An Open Affective Platform

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***Abstract*—Affective computer interfaces improve human-computer interaction by enabling the communication of the user's emotional state. To this end, subtle non-verbal methods of communication provide a rich source of information which may provide valuable affective context to the human-computer interaction. Of particular note are physiological indicators of affective state, as these are objective in nature and have been demonstrated to be successful in many studies. Physiological computing may be viewed as a data acquisition and signal processing task whereby the electrical impulses or biopotentials created by the body are captured, analyzed and recorded in a suitable format for later communication. Whilst there are a number of commercially available hardware platforms to support physiological data acquisition, these all possess limitations in a few distinct areas. Not least of these is the physical form factor. For such devices to be embedded and integrated into the next generation of computer interfaces, an open physiological platform is required. This will enable future development to build upon this foundation and concentrate on novel and unique form factors and implementation environments. This paper describes the development and implementation of an open affective platform. This hardware and software solution provides the necessary functionality to measure and describe the users underlying affective state in terms of its component dimensions. This data may then be communicated to other application software, or modules within a larger affective computing application.**

Index Terms- affective computing, physiology, biofeedback

I. INTRODUCTION

Affective computing is defined as 'computing that relates to, arises from, or deliberately influences emotions' [1]. The goal of improving the interaction between users and computers requires that emotions be taken into account in this interaction. To this end, it is necessary to have an understanding of what emotions are, how they can be identified and what the implications of various emotional patterns are for that particular situation. Emotional state is often implicitly communicated between humans in a multitude of ways such as facial expression, vocal intonation or gesture, as well as being reflected in less apparent changes in physiology such as respiration, heart rate or electrodermal response [1]. It is widely accepted that all psychological events have some corresponding physiological event [2] and it is these physiological changes that may provide continuous feedback on the state of the human computer interaction. In order for a computer to respond accordingly to this non-verbal communication, it too must have a means of acquiring emotional information from the user. Physiological signals are not generally viewed as an input method for a computer, but as computers become ubiquitous and become integrated into everyday devices, vehicles, clothing and our surroundings, the opportunity for greater physical contact between user and machine increases and makes such input paradigms increasingly viable. The surge in uptake of personal and wearable computing devices, and the widespread use of the smartphone hold tremendous potential for such embedded physiological computing interfaces to become reality. Such interfaces would be invisible to the user, and provide a rich and valuable source of communication to enhance all aspects of human-computer interaction.

This paper describes the development and implementation of an affective platform that supports physiology based inference of affective state. This solution comprises of a relatively low cost and easily replicable platform that demonstrates loose coupling and minimal hardware constraints making it an ideal foundation for the next generation of embedded and mobile affective platforms. The solution also addresses many of the shortcomings of the commercially available biofeedback hardware, and has proven to be well suited for deployment in a physiological computing research environment.

The remainder of this paper is structured as follows: Section II discusses how affective state may be described in terms of component dimensions, and how nonverbal signals such as physiology may provide information about a particular dimension of affective experience. Section III expands on the topic of physiological data acquisition and highlights some of the issues potentially associated with the reliance on closed and commercially available data acquisition platforms. Section IV describes in detail the hardware and software design and implementation of an affective platform that enables the affective state to be inferred in terms of its two component dimensions. Finally,

Section V presents some concluding remarks about the affective platform that has been introduced.

II. Inferring affective state

Affective states are internal and involve cognitive processes and are therefore not directly accessible to anyone other than the one experiencing them. Therefore it is only the observable manifestations of the affective state that may be used for the process of inference. This is where the subtle, non-verbal indicators of underlying affect become especially useful. According to dimensional models of emotions, it is assumed that emotions can be represented in terms of a number of component dimensions (e.g. [3]). This viewpoint has the benefit of removing the need to categorize emotional experience within pre-defined boundaries, and may thus allow for a more fine-grained level of description. At the most fundamental level, an emotional state may be described in terms of two dimensions. The arousal/activation dimension describes the intensity or strength of the emotion; the valence dimension describes whether the state being experienced is positive or negative. Thus, any approach to affect inference must incorporate at a minimum the means of sensing these two dimensions.

Physiological indicators have long been known to be sensitive to mental events such as positive and negative emotions, changes in workload and cognitive engagement [4]. The use of physiological measures as non-verbal indicators of affective state has several advantages. They may be obtained without interrupting the participant from their task or disturbing their concentration, and the method does not rely on a (subjective) memory of the experience [5]. Furthermore, indirect or self-report measures of affect have been shown to have some amount of method bias [6] which may cause certain emotional states to be over or under reported by the participants. As physiological responses are involuntary and often very sensitive, the effect of deception on the part of the participant is also negligible [7].

The acquisition of physiological data most often starts with electrodes placed on the skin. The skin may be prepared by the experimenter by cleaning or roughening the contact area. Next, a metal electrode is attached with the aid of an adhesive collar or Velcro strap. Often conductive pastes or gels are used to improve the electrical contact between the skin and the electrode.

From the electrodes, electrical signals pass through the leads to the measuring equipment – high gain amplifiers and filters may be employed to boost the weak signal and attenuate any interference that may be picked up during the measurement process. The types of measurement being made generally dictate the site where the electrodes are attached. For instance, cognitive activity might be measured on the scalp or via facial muscle movement on the brow or corners of the mouth whereas skin conductivity may be measured on the fingertips or palm. Many sensors measure biopotentials: biological electrical signals transmitted by the nervous system during normal activity. Sensors may also use other characteristics to detect physiological processes, such as the movement the chest during breathing or the pumping of the heart.

III. Physiological Data Acquisition

The collection and analysis of physiological data may be viewed as a basic data acquisition and signal processing problem, with many of the same associated constraints and requirements. There are a number of commercially available biofeedback devices which are commonly cited in research. For basic physiological data acquisition of signals such as skin conductance or heart rate, the commercial platforms developed by ProComp and BioPac are prominent [8] and have been used in a number of studies of affective computing and psychophysiology (e.g. [9-12]).

These devices are well suited for a research environment as they both provide an established and reliable measurement platform which is ready to operate with a minimum of hardware setup and calibration. However, commercially produced hardware such as these devices is generally designed to cater for the most commonly used applications, and may not offer a great deal of freedom to the researcher to explore novel measurement techniques or operating environments. Furthermore, there is often no straightforward way to extend the functionality of a commercial system as knowledge of the inner workings of these closed and proprietary systems is not freely available.

In some cases there are severe limitations present in these devices. The most apparent limitations are related to the choice of physical sensors and form factors, as these devices are designed only to operate with the particular choice of hardware sensors that are provided by the manufacturer. A review of the current offerings from ProComp and BioPac also revealed a substantial limitation in that many types of advanced data analysis (such as the analysis of heart rate variability) were only supported in off-line processing mode.

A more thorough study of the functionality supported by ProComp and BioPac devices for EDA and HRV measures was undertaken as part of this research, to identify any issues or limitations in the way these measures are implemented. EDA measures appeared to be relatively well implemented in both platforms, although there is little room for data processing outside of a few pre-set options, and the choice of electrodes and sensor hardware is limited to those from the original equipment manufacturer.

HRV measurement, being a more complex task, had more differences in the implementation and some limitations were identified. The most significant issue with both platforms, is the fact that the associated HRV processing modules are required to function in off-line mode and in some cases require the operator to carry out extensive manual processing on the data before use [13]. This renders this measure unsuitable for a system that aims to adapt and respond in real-time.

Whilst this above limitation alone excludes the potential for use of these two devices in a real-time system, other aspects

of the platforms were also evaluated. The HRV calculation relies on blocks of data and this block size ultimately influences the resolution (and responsiveness) of the system. The ProComp unit provides a few fixed pre-sets for data block size such as 3, 5 or 10 minutes and nothing in between is permitted [14]. The BioPac technical manual indicates that other block sizes are available as the user is able to drag a selection box to bound the data on which they wish to process [15].

In terms of sensor hardware both devices suggest that a set of ECG chest electrodes is best suited for this kind of analysis. However the ProComp unit also permits a much less intrusive fingertip pulse sensor to be used for the purposes of collecting HR (variability) data [16]. Both devices are somewhat restrictive as the manufacturers typically provide only one or two options of sensor for each physiological signal, and the potential for evaluating novel form factors or sensor arrangements is severely impaired.

A final high level concern regarding the use of commercially available biofeedback hardware is that of transferability. For any findings to ultimately be applied to end user applications such as wearable and embedded devices supporting body area networks, there must be less reliance on commercial hardware, and more consideration given to the whole system and how the various components will fit together in an open architecture.

The platform described in this paper addresses several requirements. Firstly the need for real-time operation is addressed. This was considered to be an imperative requirement as the developments are to be transferrable to adaptive and autonomous systems in the future. Secondly, the need for flexibility in terms of operational hardware and environment was addressed. This was also considered to be an imperative requirement as growth and development in this area depends on the ability for research to be transferred to new environments and devices. This flexibility enabled the investigation of several sensors designs and form factors and processing algorithms.

IV. An Open Affective Platform

A high-level model for affective computing applications has been previously developed; this model, known as the Affective Stack Model, adopts a modular approach and describes the entire affective computing application as a set of loosely coupled functional components [17]. One of these components, the Affective Platform, is responsible for the acquisition of sensory data from the user, and the associated translation of this data into a usable form for other components.

The following sections describe the development and implementation of an instantiation of this Affective Platform component. This has been successfully used as a standalone platform for physiological data acquisition and processing, as well as a functional component in a larger affective computing application. This solution addresses the limitations identified within the commercially available physiological measurement platforms and provides a robust test-bed in which future studies may be conducted.

This implementation of the Affective Platform component was intended to operate in a relatively controlled laboratory setting, with a set of well-defined system interfaces. Therefore, for this implementation, a decision was made to adopt the comma separated value (CSV) format for any data log files as this presents the least complex format with minimal data requirements. However, libraries are present within the development environment to seamlessly support output in a number of open formats such as XML, as well as proprietary formats such as Excel worksheets. In general, as potential implementation environments include wearable and unwired form factors, it is desirable to ensure that data requirements are minimized and simplified where appropriate.

The IEEE 802.15 body area network standard [18] is designed to facilitate short distance low power communications within or around the human body. The use of easily interpretable and non-proprietary data formats aims to support future development by enabling the data from the Affective Platform component to be easily transmitted over a body area network by streaming over an appropriate wireless communications medium.

A. Overview

To support future studies on affective computing it was desirable to be able to relate physiological data to the various activities that the participants are performing. Therefore it was essential that the physiological measurement platform had provisions for accurate timekeeping and associated analysis. LabVIEW is a graphical programming environment that is widely used in both industry and research, and has emerged as the standard for data acquisition software [19]. LabVIEW supports many modes of data acquisition and provides functionality for advanced signal processing and manipulation. The use of this environment made it possible to combine both physiological data acquisition and signal processing into one application running on a single machine to eliminate any potential timing or data synchronization issues.

Two physiological sensors were developed in this implementation, with the intention of inferring the dimensions of arousal and valence of the participant's emotion as per the circumplex model of affect [3]. Given the vast number of potential areas of biofeedback, the selection of physiological signals to monitor was constrained by the intended future applications of the work. Firstly, one of the strengths of physiological measures of affect is the natural and objective way that data can be obtained, generally without interrupting or distracting the user from the task they are carrying out. Therefore the sensors should be both unobtrusive and not hinder normal operation of the computer. As it is desirable that future affective interfaces should potentially be invisible to the user, additional consideration was given to choose sensors that hold the possibility to be later embedded into existing hardware, such as keyboard or mouse.

Secondly, as noted above, in the interests of producing an open and easily replicable solution an attempt was made to minimize the use of specialized or costly biofeedback equipment and to utilize more generic analogue to digital conversion hardware for data acquisition. An approach to limiting the extent (and subsequent cost) of equipment is to perform as much of the work in software as possible. Thus physical hardware built was kept to a minimum to facilitate transference to new applications and environments.

B. *Physiological Measures*

Electrodermal activity (EDA) is an established indicator of emotional arousal, and fulfils the criteria of being unobtrusive, straightforward and low cost to implement. EDA measurement simply requires skin contact, with little in the way of hardware or software. Tonic (background level) skin conductance varies with psychological arousal, rising sharply when the subject awakens and rising further with activity, mental effort, or especially stress [20]. Thus an EDA sensor was developed to provide data to infer arousal.

Heart rate (HR) based measures may be used as an indicator of emotional valence. These are commonly measured using an electrocardiogram using electrodes on the chest or a chest strap. This is quite an intrusive means of physiological measurement and this detracts from its usefulness, especially for an affective computing application [21]. HR based measures commonly include basic descriptive data such as instantaneous, minimum and maximum HR and patterns of change. An issue associated with HR based measures is that HR is influenced by many outside factors in addition to affective state. Yannakakis*, et al.* [22] identified frequency domain analysis of heart rate variability (HRV) as a more suitable approach that may provide more information than the basic HR related measures. This form of analysis makes it possible to observe specific frequency bands which correspond to certain underlying processes; for example, to discern between physiological changes due to physical exertion as opposed to affective state.

It was decided to address both of these points with the development of a novel photoplethysmogram (PPG) based sensor and associated signal processing software. The PPG sensor is a typically only a few mm across and utilizes reflected light to infer measurements. This is the most unobtrusive form of sensor, and requires only skin contact to operate. Output from this sensor may then be analysed in software to perform the frequency domain analysis of HRV as mentioned above as a potential indicator of emotional valence.

The use of EDA sensors is quite well-established, and consequently the design and development of these sensors is relatively well documented (e.g. [23]). The use of HRV, in particular the frequency domain measure implemented in this platform, is much less well understood and it is envisaged that the discussion of the topic in this paper will support future research on this measure. The following sections detail the two physiological sensors. The discussion

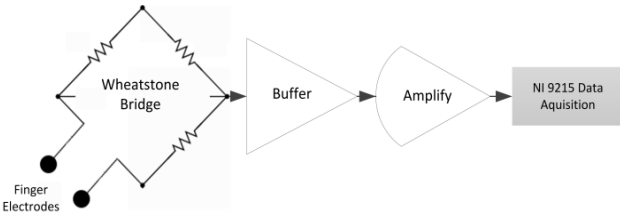

Fig. 1: Block diagram of EDA sensor

of each sensor is organized in terms of nomenclature, hardware, software and outputs of the platform.

1) *Electrodermal activity sensor*

The EDA signal is an indicator of skin conductivity and can be measured via a pair of electrodes. EDA tends to increase when a person is startled or experiences anxiety and is generally considered to be a good measure of a person's overall level of arousal [4].

a) *Nomenclature*

Conductance is usually measured in 'Siemens' (S) units. As the conductivity of the skin is very small, values are usually given in micro Siemens (μS). In measuring skin conductance, there are two types of distinguishable features, phasic and tonic ones. A tonic value is a pattern of EDA that shows a certain amount of continuity over time. The tonic component of skin conductance is called the skin conductance level (SCL). This can be thought of as a 'baseline' indication of the person's overall arousal, and this gradually changes with time. Phasic skin conductance is the type that shows changes in a short time frame, often as a response toward a specific stimulus. If a stimulus elicits a response, the skin conductance rises for a certain time period and then returns back to the normal (SCL) level. This is called a skin conductance response (SCR). Sometimes, even if no stimulus is presented there are variations in the skin conductance, these are called nonspecific skin conductance responses (NS-SCR) [24].

b) *Hardware*

EDA sensing requires a steady current to be passed between the two electrodes, and any fluctuations to be amplified to produce a clear output waveform. As the signals being measured are very small, silver-silver chloride electrodes have been identified as being suitable for this purpose as these do not polarize when current is passed through them [25]. The design of the EDA sensor hardware described is an 'instrumentation amplifier' design used in many high-gain operational amplifiers. A regulated voltage is applied across the finger electrodes which form one arm of a Wheatstone bridge. Any variations in skin conductance alter the output of the Wheatstone bridge which can be seen as a varying output voltage.

The outputs of the bridge are fed through a pair of voltage followers to buffer the output and produce a cleaner signal; this is then amplified to boost the signal to suitable levels for the data acquisition equipment to pick up. This architecture is illustrated in Fig 1. Any remaining processing and logging is done in software. The EDA amplification

circuit has been housed in a metal casing and cabling was shielded wherever possible to reduce the interference induced from power lines or nearby equipment which may introduce artifacts in the output waveform.

Initial tests revealed an unacceptably high level of noise, to the extent that the signal was being obscured to an unusable level. The source of the noise was narrowed down to switching noise generated by the AC-DC power supply in use. This was replaced with a rechargeable Ni-Cd DC battery pack to ensure a stable DC current. A test with the actual sensor using a fixed resistance in the place of finger electrodes showed a stable output with high accuracy of +/- 2mV which is several orders of magnitude smaller than the signals being observed.

A further observation during initial testing was that the output of skin conductance values was nonlinear at electrode voltages higher than 1V. Therefore the electrodes were operated with a voltage of 0.5V to keep the results consistent. A survey of published recommendations for electrodermal measurements confirmed that 0.5V is the most suitable voltage to implement [25-27].

c) Software

Data was sampled from the hardware sensors using a National Instruments NI9215 16 bit data acquisition device using LabVIEW development system software. Sampling was carried out at 1,000 samples per second (1 KHz) for initial processing, and this was later down sampled as the low frequency signals being measured did not call for such a high sample rate. The main software tasks were to acquire this signal and to 'clean' up the input signal with filters before committing it to storage. During development of the software component, data from initial test runs was studied to evaluate the quality of the data acquisition and physiological recording.

Radio frequency (RF) interference presents a challenge for the accuracy of data acquisition, and this is particularly significant if the signals being measured are of a small magnitude to begin with. The equipment and cabling was well shielded, however pilot testing revealed that noise was being picked up and appearing in the recorded data. Spectral analysis revealed that most of this noise was in a specific frequency band, with a strong component of 50-60Hz AC 'hum' induced from nearby power lines. A low pass filter was then developed to attenuate this noise. Since the baseline voltage from the sensor was the only feature of interest, a third order Butterworth low pass filter was implemented with a cut off frequency of 4Hz. This yielded a favourable output wave form which would be useful for logging and analysis. Given that the data of interest was slow changing (sub 4Hz frequency), the 1 KHz sample rate would produce more data points than required for future analysis, therefore sample compression was used to reduce

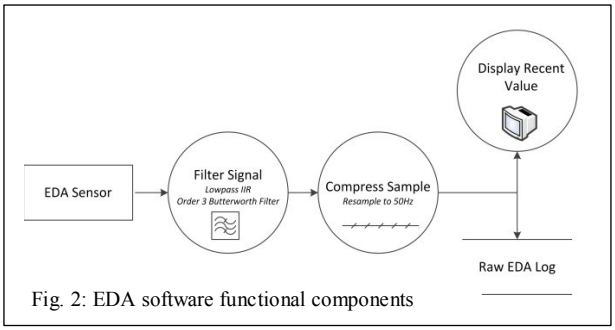

Fig. 2: EDA software functional components

the number of data points before logging these values to disk.

The down sampled rate of 50 samples per second was still higher than strictly required but in the interests of maintaining a high resolution picture of the input data for future analysis, this sample rate was selected as the 'soft' limit, and a provision was made in software to enable the operator to easily adjust the sample rate should the need arise at run time. The main functional software components are illustrated in Fig. 2.

d) Processing and output

The software created a visual output which was suitable for calibration and real time monitoring, as well as a log file (termed 'Raw EDA Log' in Fig. 2). Graphical output consisted of a real time display of the sensor output as well as a timeline plot to display trends over a user specified time period. The visual display was invaluable when setting up the equipment and also when developing the filtering mechanisms for noise and error rejection.

The output streamed to file consisted of a series of timestamps and the 5 data points that were taken since the previous output timestamp. Graphical output was also provided to plot the signal over an extended period. This made it possible to visually identify any areas of interest within the data or any possible errors caused by movement of the sensors.

As the relation between the bridge output and the unknown resistance is well understood and described by circuit laws [28], it is possible to translate the 'Raw EDA Log' output into actual skin conductance values. This enables the sensor output to be converted into an actual value for skin conductance in either real-time or offline modes depending on implementation requirements.

2) Photoplethysmogram

The PPG provides a measurement of arterial blood flow, inferred from light absorption rather than electrical activity. In a clinical environment, a common application of this technique is to measure blood oxygenation using a pulse oximeter. This works by comparing the ratio of light absorption at two different wavelengths. For the purposes of this research, data about blood oxygenation was not required. Instead the desired output was a clear waveform corresponding to the blood flow in under the sensor. Furthermore, in order to make the device as unobtrusive as

possible, a reflectance configuration was used whereby the light is measured as it reflects off the skin rather than passing through. This enabled the construction of a sensor which required contact only on one side of the fingertip.
The output waveform from this sensor follows the flow of blood in the fingertip, and peaks and troughs correspond to the heart beats. From this output waveform post-processing was carried out to extract the HR and HRV.

a) Nomenclature

The PPG produces a sinusoidal waveform output which corresponds to the light absorbance of blood flowing beneath the sensor. Within this waveform are several peaks, the strongest of which may simply be thought of as a representation of one heartbeat. This peak is labelled P, and for the purposes of calculating HRV this may be used in the same way as the main (R) peak of an electrocardiogram [29]. As the PPG peak is being used as an analogue for the electrocardiogram peak, the remainder of this paper will continue to refer to R to remain consistent with the published literature as this traditionally refers to electrocardiogram data.

For HRV the interval between successive beats is measured, this is known as the RR interval. If the variance is expressed in terms of the power spectral density function (PSD), this gives an absolute value of power (variability) in units of milliseconds squared. PSD simply indicates the distribution of signal power in the frequency domain. Therefore the total HRV is equal to the total power given by the PSD function, and may be considered analogous to the variance of the intervals between heartbeat events. However, using the PSD function to observe variability allows a finer level of understanding of the underlying factors contributing to the changes in heart rate. This is done by decomposing the PSD result into certain frequency bands of interest.

b) Hardware

For this PPG implementation, the reflectance method was adopted in which the light source and receiver are positioned in the same plane. The main advantage of this being that a single flat surface sensor may be physically positioned in a multitude of ways.

It has already been demonstrated that the reflectance method may be used to gather sufficiently accurate data to infer frequency domain information such as breathing rate [30] or HRV [31] and it is therefore a suitable approach to implement.

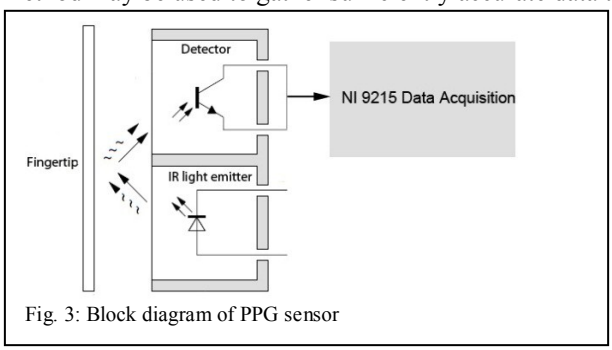

Fig. 3: Block diagram of PPG sensor

The complexity of the sensor hardware was deliberately minimized where appropriate and the majority of the work was done in software. The sensor was based around a Vishay TCRT1000 reflective optical sensor with transistor output [32]. The TCRT1000 has a compact construction where the emitting light source and the detector are arranged in the same direction to sense the presence of an object using the reflective infra-red beam from the object. A regulated 12V supply is fed to the light emitter portion of the TCRT1000, reflected infra-red light is picked up by the detector and the output is switched by the variations in this light source.

The operating wavelength is 950nm and the detector consists of a photo transistor. This made it suitable to be used as a PPG as the light level (and thus the voltage output by the phototransistor) changes as the blood is pumped by the heart. A block diagram of the main functional hardware components is given in Fig. 3.

c) Software

The output voltage supplied by the TCRT1000 provides the input into the National Instruments NI9215 data acquisition device. Data is sampled at 1 KHz and the resulting waveform is conditioned to make it suitable for analysis. The first step was to remove noise and interference from nearby mains power lines. As the signal of interest is a periodic signal corresponding to a human heartbeat it was appropriate to use a band pass filter and reject all signals that lie outside a specific range of frequencies. A second order Butterworth infinite impulse response filter was implemented with a lower cut off frequency of 0.7Hz and an upper cut off frequency of 5Hz. This yielded a clean signal suitable for logging and later analysis. The resulting signal is a sinusoidal waveform with peaks corresponding to heart beat events.

As the timing of heart beats is the primary data of interest, a peak detection mechanism was implemented to be triggered whenever an R peak occurred in the waveform. To make the peak detection more robust against noise, any peaks which lasted for under a threshold of 3ms were excluded. Each time the peak detector was triggered, a timestamp was taken from the computer's internal millisecond timer. This was compared to the timestamp taken when the software was first run to generate a list of the points (in seconds) when heart beats occurred. From this point on, the array of heart beat timestamps could be used to perform any future calculations without having to process the input waveform any further. This had the dual benefit of increasing processing speed (as real time signal processing tasks are very CPU intensive), whilst also allowing the raw data to be logged to file unaltered for future analysis and study.

As a PPG can be somewhat sensitive to movement or false readings, steps were taken to improve the reliability of the peak detection routine. Initial results from piloting the equipment indicated that errors were not being introduced by inaccuracies in the measurement but rather when one beat was picked up twice by the peak detection algorithm.

This was easy to flag in the data set as the RR interval would be 10 to 20 times smaller than previous values and could easily be 'trimmed' by software processing.

To address this potential issue, a feedback loop was created in which descriptive information about the history of HR data acquired during the session is used as an input to the peak detection routine – this allows the routine to anticipate the expected range of input readings, and reject any spurious readings which do not fall in this range. These 'HR Statistics' were created by first averaging the last 10 RR intervals, after trimming outliers that were over 50% higher or lower than the previous reading. This result was then used to calculate a heuristic upper and lower bound for 'realistic' fluctuations in the input data set. Analysis of actual data sets from pilot testing indicated that beat to beat changes in RR interval were generally of small magnitude of only a few percent. Therefore the heuristic upper and lower bounds were set at 35% higher and lower than the average HR as recorded over 10 previous beats.

As this cutoff value is several orders of magnitude greater than the range of normal HR variations, it does not pose the risk of excluding any real data; however it is still sensitive enough to pick up the errors. Implementation of this feedback loop into the peak detection routine enabled it to discard any values outside the expected range from the data set. To validate this further, detailed logs were kept by the software during its normal operation. These revealed that in most of the trials, the automatic trimming feedback loop was not triggered at all, indicating that the measurement technique was already quite sound. In the few cases where the trimming feedback loop was triggered, the errors did not make their way into the final data set. The resulting array of RR interval data is then streamed to a disk file for later re-use by routines to derive HRV or other statistical data. This processing may be carried out off-line or in real time depending on the configuration of the software. An overview of the functional software components is detailed in Fig. 4.

d) Processing and Output

Output data from the PPG (termed 'Raw HR Log', in Fig. 4) consists of a list of time values (in seconds) at which R peaks were detected. This data may be subjected to various types of manipulation to derive features of interest. The manipulation of the output data may be divided into time and frequency domain processing methods and these are discussed in the following sections.

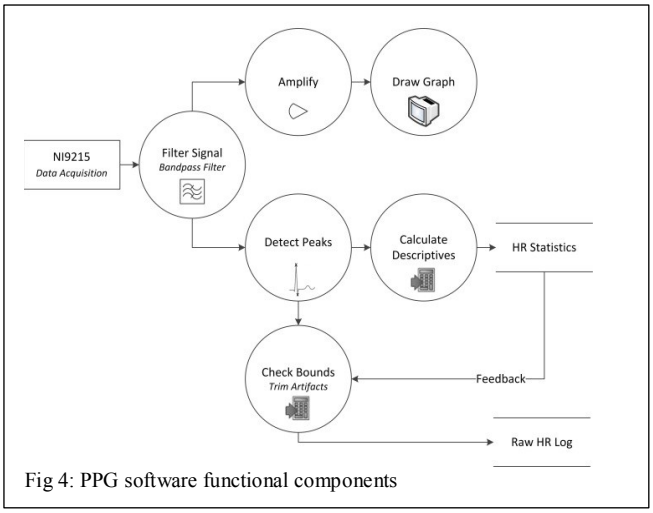

Fig 4: PPG software functional components

Simple time domain measures include the heart rate or the intervals between successive beats. This information can then be used to calculate other values of interest including the mean RR interval, mean HR and variance. Statistical measures can also be determined from this data.

HR was calculated using a moving average technique, similar to many commercially available pulse oximeters. As the instantaneous heart rate calculated from a single beat (current RR interval / 60) proved to be erratic and subject to rapid fluctuations, the averaging technique results in a more robust measure. This is at the expense of some response time, as any sudden changes in HR will not be apparent until they have persisted for long enough (typically a few seconds) to influence the running average being displayed.

Another basic measure of HRV is the standard deviation of the RR intervals, that is, the square root of variance. Since variance is mathematically equal to total power of spectral analysis, this measure reflects all the components responsible for variability in the period of recording [33].

Akselrod, Gordon, Ubel and Shannon [34] introduced power spectral analysis of HRV to quantitatively examine various components contributing to cardiovascular control. PSD analysis gives information about how power (or variance) is distributed as a function of frequency. This makes it possible to observe how the variance is being exhibited in certain frequency bands making it possible to discriminate between variance from different causes, such as rate of breathing, or exertion, or mental effort [33]. A block diagram of the steps involved in converting the Raw HR Log output from the sensor into a value for HRV is given in Fig. 5.

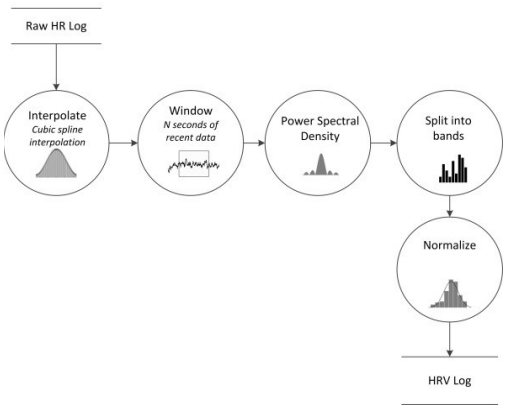

Fig 5: Frequency domain processing of HRV

The first step is to interpolate the data, to obtain a data set that is evenly spaced in the time domain. The Raw HR Log contains an array of RR intervals, this is an unevenly sampled plot with samples occurring whenever a heartbeat event occurs, and is unsuitable for frequency domain analysis. To make frequency domain analysis possible, this data was transformed into an evenly sampled time series by resampling and interpolation using the cubic spline method. This yielded a continuous signal as a function of time which is suitable for mathematical analysis of frequency components such as the Fast Fourier Transform (FFT). The sampling frequency (of interpolation) is deliberately kept sufficiently high so that the Nyquist frequency of the spectrum is not within the frequency range of interest.

The plot of RR intervals is sparse and consists of unevenly spaced data points that correspond to when heart beats occurred (i.e. at 0.6, 1.1, 1.7, 2.3 seconds into the recording). By resampling at evenly spaced points (e.g. 0.1, 0.2, 0.3, 0.4 seconds) and using the spline method to interpolate between these values, the plot may be transformed into a smooth curve. Data in this form is then suitable for spectral analysis, including the FFT and PSD functions.

The next step is to window this input data to obtain a subset of the recording that will be used for the subsequent analysis. As the total variance increases with the length of analyzed recording [35], this step is essential to ensure that the readings taken at different points are comparable. The window size (or sampling period) is adjustable in software, however a default setting of 100 seconds was used in this implementation.

As the subset of data being extracted will later be used for spectral analysis via FFT and PSD calculations, it is essential that a suitable windowing technique is employed. The FFT transform assumes that the data set provided is periodic in nature, and the endpoints of the waveform may be interpreted as though they are connected together [36]. If the input waveform is truncated, then this discontinuity would cause spectral leakage whereby the edge effects of the truncated waveform would be evident in the power spectrum. This effect is minimized by the use of a windowing function. In this implementation, a Hanning window [37] was used. This makes the endpoints of the waveform meet and therefore results in a continuous waveform without sharp transitions. This waveform may then be passed directly to the PSD function with no further pre-processing. The output of the PSD function is commonly viewed in several specific frequency bands; these correspond to activity in various branches of the autonomic nervous system. A list of the frequency domain measures is detailed in Table 1.

TABLE 1 Frequency domain analysis of HRV

Variables	***Units***	***Descriptions***
Very low frequency (VLF)	ms^2	Power from 0–0.04 Hz.
Low frequency (LF)	ms^2	Power from 0.04–0.15 Hz.
High frequency (HF)	ms^2	Power from 0.15–0.4 Hz.
LF Norm	n.u.	LF power in normalized units: LF/(Total Power–VLF)*100.
HF Norm	n.u.	HF power in normalized units: HF/(Total Power–VLF)*100.
LF/HF Ratio		LF [ms^2]/HF [ms^2].

As can be seen in the table, the Low Frequency (LF) and High Frequency (HF) components may also be represented in normalized units; this minimizes the influence of changes in total variance on the values of LF and HF. When spectral components are expressed in absolute units, the changes in total variance influence LF and HF in the same direction and obscure any changes in the fractional distribution. For example, the effect of certain drugs reduces both LF and HF components. Because of the reduction in total power, LF appears to be unchanged if considered in absolute units. However normalization makes this change more apparent [38]. Thus the provision was made in the software to produce normalized values wherever possible in addition to the other components.

Frequency domain analysis has the advantage of observing activity in specific areas as opposed to viewing the total variance in the sample. Thus, it is also somewhat resistant against being influenced by errors outside the frequency band of interest. For example, initial tests demonstrated that the sampling artifacts introduced by noise or by false readings had a large impact on the Very Low Frequency (VLF) band of the spectral analysis (simply because the artifacts were uncommon but large in magnitude). However, the normalized low frequency score which was being observed proved to be quite robust against the potential errors as it was not affected by changes in the VLF component.

V. CONCLUSION

This paper has described the development and implementation of an open affective platform. This platform has the provisions for physiological data acquisition (from

the user), processing and analysis and finally communication to make this information available to other applications. This approach has addressed the shortcomings identified with the use of commercially available platforms. In particular, this platform brings the flexibility to make dramatic changes and improvements in all aspects of the way in which physiological data is acquire, stored and transmitted.

The experimenter is free to use any types of sensor hardware or physical interface to the user; internally the way in which the data is processed is also not constrained to a few pre-set routines, but completely customizable. For example, the feedback loop described in the HR processing section of this implementation is a refinement that would not have been possible had an open environment not been used. The solution is also not constrained to any specific data acquisition hardware and the solution may be modified to accommodate various platforms. Indeed, a separate and complementary area of research currently being undertaken aims to evaluate alternative data acquisition solutions with the objective of establishing the most low cost and widely available platform in the hope of encouraging growth and developments in this field.

The affective platform described in this paper has been used successfully in over 80 data collection sessions. The flexibility of this implementation has made it possible to evaluate many aspects of data acquisition and processing and test many variables that would not have been possible without full control over the measuring environment. The ability to perform real-time analysis of certain frequency domain HRV measures as indicators of affective valence is a substantial step forward and improvement over currently available physiological data processing environments. This platform is one functional component of a complete affective application model. The proposed model aims to streamline and support the development of affective computing applications and make these more accessible to the wider community of developers. Future research will build upon the strengths of this platform and associated model and iteratively incorporate new capabilities. Of particular significance is the transference of these technologies into more widely accessible physical interfaces, such as portable or wearable devices. It is hoped that these developments will stimulate growth and development in the field of affective computing - an area that holds promise to play a pivotal role in the development and design of the next generation of computer interfaces.

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