Biomed. Inform.*, vol. 59, pp. 49–75, 2016.

[8] J. Hernandez, D. McDuff, X. Benavides, J. Amores, P. Maes, and R. Picard, "AutoEmotive: Bringing Empathy to the Driving Experience to Manage Stress," *Proc. 2014 companion Publ. Des. Interact. Syst. - DIS Companion '14*, pp. 53–56, 2014.

[9] D. Sun, P. Paredes, and J. Canny, "MouStress: Detecting Stress from Mouse Motion," *CHI '14-Proc. SIGCHI Conf. Hum. Factors Comput. Syst.*, pp. 61–70, 2014.

[10] M. A. Hogervorst, A. M. Brouwer, and W. K. Vos, "Physiological correlates of stress in individuals about to undergo eye laser surgery," *Proc. - 2013 Hum. Assoc. Conf. Affect. Comput. Intell. Interact. ACII 2013*, pp. 473–478, 2013.

[11] Statista, "Statistics and facts about smartphones," 2016. [Online]. Available: https://www.statista.com/topics/840/smartphones/. [Accessed: 26-Aug-2016].

[12] D. S. Moskowitz and S. N. Young, "Ecological momentary assessment: what it is and why it is a method of the future in clinical psychopharmacology.," *J. Psychiatry Neurosci.*, vol. 31, no. 1, pp. 13–20, 2006.

[13] A. M. Cohn, D. Hunter-Reel, B. T. Hagman, and J. Mitchell, "Promoting Behavior Change from Alcohol Use through Mobile Technology: The Future of Ecological Momentary Assessment," *Alcohol. Clin. Exp. Res.*, vol. 35, no. 12, pp. 2209–2215, 2011.

[14] J. Allanson and G. M. Wilson, "Physiological Computing," pp. 21–42, 2002.

[15] S. Fairclough and K. Gilleade, "Construction of the Biocybernetic Loop: A Case Study," *Proc. 14th ACM Int. Conf. Multimodal Interact.*, vol. Santa Moni, pp. 571–578, 2012.

[16] O. Postolache, P. S. Girao, M. Ribeiro, H. Carvalho, A. Catarino, and G. Postolache, "Treat me well: Affective and physiological feedback for wheelchair users," *Med. Meas. Appl. Proc. (MeMeA), 2012 IEEE Int. Symp.*, pp. 1–7, 2012.

[17] L. Nacke, M. Kalyn, C. Lough, and R. Mandryk, "Biofeedback game design: using direct and indirect physiological control to enhance game interaction," *Proc. SIGCHI …*, pp. 103–112, 2011.

[18] S. D'Mello and R. a. Calvo, "Beyond the Basic Emotions: What Should Affective Computing Compute?," *CHI '13 Ext. Abstr. Hum. Factors*

Comput. Syst. - CHI EA '13, pp. 2287–2294, 2013.

[19] M. Soleymani, G. Chanel, J. J. M. Kierkels, and T. Pun, "Affective characterization of movie scenes based on multimedia content analysis and user's physiological emotional responses," *Proc. - 10th IEEE Int. Symp. Multimedia, ISM 2008*, pp. 228–235, 2008.

[20] D. Mcduff, A. Karlson, A. Kapoor, A. Roseway, and M. Czerwinski, "AffectAura: An Intelligent System for Emotional Memory - Microsoft Research," *Proc. SIGCHI Conf. Hum. Factors Comput. Syst.*, pp. 849–858, 2012.

[21] I. Kosunen, M. Salminen, S. Järvelä, A. Ruonala, N. Ravaja, and G. Jacucci, "RelaWorld: Neuroadaptive and Immersive Virtual Reality Meditation System," *Iui 2016*, pp. 208–217, 2016.

[22] M. Zubair, C. Yoon, H. Kim, J. Kim, and J. Kim, "Smart Wearable Band for Stress Detection," pp. 1–4, 2015.

[23] J. Bakker, M. Pechenizkiy, and N. Sidorova, "What's your current stress level? Detection of stress patterns from GSR sensor data," *Proc. - IEEE Int. Conf. Data Mining, ICDM*, no. 1, pp. 573–580, 2011.

[24] D. Liu and M. Ulrich, "Listen to Your Heart: Stress Prediction Using Consumer Heart Rate Sensors," *Cs229.Stanford.Edu*, 2014.

[25] A. Sano and R. W. Picard, "Stress Recognition using Wearable Sensors and Mobile Phones," *Hum. Assoc. Conf. Affect. Comput. Intell. Interact. Stress*, pp. 671–676, 2013.

[26] U. Panniello, A. Tuzhilin, and M. Gorgoglione, "Comparing Context-Aware Systems in Terms of Accuracy and Diversity: Which Contextual Modeling, Pre-filtering and Post-Filtering Methods Perform the Best," *J. Chem. Inf. Model.*, 2012.

[27] A. K. Dey and G. D. Abowd, "Towards a Better Understanding of Context and Context-Awareness," *Comput. Syst.*, vol. 40, no. 3, pp. 304–307, 1999.

[28] A. Solanas, C. Patsakis, M. Conti, I. Vlachos, V. Ramos, F. Falcone, O. Postolache, P. Perez-martinez, R. Pietro, D. Perrea, and A. Martinez-Balleste, "Smart health: A context-aware health paradigm within smart cities," *IEEE Commun. Mag.*, vol. 52, no. 8, pp. 74–81, 2014.

[29] T. J. Marin, T. M. Martin, E. Blackwell, C. Stetler, and G. E. Miller, "Differentiating the impact of episodic and chronic stressors on hypothalamic-pituitary-adrenocortical axis regulation in young women.," *Health Psychol.*, vol. 26, no. 4, pp. 447–455, 2007.

[30] F. Ongenae, P. Duysburght, M. Verstraete, N. Sulman, L. Bleumerst, a Jacabst, a Ackaert, S. De Zutter, S. Verstichel, and F. De Turck, "User-driven design of a context-aware application : an ambient-intelligent nurse call system," *Pervasive Comput. Technol. Healthc.*, pp. 205–210, 2012.

[31] L. Barkhuus and A. K. Dey, "Is Context-Aware Computing Taking Control away from the User? Three Levels of Interactivity Examined," *Ubicomp 2003 Ubiquitous Comput.*, vol. 2864, pp. 149–156, 2003.

[32] J. F. Brosschot, "Markers of chronic stress: Prolonged physiological activation and (un)conscious perseverative cognition," *Neurosci. Biobehav. Rev.*, vol. 35, no. 1, pp. 46–50, 2010.

[33] C. Setz, B. Arnrich, J. Schumm, R. La Marca, G. Tröster, and U. Ehlert, "Discriminating stress from cognitive load using a wearable eda device," *IEEE Trans. Inf. Technol. Biomed.*, vol. 14, no. 2, pp. 410–417, 2010.

[34] M. Soleymani, M. Pantic, and T. Pun, "Multimodal emotion recognition in response to videos," *IEEE Trans. Affect. Comput.*, vol. 3, no. 2, pp. 211–223, 2012.

[35] R. Logier, A. Dassonneville, P. Chaud, and J. De Jonckheere, "A multi sensing method for robust measurement of physiological parameters in wearable devices," *2014 36th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. EMBC 2014*, pp. 994–997, 2014.

[36] S. Begum, M. . Islam, M. . Ahmed, and P. Funk, "K-NN Based Interpolation to Handle Artifacts for Heart Rate Variability Analysis," *IEEE Int. Symp. Signal Process. Inf. Technol.*, pp. 387–392, 2011.

[37] A. Chęć, D. Olczak, T. Fernandes, and H. A. Ferreira, "Physiological Computing Gaming - Use of Electrocardiogram as an Input for Video Gaming," *Proc. 2nd Int. Conf. Physiol. Comput. Syst.*, pp. 157–163, 2015.

[38] P. Du, W. A. Kibbe, and S. M. Lin, "Improved peak detection in mass spectrum by incorporating continuous wavelet transform-based pattern matching," *Bioinformatics*, vol. 22, no. 17, pp. 2059–2065, 2006.

[39] H. P. Martinez, Y. Bengio, and G. Yannakakis, "Learning deep physiological models of affect," *IEEE Comput. Intell. Mag.*, vol. 8, no. 2, pp. 20–33, 2013.

[40] L. Hazelhoff, J. Han, and P. H. . de With, "Video-based fall detection in the home using principal component analysis," *ACIVS*, pp. 298–309, 2008.

[41] Z. Dharmawan, "Analysis of Computer Games Player Stress Level Using EEG Data," no. August, 2007.

[42] P. Comon, "Independent component analysis, A new concept?," *Signal Processing*, vol. 36, no. 3, pp. 287–314, 1994.

[43] A. Muaremi, B. Arnrich, and G. Tröster,

"Towards Measuring Stress with Smartphones and Wearable Devices During Workday and Sleep," *Bionanoscience*, vol. 3, no. 2, pp. 172–183, 2013.

[44] J. Zhai and A. Barreto, "Stress detection in computer users based on digital signal processing of noninvasive physiological variables," *Eng. Med. Biol. Soc. 2006. EMBS'06. 28th Annu. Int. Conf. IEEE*, no. Ic, pp. 1355–1358, 2006.

[45] A. de Santos Sierra, C. Sanchez Avila, G. del Pozo, and J. Guerra Casanova, "A stress detection system based on physiological signals and fuzzy logic," *Ind. Electron. IEEE Trans.*, vol. 58, no. 99, p. 1, 2011.

[46] M. a. . Hosseini, S.A.; Khalilzadeh, "Emotional stress recognition system using EEG and psychophysiological signals:," *Biomed. Eng. Comput. Sci. (ICBECS), 2010 Int. Conf.*, pp. 1–6, 2010.