Mental Stress Assessment - A Comparison Between HRV Based and Respiration Based Techniques

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Abstract

Quantitative mental stress measurement is becoming important due to increasing stress in daily routine. There are many academically used methods based on Heart Rate Variability (HRV) for measurement of stress, yet the sensitivity of these methods is questioned in real life setting.

Inhalation and exhalation during breathing is related to the sympathetic (SNS) and parasympathetic nervous system (PNS) balance. Stress being the disturbance of the SNS and PNS, changes the patterns of breathing. In this paper we present a comparative study of stress measurement methods including a novel respiration based method and their dependency on factors such as health condition. Data was collected from a population of 253 subjects using wearable sensors.

1. Introduction

Chronic stress is a well-known cause of a range of health problems such as hypertension, diabetes, cardiovascular disease, gastrointestinal problems, mood disorders, substance abuse etc. To manage and monitor such disorders, it is essential to have effective methods to measure acute/chronic stress.

Several methods for measuring stress have been proposed including Heart Rate Variability [1], [2], salivary cortisol, questionnaire, facial expressions, pupil diameter, voice analysis, skin conductance and skin temperature. Though there has been a lot of research on methods to quantify stress, the relative performance of those methods is still debated. Many of these methods exhibit limited sensitivity and accuracy.

The most widely used methods are based on Heart Rate Variability (HRV). HRV is calculated form ECG or photoplethysmography or impedance-plethysmography. HRV measurement can be based on both time domain and frequency domain approaches. The most prevalent HRV based methods are pNN50, SDNN, SDANN and RMSSD [3] in the time domain and LF-HF method in the frequency domain [2].

1.1. Limitations of current methods

Time-domain methods are computationally simple and robust under artifacts but, they lack the ability to discriminate between complex physiological etiologies to HRV such as relative contribution of various components of autonomic nervous systems (sympathetic and parasympathetic) [4].

Spectral analysis via LF/HF has been shown to be more sensitive and descriptive but has extremely low resilience to artifacts, especially in the HF part of the spectrum [5]. They also require longer measurement epochs that hamper their applicability to acute forms of stress. There are also several contradictory results such as in [2], [6], where it is established that LF/HF directly correlates to stress, while in [7] no particular correlation was observed between such a measure and the short-term stress.

There are several contradictory results reported which needs a thorough comparison. We present a novel respiration based method and a comparison against HRV methods. This study was done using wearable sensors that can be deployed for long term monitoring.

1.2. Beyond HRV: Respiration based method

Controlled or deep breathing is a well-known method for stress reduction [8]. The relation between the inspiration/expiration and SNS/PNS are well known. Stress can also be defined as a disturbed balance of (Sympathetic Nervous System) SNS and (Parasympathetic Nervous System) PNS, which should reflect in the breathing patterns, given the person is not doing controlled breathing.

The motivation of the respiration-based stress measurement technique is the interesting correlation between breathing and mental stress [8]. The duration of inhalation-exhalation and ventilation directly affect the SNS and PNS balance, thus affecting stress [10]. During stress, the breathing becomes fast, deep and irregular. This can be distinguished from the normal breathing which is rhythmic and normal paced in absence of physical stressors like exercise. The changes in breathing rate and HRV is well known[10], but the stress induced changes in breathing are more than just the breathing rate.

During stress, both the rhythm and the amplitude of the breathing get disturbed. We use the changes in the spectral power of the breathing as a means to detect this disturbance and correlate with stress. We present protocol and outlines of a study on 253 subjects whose stress was measured in a carefully controlled setting via analysis of data collected by sensitive but readily available mobile sensors. Variation in detected stress (due to diseases) for HRV based methods is discussed and same analysis is shown for respiration-based method.

2. Methods

2.1. Subject Population

This study was approved by the Birla Hospital and Research Center Ethics committee at Satna, India. Informed consent was obtained from all subjects participating in the study. The target population for this study was males belonging to healthy category. The sample was distributed such that the study was not centered or evaluated on any age group. The subject ages were evenly distributed. 253 subjects were chosen with an average age of 48 ($SD = 11.59$) and average BMI 25 ($SD = 4.16$).

2.2. Measurements

The subjects were grouped in different categories based upon an initial screening by the hospital physicians that was confirmed and refined by subsequent medical tests (blood analysis chemistry and blood pressure measurements). Per protocol, subjects were called fasting at 9AM for a blood draw (fasting blood glucose, glycosylated hemoglobin, and lipids). This phase was followed by clinical examination that included a detailed medical history along with resting heart rate and resting, average, blood pressure by automated oscillometric method.

In the subsequent phase, subjects were monitored using wearable ECG meter [9] for 20 minutes and this phase was tagged as normal phase. After normal phase, subjects were asked to solve a arithmetic questionnaire and subjects were informed about the monitory reward for each correct answer. The questions were designed as per subject's qualification to maintain equal difficulty level for all.

3. Results

To visualize the respiration power spectra and time induced variation in it, we calculated power spectra every second and represented it as shown in Fig. 1 It shows the time sliced spectra of three subjects. X-axis denotes the time in seconds and Y-axis denotes the scaled frequency. The power spectrograms were computed every second over signal of width 20 second around it. Power-spectra is shown as vertical slices of 1 second width, with gray tone denoting the amplitude. Darker the tone, higher is the amplitude. This allows for visualization of the time localized power spectra.

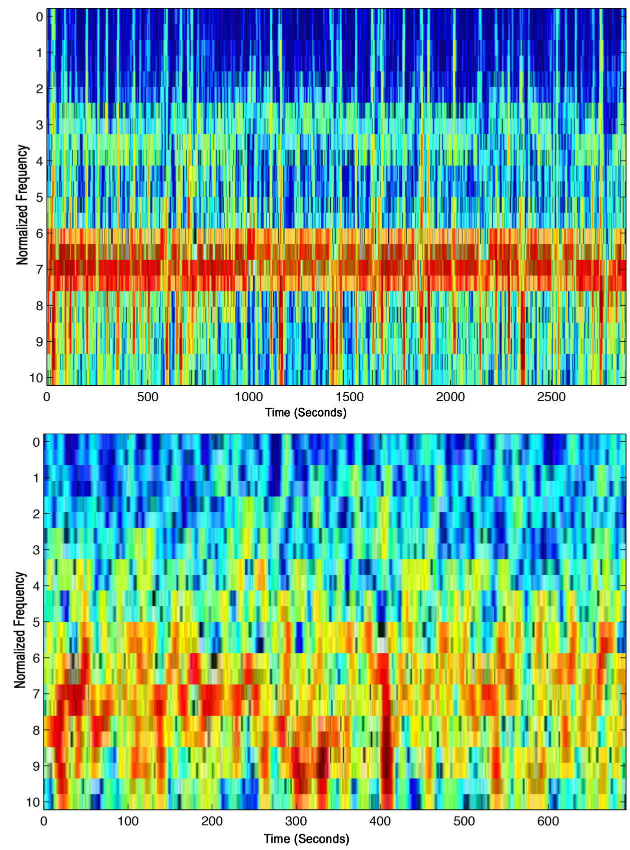

Figure 1. Time sliced power spectra in normal (above) and stress (below) phase.

Overall, Fig.1 shows the spread of the power in the normal and stress phases. In the normal phase, power spectra is consistent and there are no significant time induced changes from start to end of normal phase. The distribution shows that there is a band of high amplitude implying that there is a dominant frequency present. This frequency corresponds to the inhalation/exhalation frequency. As shown in Fig. 2, the power spectra of a particular subject shows the dominant frequency peak. The variation during the 40 minutes of monitoring are negligible and it can be assumed that the respiration was consistent throughout the normal phase.

In the stress phase, power spectra is distributed over a larger frequency spectrum. There is no consistent dominant frequency of respiration. The rate and the amplitude varies, showing the non-rhythmic breathing. The disturbance is also not consistent during the stress phase. The extent of disturbance changes with the acute stress instances.

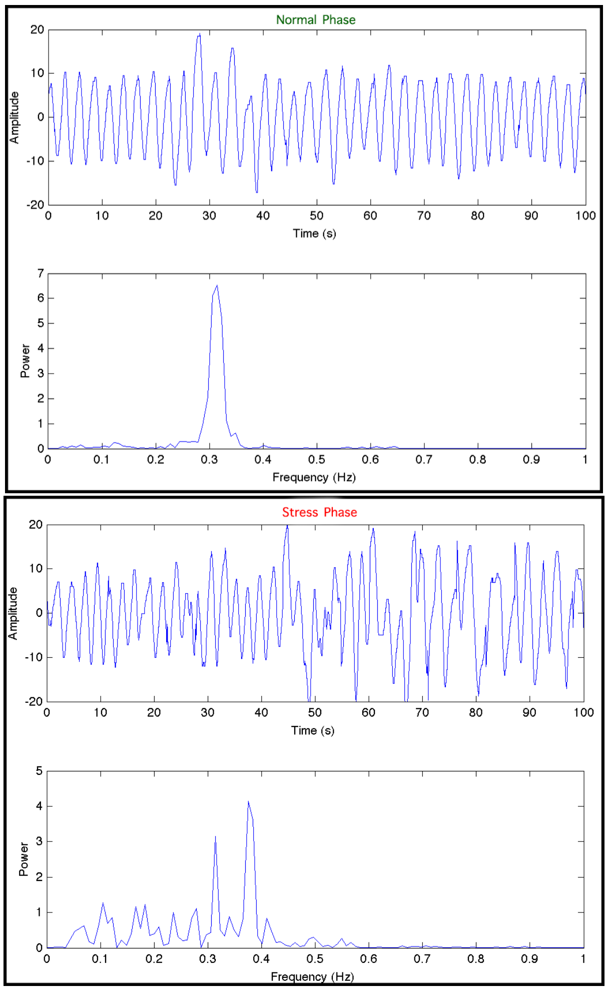

Figure 2. Respiration waveform and corresponding power spectra for normal (above) and stress (below) phases

To understand this phenomenon in more intuitive way, Fig.2 shows a subjects original waveform and its power spectra in the normal and stress phases. The respiration waveform in the stress loses the rhythm, as a result, power spectra in stress is distributed over larger frequencies as compared to the normal phase spectra.

In order to capture this phenomenon, we are comparing the percentage of total power around the major peak in the spectra. When the respiration is rhythmic, there will be high power density around the major peak as compared to the case when respiration is not rhythmic. In latter case, power density will be spread across a large frequency band, hence small percentage of total power around the major peak.

EKG sampled at 1kHz was used for analysis. For HRV calculations, a window of 5 minutes was taken and all such HRV readings were averaged over the normal/stress phase. The respiration waveform was sampled at 20Hz and stored. For post processing, the data of each phase was divided into 5 minute segments and power spectra were computed for each segment.

The power in the $\pm 0.5Hz$ band at the location of most significant peak was calculated. All such powers were normalized against the max power in the spectra (P_{i-max}) to get P_i, the normalized power for each spectra. C_i is the total normalized power for each spectra.

$$P_i = \frac{\int_{f_0-0.5}^{f_0+0.5} S_i}{P_{i-max}} \qquad C_i = \frac{\int_0^{f_{max}} S_i}{P_{i-max}} \qquad P_{\%} = \frac{\sum_{i=1}^{n} P_i}{\sum_{i=1}^{n} C_i}$$

where, f_0 is the frequency of dominant peak, S_i is the power spectra of the i^{th} segment (2 minute duration), f_{max} is the maximum frequency in the computed spectra, n is the number of segments in the normal/stress phase.

$P_{\%}$ is the percentage of the total power containing the major spectral peaks over normal/stress phase, similar to the spectral power in the major frequency components for duration of whole normal/stress phase.

To visualize the respiration power spectra and time induced variation in it, we calculated power spectra every second and represented it as shown in Fig. 1. It shows the time sliced spectra of three subjects. X-axis denotes the time in seconds and Y-axis denotes the scaled frequency. The power spectrograms were computed every second over signal of width 20 second around it. Power-spectra is shown as vertical slices of 1 second width, with color blue to red denoting the increasing amplitude. This allows for visualization of the time localized power spectra.

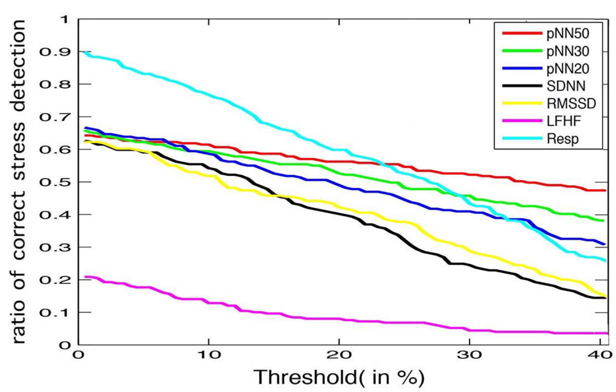

Figure 3. Comparison of HRV and Respiration methods for different thresholds

Figure 3 shows a brief comparison between different

HRV methods and respiration method. Using the respiration method, we are able to detect 90% of the stress cases, but HRV was able to detect around 65% of cases at low thresholds.

4. Discussion

Results demonstrate that respiration based method is at-par with HRV based methods and better than HRV when low thresholds are considered. It can be used with a small time window (20-30s) as compared to the LF/HF method, which requires longer time windows (> 10 min) to be able to capture the LF part of spectrum. The real time noise filtering is also easy for respiration-based method, which is based on using data with band-limited amplitude and skipping parts where accelerometer shows quick movements.

To develop a more robust method, real time filtering and signal stitching should be considered. A study on the sensitivity of different methods towards real-life noise and distortions can be helpful. Present methods of HRV measurement are based on the disease quantifying methods. A new measure that combines HRV and respiration, which is more robust and sensitive for stress measurement, can also be explored.

A better understanding of how popular stress models perform based on both context as well as cohort characterization should have a significant impact in increasing their utility in real-life settings. A stress method that uses combination of different bio-data may be more robust in real life setting. The respiration-based method will not be applicable when subject does voluntary breathing, in such cases the stress model may use the standard HRV based measurement. Respiration based method would combine robustness with its capability to capture physiological characteristic of diverse disease traits.

5. Conclusion

There is a paucity of large-scale trial data comparing effectiveness of academically established stress methods. Further, there is minimal information about their robustness in a mobile setting using wearable and affordable sensors. This paper present a study of 253 subjects that provides crucial data to address above shortcomings, and overview of analysis results comparing the most popular time-domain and frequency-domain Heart Rate Variability methods and the respiration based method.

We believe the main reason for the limitation of HRV is in the generalization over age, gender, health condition, etc. A more robust model is needed which can incorporate the changes in HRV due to factors other than mental stress.

We believe that our trial design is instructive for such endeavors for data collection - a key weakness hampering current state of the art and our experimental analysis adds to the knowledge of the factors on which stress models depends on, making it possible to compare these methods for a variety of real-life and experimental settings.

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