BVP Signal Feature Analysis for Intelligent User Interface

Simon Luo
Data61, CSIRO and HIT Lab
Australia, University of Tasmania
13 Garden St. Eveleigh NSW
2015 Australia
simon.luo@data61.csiro.au

Henry Been-Lirn Duh
Department of Computer
Science & Information
Technology La Trobe University
Melbourne, Victoria, Australia
b.duh@latrobe.edu.au

Jianlong Zhou
Data61, CSIRO
13 Garden St. Eveleigh NSW
2015 Australia
jianlong.zhou@data61.csiro.au

Fang Chen
Data61, CSIRO
13 Garden St. Eveleigh NSW
2015 Australia
fang.chen@data61.csiro.au

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Abstract
The Blood Volume Pulse (BVP) sensor has been becoming increasingly common in devices such as smart phones and smart watches. These devices often use BVP to monitor the heart rate of an individual. There has been a large amount of research linking the mental and emotional changes with the physiological changes. The BVP sensor measures one of these physiological changes known as Heart Rate Variability (HRV). HRV is known to be closely related to Respiratory Sinus Arrhythmia (RSA) which can be used as a measurement to quantify the activity of the parasympathetic activity. However, the BVP sensor is highly susceptible to noise and therefore BVP signals often contain a large number of artefacts which make it difficult to extract meaningful features from the BVP signals. This paper proposes a new algorithm to filter artefacts from BVP signals. The algorithm is comprised of two stages. The first stage is to detect the corrupt signal using a Short Term Fourier Transform (STFT). The second stage uses Lomb-Scargle Periodogram (LSP) to approximate the Power Spectral Density (PSD) of the BVP signal. The algorithm has shown to be effective in removing artefacts which disrupt the signal for a short period of time. This algorithm provides the capability for BVP signals to be analysed for frequency based features in HRV which traditionally could be done from the cleaner signals from electrocardiogram (ECG) in medical applications.

Author Keywords
Blood Volume Pulse; Heart Rate Variability; Heart Rate; Signal Processing; Cognitive Load; Intelligent User Interface

ACM Classification Keywords
H.5.m [Information interfaces and presentation (e.g., HCI)]: Miscellaneous

Introduction
Research has found that changes in various physiological states are closely related to human physical, mental, and emotional changes [2, 14]. For example, the physiological approach has been intensively investigated for cognitive load measurement [2], which assumes that any changes in the human cognitive functioning are reflected in the human physiology. One major advantage of physiological measures is the continuous availability of bodily data, allowing human mental or emotional states to be measured at a high rate and with a high degree of sensitivity. It has wide applications ranging from our daily activity such as monitoring an individual's health [10] and emotions [12], to more domain specific task such as monitoring stress levels of an individual when performing stressful activities (e.g. driving a car [6], and monitoring the cognitive load or user confidence in decision making [21]). Various physiological signals have been widely investigated for such purposes, which include Galvanic Skin Responses (GSR), pupil dilations, and heart rate [2]. Furthermore, recent research in Human-Computer Interaction (HCI) tend to use various low-cost non-invasive sensors for wide HCI applications [13, 14]. In particular, with the advancement of mobile communication technologies such as smart phones and smart watches, it is highly expected to use widely available mobile sensors in the monitoring of human physical, mental, and emotional changes.

The Blood Volume Pulse (BVP) sensor is one of the typical sensors available in most modern mobile devices. It can be used to monitor human Heart Rate (HR) or Heart Rate Variability (HRV). There has been extensive research in investigating the correlation between the HR, HRV, and Respiratory Sinus Arrhythmia (RSA) changes with the mental and emotional state of an individual [8]. For example, the HR and HRV are used to measure cognitive load in conducting cognitive tasks [15, 16, 9]. The BVP sensor has the advantage to be a user-friendly method to obtain an individual's HRV compare to other methods such as electrocardiogram (ECG) which are used in medical settings [18]. ECG are cumbersome and not easy to use, as it requires electrodes to be attached to the chest of the subject. This makes it quite impractical to use in everyday activities. The BVP sensor uses a light to illuminate the skin to measures changes in blood volume in arteries and capillaries to obtain the HRV which makes it much more convenient to use compared to ECG [18].

However, the HRV information obtained through the BVP sensor often contains noises and artefacts because of different factors such as missing samples, movement of the sensor and the external environment. These noises and artefacts in the signal could be problematic when analysing frequency based features in the signal such as RSA [18]. Due to the large number of noises and artefacts in the signal, this makes it difficult to use the BVP to measure any frequency based features such as RSA activity for any application.

Various methods have been proposed to remove noise and artefacts from signals. A typical method is using a linear filter to remove the corrupt signal. However, the corrupt signal created by the sensor movement does not have a distinct frequency profile, thus making it difficult to filter. Another

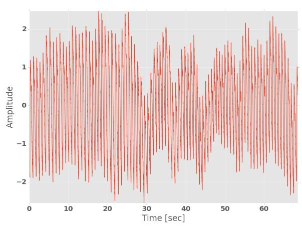


Figure 1: Noiseless Signal.

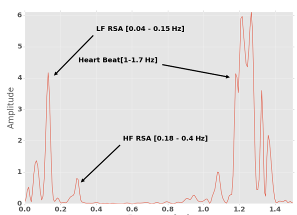


Figure 2: The PSD of a HRV signal.

commonly used method is an adaptive filtering [20]. These techniques are only effective if the noise is Gaussian, as it attempts to produce an optimal solution by minimising the mean squared error. However, the movement artefacts created in the BVP signal are not Gaussian and generally several order of magnitudes larger than the BVP signal (see Figure 3). This makes it difficult for adaptive filter techniques to remove artefacts created by movement.

This paper proposes an algorithm to analyse the frequency based features in BVP such as RSA which may be difficult to process due to artefacts in the signal. The algorithm consists of two stages, the first stage is to detect and remove the artefacts from the signal. The second stage is to estimate the Power Spectral Density (PSD) of the signal with missing data. The advantage of this algorithm is that it does not require the corrupted signal to be predicted or restored but to use regions which are considered to be the error-free signal to estimate the overall PSD of the BVP signal.

Background

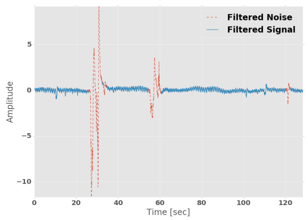
Figure 1 shows a typical signal detected by the BVP sensor, the PSD of the HRV contains three major components as indicated in Figure 2: the heart beat, high frequency RSA and low frequency RSA. The heart beat can be seen as the most dominant component which usually occurs between the frequency ranges of 1 and 1.7 Hz, and correlates to about 60 to 100 beats per minute. The two lower frequencies are considered to be a quantitative method to measure RSA. RSA refers to the periodic fluctuations in the rates which are closely linked to breathing. The Higher Frequency (HF) component of RSA ranges between 0.18 to 0.4 Hz which is mediated by the vagus nerve. The second Low Frequency (LF) component which ranges between 0.04 and 0.15 Hz is mediated by both the vagus and the cardiac sympathetic nerves [10].

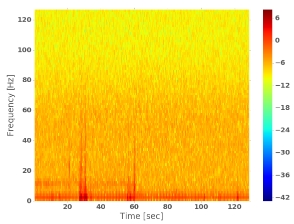
There have been a large amount of studies which use RSA to attempt to classify an individual's health or mental state. For example, Kristal-Boneh et al. [10] used RSA to predict patients at risk of heart diseases. Healey and Picard [6] had successfully found the physiological links between the RSA and drivers' stress level. Bulter and Wilhelm [1] has found links between RSA and emotions during social interactions. These previous studies have shown that there is a link between the mental state and changes in RSA. These research in finding the correlation between health and mental state have largely been analysed manually. While the work by Nilsson and Funk [17] have designed an automated system to classify RSA in real-time.

Most research in HRV in the past have been using ECG sensors, which often produce much cleaner signals and are less susceptible to noise introduced by external factors. However, ECG sensors are rarely used outside of medical settings as it is less user friendly and it requires electrodes to be attached to the user's chest. Being able to classify BVP signals would provide a non-invasive method to measure HRV in our everyday activity. This would allow BVP sensors in mobile devices such as smart phones and smart watches to not only measure the heart rate, but also the RSA activity. This allows us to have a quantitative measure of our mental state at any moment in time.

Methodology

This section introduces the algorithm to detect and remove artefacts in the BVP signal and then approximate the PSD with missing data. To detect the artefacts in the signal, a spectrogram is created to calculate the power at a given time of a signal. A moving standard deviation is then used to detect any artefacts in the signal. Once the artefacts are removed from the signal the PSD can then be estimated using a least square spectral analysis method.





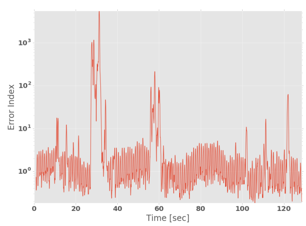


Figure 5: Error index of the BVP signal

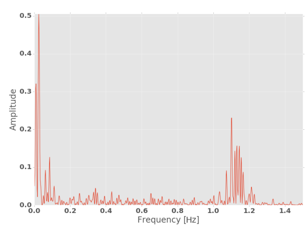


Figure 6: The estimated PSD using the LSP method of the filtered signal.

Let $s(t)$ be the observed signal with the corrupted data segments. Figure 3 shows that the corrupt sections of the signal have much larger amplitude compared to the desired signal. This trait can be seen common to all corrupt BVP signals. Therefore the corrupt signal can be identified by detecting sections of the signals with much larger amplitude. A method to detect these anomalies is to use a spectrogram. A spectrogram can be constructed by applying a window to the signal, then applying a STFT to every segment of the signal.

$$X(n,\omega) = \sum_{m=0}^{N-1} x(m)w(n-m)e^{-2\pi jkn/N} \tag{1}$$

A Hanning window of twice the expected heart rate is applied with the STFT to filter all the high frequency noise. Figure 4 shows the spectrogram of the signal shown in Figure 3. Figure 4 shows that the corrupt data has a very distinct profile, with a much higher amplitude across most frequency ranges. The corrupt data can then be detected by calculating the power of the signal at each window. This can be done by summing the amplitude of the signal at each time across all frequencies as shown in Figure 5.

Figure 5 shows that the corrupt signal has higher power. A moving standard deviation is applied to the signal to detect any region of the signal with much larger power. The same window length chosen to create the spectrogram is used for the moving standard deviation. The amplitude of each STFT can be added together to create an error index. This error index can be seen as a scalar multiple of the power at each STFT. A standard deviation of a cut off power is then determined by analysing noiseless BVP signals. This was determined to be $\chi = 10$. The artefact-free signal can then be expressed as Equation 2.

$$\tilde{s}(t) = \{s \in s(t) | s < \chi\} \tag{2}$$

The artefact-free signal ($\tilde{s}(t)$) can then be used to approximate the PSD by using Lomb-Scargle Periodogram (LSP). The corrupt data can be treated as missing data points. The PSD at frequency ω can be approximated using Equation 3 [11].

$$P_{LS}(\omega) = \frac{1}{2\sigma}\left\{ \frac{\left[\sum_{k=1}^{N}(x_k - \bar{x})\cos\left(2\pi\omega(t_k-\tau)\right)\right]^2}{\sum_{k=1}^{N}\cos^2\left(2\pi\omega(t_k-\tau)\right)} + \frac{\left[\sum_{k=1}^{N}(x_k - \bar{x})\sin\left(2\pi\omega(t_k-\tau)\right)\right]^2}{\sum_{k=1}^{N}\sin^2\left(2\pi\omega(t_k-\tau)\right)} \right\} \tag{3}$$

where the time delay (τ) can be defined as Equation 4.

$$\tan(2\omega\tau) = \frac{\sum_{k=1}^{N}\sin(2\omega t)}{\sum_{k=1}^{N}\cos(2\omega t)} \tag{4}$$

The PSD from applying the LSD can be seen in Figure 6.

Results

The robustness of the algorithm outlined in the methodology section is tested by manually picking 9 error-free signals. The length of these signals ranges from 53.1 seconds to 101.3 seconds as shown in table 1. A large noise is added to the signal to corrupt the data by superimposing noise data created by movement artefacts onto the error-free signal. The size of this noise is varied from 0 to 30 seconds to determine the robustness of the algorithm. An Euler integration is used to calculate the Autonomic Balance (AB) which is the ratio between the LF and HF components of RSA for all signal. The relative error is then calculated and plotted against the length of the missing samples. The results are shown in Figure 7.

The error of each signal is calculated, then the mean and standard deviation of the error are calculated for all signals

Data Collection
To collect the BVP signals, a scenario was developed, where the participants conducted different predictive decision making tasks with different prediction probability presentations. The participant was also requested to remember a three, five, seven or nine digit number before performing the task and recall the number after the task in order to induce a cognitive load [3]. These tasks were used to introduce variations in the BVP signal. The BVP sensor was attached to the middle finger on the left hand. The participant was allowed to use their right hand to use the mouse to select their options during task time. An on-screen keypad was used to receive the input of the numbers. Instructions were given to the participant to have minimum movement on their left hand to reduce the number of artefacts in the signal created by movement.

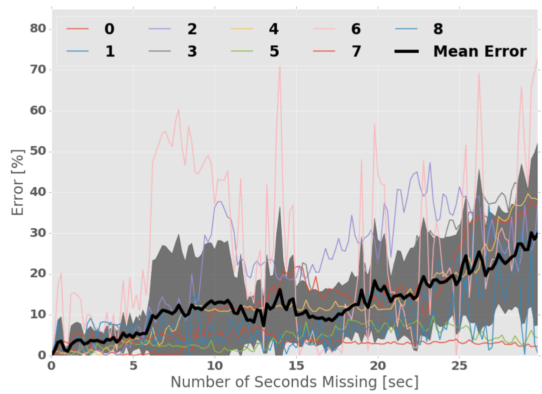


Figure 7: Data quality check to measure the ratio between the low frequency and high frequency component of RSA.

Table 1: The length of each signal used in the data quality test

Signal Number	0	1	2	3	4	5	6	7	8
Signal length [sec]	68.7	53.1	57.5	72.5	75.3	86.0	51.6	101.3	88.7

for each missing samples. Figure 7 shows that the algorithm has a mean error peaking at 5.5% and a standard deviation of 5.5% when the corrupt segment is shorter than 5 seconds. However, the standard deviation increases after 5 seconds which may make it difficult to determine the quality of the data. The percentage of length missing from the signal may also contribute as a factor of the data quality. The algorithm produces a less accurate solution for shorter signals such as signal 6 and signal 2. While longer signals such as signal 7 tend to have less error. However, it is difficult to take both the absolute time and percentage in time in consideration. Since the features of the RSA signals are considered to be low frequency, the signal is usually assumed to be longer than 50 seconds. Therefore the absolute time was determined to be the method used to measure the data quality.

Discussions
The algorithm proposed in this paper identified sections of signals which have large changes. These changes are outside of the frequencies which are known to be associated with HRV by using a spectrogram. This is much more effective than using a linear filter, as linear filters are not able to remove all of the noise created by an artefact. A linear filter only filters the signal at each frequency rather than each time step. This approach would leave some residuals of the artefact as they may occur at the same frequency as the HRV signal. The proposed method uses a spectrogram to obtain a time series representation of the frequencies. This approach removes the entire section of the signal in the time domain which may be corrupted by an artefact created by movement of the user. However, the best method to reduce the number of artefacts in the signal is to minimise the number of factors which create artefacts in the signal. These include ensuring that the sensor is properly and tightly attached to the surface of the skin and minimise the amount of movement where the BVP sensor is located.

By combining the noise detection algorithm with the LSP algorithm, the proposed algorithm is much more effective compared to traditional methods such as FFT and Welch as they have the assumption that the signals are sampled equally spaced in time. The spectrogram provides the time-frequency domain relationship. This relationship allows the entire corrupt signal to be removed in the time domain. This could not be done with the traditional methods such as linear filtering, FFT and Welch's method. When the artefacts are removed from the signal, the LSP allows the PSD to be approximated using a least squares method.

The proposed method has wide applications such as in the IUI design and HCI. One such application is dynamic workload adjustment, software could be developed to dynamically update the task such that it is best suited for the user. In such applications, BVP can be used to measure user cognitive load in real-time [7]. The proposed algorithm can handle more noisy BVP signals for cognitive load measurement. Furthermore, the proposed algorithm can also be used in other human mental state measurement (e.g. user confidence in decision making). Such measurement can be integrated into an IUI where human mental states can be revealed in real-time. BVP has been already widely available on most smart phones and smart watches to monitor the heart rate of users. As this algorithm provides the capability to process noisy BVP signals, these applications could be further extended to monitor the user's emotion and health in real time.

Ongoing Work

Our ongoing work focuses on comparing the algorithm with existing methods in different situations. Currently there are a number of existing techniques to remove the noise which uses adaptive filtering techniques which can be seen in [19, 5, 4]. These techniques often use additional hardware such as accelerometers and strain gauges to assist in removing the artefacts created by movement. A comparison of these techniques can be made in different situations such as running, driving and undergo stressful conditions such as an exam to see how each of the algorithms perform. If successful the proposed algorithm provides a method to provide an approximation for HRV and RSA for an off the shelf BVP sensor without using additional hardware such as accelerometers and strain gauges.

Conclusion and Future Work

This paper proposed an algorithm capable of processing BVP signals which contain artefacts in signals. These artefacts usually make it difficult to process the frequency based features in HRV as the artefacts in the signal is usually orders of magnitude larger than the features in the PSD. This algorithm is in particularly effective in analysing low frequency features in HRV such as RSA when a signal is disrupted for a short period of time. When analysing AB for signals which are longer than 50 seconds, the AB can be estimated with a mean error of 5.5% and a standard deviation of 5.5% if the corrupt section is less than 5 seconds long. However, if the signal is longer than 5 seconds, the standard deviation of the error increases. This algorithm provides the capability for BVP sensors to analyse frequency based features which previously can only be done with ECG sensors.

The capability to approximate RSA features from HRV signal of BVP paves the way for research into BVP sensors to monitor our mental state on mobile devices such as smart phones, smart watches and IUI. There has been a number of studies which have found correlations between physiological features such as RSA to the mental state such as stress and emotion of an individual [10, 6]. Some future work includes implementing methods which can be used to classify the emotion, health and fitness level of an individual by using machine learning algorithms which can be developed to process the BVP signal. These algorithms can be further be implemented in mobile devices on monitoring human mental states.

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