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A Mobile Lifelogging Platform to Measure Anxiety and Anger During Real-Life Driving

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***Abstract*— The experience of negative emotions in everyday life, such as anger and anxiety, can have adverse effects on long-term cardiovascular health. However, objective measurements provided by mobile technology can promote insight into this psychobiological process and promote self-awareness and adaptive coping. It is postulated that the creation of a mobile lifelogging platform can support this approach by continuously recording personal data via mobile/wearable devices and processing this information to measure physiological correlates of negative emotions. This paper describes the development of a mobile lifelogging system that measures anxiety and anger during real-life driving. A number of data streams have been incorporated in the platform, including cardiovascular data, speed of the vehicle and first-person photographs of the environment. In addition, thirteen participants completed five days of data collection during daily commuter journeys to test the system. The design of the system hardware and associated data streams are described in the current paper, along with the results of preliminary data analysis.**

Keywords—Mobile Device; Wearable Device; Pervasive Computing; Lifelogging; Emotion Recognition; Self-Reflection; Driving

I. Introduction

Driving is a common activity that millions of people undertake each day. This daily occurrence can be associated with high levels of anger, which can be significantly correlated to risky/aggressive driving behavior [1, 2]. Driver aggression can range from extreme acts of violence (such as assault) to arguments, confrontations and behavior that deliberately endangers others (e.g. speeding and tailgating) [1, 3]. Driver aggression is a common phenomenon on the road, with 90% of drivers in the United States having been involved in at least one incident of aggressive driving [1]; furthermore angry drivers are twice as likely to be involved in accidents [2, 4]. Driver aggression is a risk to health as well as traffic safety. The experience of negative emotions, such as anger and anxiety, has a cumulative impact on long-term cardiovascular health and is associated with the development of hypertension (high blood pressure) and coronary heart disease (CHD) [5, 6]. CHD is the number one cause of death globally and generates vast economic effects worldwide [7]. In 2012/13, £6.8 billion was spent on treating CHD within the NHS in England, whilst the annual direct/indirect cost of CHD in the United States is an estimated $320.1 billion [8, 9].

The average American driver spends 46 minutes driving per journey, whilst UK drivers spend an average of 22 minutes per car trip [10, 11]. Over a period of weeks and months, this average journey duration amounts to a substantial amount of time spent on the road. In order to counteract the risks of anger exposure on safety and health, it is important for drivers to develop adaptive strategies that are ameliorative and adaptive [12]. However, the development of these coping strategies requires both *insight* and *self-awareness* on the part of the individual. It is argued that mobile lifelogging technology can be used to promote the necessary degree of self-reflection that is required in order to develop effective coping strategies. A lifelogging platform can provide insight into behavior, emotions, their physiological correlates and environmental triggers that are based upon objective data sources; these data are gathered from multiple sensors to capture context and daily activity in a way that is permanent and comprehensive. The resulting analysis and presentation of data from a lifelog can subsequently be consulted by the user and used as the basis for self-reflection and insight.

The development of a mobile lifelogging platform begins with the process of measurement and inference. Miniaturization of sensors and increased computational power has enabled mobile devices to acquire a variety of personal data, including physiological signals and contextual information [13]. This availability of this hardware has afforded us the opportunity to collect a greater amount of data "in the wild" within real-life situations. Ambulatory data collection in the field has greater ecological validity than data from laboratory studies, particularly when measuring stress and negative emotional states [14]. Since the setting is not artificial, emotional and physiological reactivity to naturalistic stimuli is representative of responses in the real-world and the resulting conclusions improve the generalizability of the findings [15]. Whilst the availability of wearable sensors improves the ease with which data can be collected, ambulatory measurement is associated with different types of challenges, particularly with respect to collecting high-quality data [16] and controlling key variables and eliminating the effects of confounding factors [17]. Extensive signal processing and data analysis must be performed on data collected in the field in order to draw robust inferences about behavior and emotional states.

This paper presents a mobile lifelogging platform that has been developed to measure anxiety and anger during real-life driving. The platform incorporates a number of wearable sensors

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and mobile devices to capture specific streams of driving data, including speed, distance travelled and photographs, as well as physiological data, which has been obtained from an electrocardiogram (ECG). This device has been used to measure two dimensions of cardiovascular activity, including heart rate (HR) and heart rate variability (HRV), specifically the high-frequency component of HRV.

The remainder of this paper is constructed as follows. Section 2 describes related work within the field of lifelogging and psychophysiological markers of stress. Section 3 presents the case study that has been undertaken using our platform, whilst section 4 illustrates some preliminary results that have been obtained from this study. The paper is then concluded in section 5.

II. RELATED WORK

In the late 1980's, Mark Weiser proposed the vision of ubiquitous computing; a paradigm where computing devices fit into our environment to the point that they become so familiar that they disappear [18]. We are now living in an era where this concept is a reality. Mobile, and increasingly wearable, devices have been integrated into everyday activities in a manner that is seamless and ubiquitous. At any one time, we have access to over 14 different types of sensors in our smartphones, which measure: 1) motion (e.g. using the accelerometer), 2) the environment (e.g. using the barometer), 3) position (e.g. using the magnetometer) and localization (e.g. using GPS). Furthermore, wearable sensors are becoming more mainstream and can be used to gather a wealth of physiological data [19]. Having instant access to this type of technology, which is continuously available on our person, has enabled this domain of pervasive computing to flourish.

A. Sensing Emotion using Lifelogging Technologies

Through the prevalence of pervasive computing, the area of lifelogging has emerged as an application that is designed to continuously measure personal data with the purpose of supporting recall and self-reflection [20]. Detecting emotion using this outlet has great advantages in that data can be captured continuously and in an unobtrusive manner. For instance, *Affective Diary* collects sensor data, including pulse, pedometer and acceleration, as well as mobile phone activity, such as SMS, MMS and photographs to create a desktop abstraction of the users emotional state [21]. Meanwhile, *AffectAura* is an "emotional prosthetic" that uses a variety of sensors to capture audio, visual, physiological and contextual data to allow users to "reflect on their emotional states over long periods of time" [22]. Similarly, to *Affective Diary*, whilst some portable sensors have been used, the setup also requires the user to sit at a desktop computer to interact with the system.

Hansal *et al.* [13] have used a smartwatch and mobile phone to log the current emotional state of the user. Instances of location, heart rate, prior physical activity (steps and workouts), ambient noise and wrist movements, from the watch accelerometer, have been passively collected [13]. However, the system does require users to rate their current emotional state multiple times a day via a questionnaire. In other works, *eMotion* is a mobile application that uses front/back cameras to unobtrusively capture the facial expressions of drivers, as well as 10-second videos of the outside scenery, location, and speed of the car [23]. This information is then presented to the user in order to help them recall their experience. This work is interesting as it is being used within a real world driving experience. However, by neglecting to include physiological data it is unclear what the internal responses to the driving situation is.

A wide body of work exists that uses pervasive mobile and wearable devices to sense emotion. Nevertheless, whilst a wide range of personal data has been collected, manual input is still required. However, in order to be truly pervasive, sensing and measuring emotion needs to occur unobtrusively. Furthermore, the inclusion of physiological data is important as these body signals are capable of being used to predict emotional states [13, 22, 24].

B. Psychophysiological Markers, Negative Affect and the Process of Inference

Previous research on measurement of stress in the real-world using ambulatory sensors has focused on quantification of perceived stress, e.g. [25]. For example, mobile monitoring data derived from the cStress model was used to successfully predict 72% of self-reported stress [26]. The use of self-reported stress as a 'ground truth' is associated with a number of problems. In the first instance, these data can be very inconsistent [27] although this problem may be corrected with supplemental data, such as combining self-report with observer ratings [28]. The second problem with reliance on subjective self-report concerns the role of unconscious psychological processes. Models of psychological stress have recently developed to embrace physiological changes that may be related to unconscious psychological processes, such as rumination [29]. In addition, psychophysiological measures are sensitive to both unconscious and conscious psychological processes. It is argued that reliance on subjective self-report data as a 'ground truth' effectively restricts the explanatory power of psychophysiological markers to that component of psychological stress that is consciously experienced by the person.

An alternative approach is to develop a psychophysiological profile of stress and other negative emotional states based upon previous research literature. This expert system is developed primarily from laboratory-based research and related literature reviews. For example, anger is generally associated with increased heart rate, respiration and cardiac output [30]. The presence of this pattern of psychophysiological reactivity and its associated magnitude can be categorized as 'anger' without any overt requirement to consult subjective self-report.

It is known that negative emotional states, such as anxiety, anger and depression, are associated with the process of inflammation in the human body [31, 32], and this inflammatory process is predictive of CHD in the long-term. Therefore, one could quantify the presence of stress with reference to inflammatory processes via measures of heart rate variability (HRV) [33, 34], i.e. measures of HRV have an inverse relationship with biochemical markers of inflammation. This approach has been adopted in the current paper where the presence of negative emotional states during the driving task is characterized in a way that: (1) is biologically defined, (2) does not rely on subjective self-report and (3) accommodates unconscious as well as conscious psychological processes. It is argued that one key benefit of a mobile lifelogging system is to provide insight based on objective data to those psychological processes, which may not be accessible to conscious awareness but have significant implications for the health of the person.

III. Case Study

Our lifelogging platform has been developed to measure negative emotional states during real-life driving. The platform utilizes commercially available pervasive devices to collect physiological and contextual lifelogging data for each driver. In order to assess the validity of our approach, a case study has been undertaken that has focused on collecting a variety of lifelogging data from participants on their daily driving commute to and from work. The data that has been collected includes acceleration (to calculate speed), photographs of the road in front and ECG signals (to calculate cardiovascular activity). Fig. 1 depicts the sensor hardware that has been used for the study. As it can be seen in this figure, our hardware configuration consists of two mobile Shimmer3™ sensors[1] that collect ECG signals, via a five-lead electrode (1), and acceleration via an accelerometer (2). Photographs have been captured using a Samsung™ Galaxy S5/S6 smartphone (3). A mobile holder (4) was also provided to place the phone into so that photographs could be taken out of the front windshield. The Shimmer3 sensors have been configured at a sample rate of 512 Hz and the data was stored on the internal microSD cards of all devices. The system does not pose a risk to the participants, whilst they are driving, as the sensors are unobtrusive and do not cause discomfort or distraction from the task of driving.

A. Participants

Thirteen participants, seven female and six male, with an age range from 25 to 57 (mean = 42, SD = 12), were recruited for the study. Participants did not have a pre-existing heart condition and were not on any medication that could affect cardiovascular activity. The University Ethical Committee has approved all procedures for participant recruitment and data collection prior to commencement of the study.

Fig. 1. Mobile sensor equipment used for the case study, including Shimmer3™ ECG wearable sensors (1) and Accelerometer (2) units, mobile phone (3), and mobile phone holder (4)

[1] http://www.shimmersensing.com/

B. The Driving Task

Each participant undertook the study for five working days and recorded data during each of their driving journeys to and from work, i.e. ten drives (five morning and five evening) were recorded per participant. A minimum of 20 minutes of continuous driving per journey was required to ensure a sufficient period of data collection. Before commencing the study, participants were briefed with a description of the task and received a demonstration of how to use the equipment. Once the participants had reached their destination, they were then required to stop recording data and remove the equipment. As an incentive, after completing the study, participants were paid using a gift voucher to the value of £10.

C. Signal Analysis and Experimental Measures

All of the collected data has been analyzed using three-minute windows. This period was selected as the minimum epoch necessary for Fast Fourier Transform analysis of heart rate variability (HRV). Electrical activity of the heart has been captured from the ECG signal. This signal is recorded as "waves," which are known as the QRS Complex (see Fig. 2). By detecting the QRS Complex, and measuring the time between consecutive R-R intervals, we can calculate the heart rate (HR) and HRV [35]. However, before detecting the QRS Complex, the signal was filtered using a Chebyshev Type I 2nd order highpass/lowpass filter with a cutoff frequency between 0.5 and 200 Hz [36]. Once the ECG signal has been filtered, windowed and the QRS Complex has been detected, the R-R intervals were subsequently calculated in order to calculate: (1) HR – heart rate in beats per minute (bpm), and (2) HRV – mean power in the 0.15-0.4Hz band, which is also known as high-frequency HRV.

The acceleration signal has been filtered using a 1st order Butterworth low-pass filter, with a cutoff frequency of 30 Hz [37, 38]. Speed has then been calculated from this signal by combining the acceleration vectors (x, y and z) into one vector and then converting this acceleration signal, which is captured in meters per second squared (m/s^2), into velocity, (m/s). This has been achieved using cumulative trapezoidal numerical integration (see (1) [39]), where v is the velocity, t is the time and a is the acceleration vector.

$$v_t \simeq \int_t^{a_t} f(a)\,da \tag{1}$$

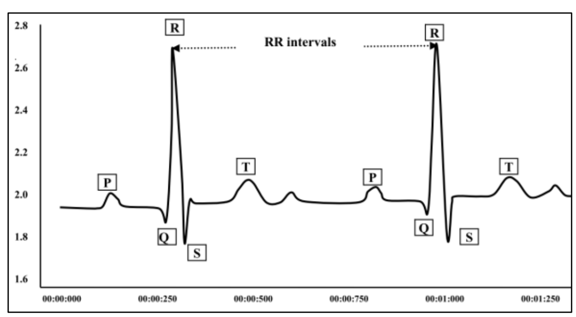

Fig. 2. QRS Complex and R-R Interval [35]

Once data were filtered, processed and windowed, various features of speed have been calculated. These include mean, median, standard deviation, variance, distance travelled (per window), range, minimum, maximum and interquartile range. The time (in seconds) spent within certain speed bands has also been calculated. These bands start at 0 – 5 mph and increase incrementally in 5 mph blocks (i.e. 0 – 5 mph, 5 – 10 mph, 10 – 15 mph, etc.) up to > 95 mph.

A custom-built Android application has also been developed to run on the mobile phone to capture one photograph per three-minute window. Fig. 3 depicts an example of photos that have been taken using this application. As it can be seen, the photos clearly depict the road conditions (traffic density, road topology, etc.), which have been used as context for the physiology data. These photographs have then been manually analyzed to extract contextual information about the drive, including traffic density, road complexity and any obstacles that could induce stress, such as being stopped in traffic, roundabouts and pedestrian crossings (see Table I).

This mobile lifelogging platform has been developed to collect indices of heart rate, speed of the vehicle and photographs of the environment. The following section will examine preliminary results that have been obtained using this platform.

IV. Preliminary Data Analysis

Selected data from participants have been selected for preliminary analysis in order to understand the relationship between the speed of the vehicle and cardiovascular parameters. In this case, mean vehicle speed, within each three-minute window, was captured as a proxy measure of journey impedance, i.e. lower mean speed = higher journey impedance.

The purpose of the analysis was to quantify the relationship between vehicle speed and two measures of cardiovascular activity: heart rate (HR) and high frequency component of heart rate variability (HRV). The former provides an index of autonomic activation and has been associated with anger [30]. The HRV measure is used to quantify vagal tone and has an inverse relationship with inflammation [34], i.e. low HRV = increased levels of biochemical markers of inflammation. Data from all ten journeys for each participant were subjected to a linear regression analysis, where mean speed acted as a dependent variable and HR and HRV acted as independent variables. The results from these analyses are presented in Table II.

Fig. 3. Example of photos that have been taken using the mobile phone

TABLE I. Data That Has Been Extracted From The Photographs

Data	Description
Traffic Density	A count of the number of moving cars that are in front of the participant, travelling in the same direction
Road Complexity	A count of the number of lanes on the road
Traffic Lights	Whether there are any traffic lights in front of the participant (yes/no)
Traffic Light Color	The color of the traffic lights (if any)
Pedestrian Crossing	Whether there is a pedestrian crossing in front of the participant (yes/no)
Roundabout	Whether there is a roundabout in front of the participant (yes/no)
Stopped In Traffic	Whether the participant is stopped in traffic (yes/no)
Weather	The current weather (e.g. sunny, clear, raining, cloudy, tunnel or overcast)

Inspection of the R^2 scores indicates that 1–21% of the variance associated with the mean speed signal was explained by the cardiovascular measures. Significant correlations (represented by standard beta weights and semi-partial correlations) between mean speed and either HR or HRV were found for ten of the thirteen participants (77%). When the relationship was significant, both HR and HRV had a negative (inverse) relationship with mean speed. Therefore, low mean speed was associated with increased HR, which was indicative of anger due to journey impedance.

On this basis, it was expected that inflammation would also increase when mean speed was low. However, the opposite pattern was observed and high mean speed was associated with low HRV. This unexpected result may be due to the influence of mental workload on cardiovascular activity. Previous research has reported an inverse relationship wherein low HRV is associated with increased mental workload [40]. It could be assumed that driver mental workload increases with respect to information processing load as the driver travels at higher speed, hence the inverse relationship between speed and HRV. However, this link is speculative because mental workload is also strongly influenced by other factors, such as traffic density. Nevertheless, this preliminary data analyses has revealed supporting evidence that cardiovascular markers of anger were associated with reduced vehicle speed and journey impedance. However, there was no strong association between these instances of anger and increased inflammation as indicated by HRV. Further analyses are necessary to assess the explanatory value of traffic density and other roadway features associated with negative emotion/journey impedance, such as traffic lights.

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TABLE II. RESULTS FROM REGRESSION ANALYSIS (STD, BETA = STANDARD BETA WEIGHT, PARTIAL R = SEMI-PARTIAL CORRELATION) STD. B AND PARTIAL R IN BOLD REPRESENTS SIGNIFICANT RELATIONSHIPS AT P<.05.

			Std. Beta		Partial r	
Participant	***R²***	***p***	***HR***	***HRV***	***HR***	***HRV***
1	.16	<.01	-.06	**-.45**	-.04	**-.31**
2	.03	.07	**-.31**	-.24	**-.21**	-.16
3	.01	.33	-.15	.01	-.08	.01
4	.05	.07	-.22	**-.37**	-.17	**-.28**
5	.02	.37	-.08	-.20	-.05	-.13
6	.08	.03	**-.31**	**-.38**	**-.23**	**-.28**
7	.21	<.01	**-.50**	**-.76**	**-.31**	**-.50**
8	.07	.03	**.24**	-.04	**.20**	-.03
9	.09	.02	**-.31**	**-.41**	**-.22**	**-.29**
10	.11	<.01	**-.48**	-.25	**-.32**	-.17
11	.01	.92	-.01	-.05	-.01	-.04
12	.05	.06	**-.30**	**-.35**	**-.20**	**-.23**
13	.06	.01	**-.38**	-.19	**-.22**	-.11

In order to provide insight to the end user, the collected data must be communicated in a visually appealing and informative manner to facilitate self-reflection and learning. This outcome can be achieved by transforming multivariate data into a clear visualization so participants can easily interpret the context for changing patterns of psychophysiology (see Fig. 4). The illustration in Fig. 4 depicts a prototype of this concept. Heart rate data has been coded into three bands for each individual. Green markers indicate a low heart rate where the heart rate is below the 50th percentile. Yellow indicates a normal heart rate where the readings are between the 50th and 75th percentile, whilst red markers indicate periods of anger where the heart rate has increased beyond the 75th percentile. Speed and photos have also been linked to this information and provide context for heart rate and location data. For example, in the case of Fig. 4, our driver gets angry early in the journey because of slow moving traffic (1). Their heart rate is lowest when speed is high and the road is clear (2). It then increases slightly, but still within the normal range, when they return to the city and speed decreases (3).

This visualization has been developed to aid users in reflecting on their collected lifelogging data and supports the findings in Table II. It also illustrates how multiple streams of lifelogging data can be combined to depict an informative representation of complex data. However, further work is required in order to assess the effectiveness of such visualizations on altering behavior.

V. CONCLUSION AND FUTURE WORK

The purpose of the study has been to develop a mobile platform to measure negative emotion and their effects on the human cardiovascular system. In order to measure such emotions, the system has been used in the context of driving. Driving is a common activity that can be associated with levels of stress, which when experienced repeatedly has a growing impact on our health. In order to complete this preliminary evaluation, data has been collected that captures heart rate, speed of the vehicle and first-person photographs of the environment.

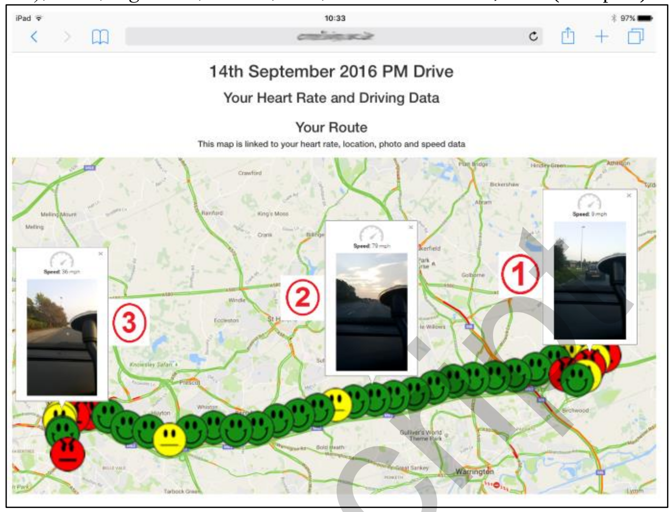

Fig. 4. Potential visualization of the data. Red markers indicate a high heart rate; yellow is a normal heart rate, whilst green indicates low heart rate.

A prototype visualization has also been developed to illustrate the potential avenue that could be utilized to display lifelogging data in a concise and meaningful manner.

Future work aims to build on these findings by assessing the impact that the traffic/road configuration has on our cardiovascular system. Furthermore, we plan to undertake another user study in order to evaluate the effect that the visualization has on driver behavior. This will allow us to assess the impact that reviewing our lifelogging data has on altering behavior.

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