Analysis of work-related stress from various physiological signals using SWELL dataset

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Abstract- This article studies the impact of mental stress induced by knowledge-based work on heart rate variability (HRV), which measures the specific changes in time (or variability) between successive heartbeats. We use SWELL knowledge dataset containing ECG recording of 21 participants and analyze the signals. We described the heartbeats not as a continuous signal, but as a point process history dependent inverse Gaussian model. Later, we track the signal based on the p previous interval, where p is model parameter and relate stress and other recorded values from the dataset with the mean R-R interval of each participant.

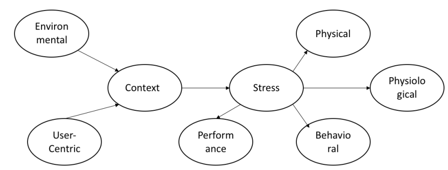


Fig. 1: The multimodal approach to the stress recognition problem has been described. On the left-hand side, all the elements that can affect stress are mentioned and on the right-hand side, all elements that can be observed during stress. [6]

I. Introduction

Knowledge workers have become a key human resource in the industry. In the context of restructuring, the intensified market competition enhances the external stress on companies and compels the companies to put organizational transformation in practice. And the changes related to working characteristics firmly affect workers' psychological status and work stress. [1]

In the United States, a large majority of the people are suffering from the anxiety disorder. Most of them are adult and though it can be treated easily, a few portions of the people actually get the correct treatment. [1].

There has been a lot of study in the field of stress analysis pertaining to different actions and different situations. According to Selye [2], stress can be defined as the changes happen due to the external command. Stress involves an alteration in behavior, autonomic function and the secretion of several hormones such as cortisol, corticosterone, and adrenal catecholamines [3] [4].

Although stress can occur and build up among a lot of environments, our primary focus here is work-related stress. The work-related stress has a tremendous effect on the workers, especially on their satisfaction, health, family life, economic conditions etc [5]. A rapidly growing part of the workforce uses computers and the amount of time spent in front of the computer is increasing too. In general, computer work can be characterized by high visual and cognitive demands.

Fig.1 defines the multimodal approach for identifying stress-related problems. The causes of the stress have been described on the left side of the figure and on the right side of the figure, the external responses of the stress have been mentioned. The causes of the stress can be further classified into 1. "environmental" 2. "user-centric".

Little stress is good, that helps us to do our everyday work, but prolonged exposure to it causes blood pressure, increase heartbeat and also increases the secretion of different stress hormones [7]. From laboratory experiments, it has been noticed that change of heart rate variability (HRV) has an impact on the autonomic nervous system [8]. With the decrease of the HRV, the response time for a complex situation increases [8]. If this situation lasts for prolong period, it may take a toll on the cardiovascular system [9].

Based on the information aforementioned, we realized that theoretically, heart rate and heart rate variability can be used to identify temporally localized events during which a person experiences a certain degree of stress. Hence, our prime focus is to see if there is any direct correlation between heart rate and/or heart rate variability and the amount of stress a person undergoes.

The most common way to measure stress is with the help of physiological sensors. These physiological sensors extract features of the physiological signals, which can be later analyzed using pattern recognition and machine learning to learn about the relationship between stress and physiological conditions. The analysis of the fluctuations in heartbeat intervals, which is commonly referred to as HRV analysis, is a frequently studied physiological rhythm. Some of the HRV analysis methods include statistical measures analysis [10], spectral analysis [11], [12], [13], nonlinear dynamics [14], and point-process modeling [15], [16].

A large portion of the experiments are done with different cognitive tests, e.g. mental arithmetic, color word test (CWT). When Garde et al [17] did the same experiment, they came to the conclusion that in laboratory condition, HRV cannot be related to the computer work-related stress. On top of this, Wahlstrom et al. [18] found that there is no effect of applying time pressure on the computer-related work with the HRV experimented in the laboratory. Also, Hjortskov et al [9] expressed their concern on the same topic.

Salahuddin et al [19]. worked on finding the relationship

between stress and other measured parameters with the HRV and its features. It was done with the help of Stress Response Inventory (SRI), used as a scoring device of mental and physical symptoms. The relationship between age and stress had been measured using Pearson's correlation analysis. For further statistical analysis, they used different regression models and divide the physiological signals into stressed and not stressed groups.
According to Cinaz et al. [20], Linear discriminant analysis (LDA), support vector machine and k-nearest neighbor (kNN) are usually used for predicting stress. Yang et al. [21] found the relationship between HRV features and stress from the ECG measured by a wearable patch.

II. Methodology

In this section, we will discuss all the algorithms used in this study and how we work on finding a relationship between stress and the different features of the heartbeat.

A. Theory

In this section, we will be discussing some of the theory we need to describe the algorithm, so it will be more clear in the later stage to explain the point process adaptive filtering algorithm.

1) Introduction to point process

Point process can be defined as an irregularity of points. In our research, we are using point process which is associated with R-R spikes. We define the R-R spikes as a function of random events, which happens at the times $t_1, t_2, ...$ of the total heartbeat recorded. The concept can be understood with the help of Fig. 2 where spikes occur at the t_i time and we model the system using point process. [23].

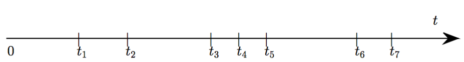


Fig. 2: Simple point process where R-R spikes occur at the time $t_1, t_2, ..., t_k$.

2) Conditional Intensity Function

In a specified time interval, let $N(t)$ be defined as the total number of spikes occurred, such that $t \in (0, T]$. This point process can be represented with the help of conditional intensity function, $\lambda(t|x(t), \theta(t), H(t))$. Here, $x(t)$ is the signal in vector form on which the study has been done. $H(t)$ is the spike history up to time t and $\theta(t)$ is the tuning parameters chosen for the specific model. This conditional intensity function is defined as

$$\lambda(t|x(t), \theta(t), H(t)) =$$

$$\lim_{\Delta \to 0} \frac{Pr(N(t + \Delta t) - N(t) = 1|x(t), \theta(t), H(t)}{\Delta t}$$

In a small time interval $(t, t + \Delta t]$, the probability of spikes can be represented by $\lambda(t|x(t), \theta(t), H(t))\Delta t$. This is a history based inhomogeneous poisson rate function.
In this study, we switch from the continuous system to discrete in order to make the calculation easier. In discrete system, the parameters are defined as x_k for $x(t_k)$, N_k for $N(t_k)$. ΔN_k is a new parameter which contains the spiking information. If there is a spike over a time interval Δt_k, then ΔN_k is represented by 1 or else it is 0. [23] [24] [22]

B. Physiology of heartbeats

The cardiac cycle is all about the flow of the blood from the body to lungs and from the lungs to the body. Though cardiac cycle occurs simultaneously on both sides of the heart, for simplicity, we will start the process from the right side of the heart. The cardiac cycle starts when the de-oxygenated blood flows from the body using the superior and the inferior vena cava and then it enters into the right atrium. As the right atrium contracts, blood proceeds to the right ventricle. Once blood enters into the right ventricle, the tricuspid valve closes, so that blood does not flow back to the atrium. When right ventricle contracts, blood flows to the pulmonary artery and from there it reaches the lungs. After lungs put oxygen to the blood, it flows back to the left atrium to the other side of the pulmonary veins. When left atrium contracts, blood flows into the left atrium through the pulmonary vein and pass to the left ventricle and once it is full, the mitral valve closes, so blood can not flow back the atrium. Then blood flows to the body through the aortic valve.
ECG measures the electrical impulse of the heart. The P-wave is created due to the contraction of the left and the right ventricles. P-wave is called "Atrial Depolarization". Then the electric impulse travels through the muscle, which causes the flat nature of the curve called PR-segment. Then the Q-wave is produced when the electrical impulse passes through the "bundle of his" and causes small repolarization. Then due to the contraction of the left and right atrium, a huge depolarization occurs, which causes the QRS-complex. As ventricles remain open, the impulse is not changed, which causes the ST-segment. Once the ventricles close, repolarization occurs and causes the T-wave to be generated. [25] [26]

1) Derivation of the point process adaptive filter

The key assumption to derive adaptive filter, is that the time-varying parameters θ_k need to be predicted and updated at each point of time. This time-varying parameter can be calculated from the history of the R-R spike and past θ_{k-1}. Thus, θ_k can be computed with the help of the history dependent function H_k and also with the R-R spiking information function ΔN_k. This estimation is done over each time interval and it allows the real-time tracking of the conditional intensity function over the observed data.

C. Linear Regression

Linear regression captures the relation between two variable. It then tries to fit a linear model to the variables. In our study, we are trying to find a relation between heart rate and other parameters based on different cases. In fact, using linear regression on the observed values does not

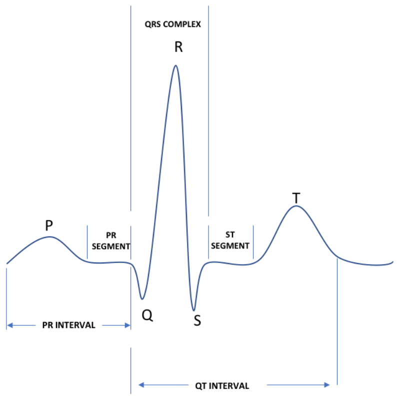


Fig. 3: The typical electrocardiogram (ECG) of the human heart has been shown. When electrical impulses pass through the ventricles, the P-wave occurs. As impulse does not pass through the muscle, the flat section of the ECG (PR-segment) generates. Q-wave is created due to the small repolarization created after PR-segment. Due to the contraction of the atrium, QRS-complex generates. Then, due to the opening of the ventricles, ST-segment generates and finally due to the repolarization T-wave has been created.

help to conclude the relationship between the variables. For representing a linear regression between two variables (where one variable is called explanatory and and the others are called dependent variables.), scatterplot has been proven the best representation. More strong the relation, the observed point will more close the linear model fitted. [27] [28].
The equation for linear regression is

$$Y = a + bX \tag{1}$$

The Eq. (1), X is defined as the explanatory variable, Y is defined as the dependent variable and b is the slope of linear model.

D. Pearson's correlation model

Pearson's correlation coefficient measures the statistical correlation between two variables. If X and Y are two variables on which observation have been made. The Pearson's correlation coefficient can be calculated using the formula shown below.

$$\rho_n = \frac{E(XY) - E(X)E(Y)}{\sigma_X \sigma_Y} \tag{2}$$

In the Eq.(2) ρ_n is defines as the Pearson's correlation coefficient, $E(XY)$ is the expected value of the product of two observed values, X and Y. $E(X)$ is the observed value of the variable X, $E(Y)$ is the observed value of the variable Y, σ_X and $\sigma(Y)$ are the standard deviation of values X and Y respectively.
The range of the Pearson's correlation coefficient lies within 1 and -1. If the value is in the positive range, greater the value, stronger the relationship between the two variables. It means, if one value increases, the other value increases too. In the same way, if the value is in the negative range, lesser the value, stronger the negative relationship between two variables. It means, if one value increases, the other value decreases.

E. Dataset

To utilize the point-process model, we are currently using the heart rate data captured from the SWELL dataset and correlating it with the stress and other parameters. SWELL dataset is typically a knowledge dataset, where participants are given a knowledge based task, instructed to work on those tasks and physiological recordings are measured during that. In this experiment, 25 people participated. Every participant was given tasks e.g. report writing, designing presentation, composing e-mail and etc. Besides ECG data, facial expression, body movement, skin conductance were also captured. But, for our study, we are only using the heartbeat data captured using Mobi device. Out of 25 participant's recording, we are able to use only 21 of them and we calculate heart rate of each individual from the ECG data by modeling the heart as a history dependent inverse Gaussian model with the adaptive filter to track and estimate the time-dependent features. [6].

1) Design

The recordings were captured when participants were given three different levels of tasks.

- Neutral: In this condition, participants were given a task and asked to complete it in 45 minutes.
- Stressor 'Time pressure': The same tasks from the Neutral condition were repeated here, but they were asked to complete it in less time. Generally, 2/3 of the original time, which is approx 30min.
- Stressor 'Interruptions': In this condition, participants were interrupted by sending e-mails while they were doing the tasks. Some of the e-mails were on the same topic, he/she was working on and some of them were not.

TABLE I: The order in which tasks are assigned for the participants.

Order		Task1		Task2		Task3
1	Relax	Neutral	Relax	Interru-ption	Relax	Time-pressure
2		Neutral		Time-pressure		Interru-ption

The tasks are assigned to the participants in two different orders mentioned in Table I.

2) Tasks

During the experiment, mainly 6 knowledge-based tasks were given and on which participants were instructed to design a presentation or compose a reports etc. These tasks were chosen from opinion and information topics.

- Opinion topics: 3 tasks were selected based on participant's opinion about various situations.
- Information topics: 3 informative tasks were given in this category.

In this whole experiment, users were allowed to use Google or other search engines to search about the topics they were asked to work on and all these conditions simulated an office like environment which is good for recording a real-life scenario. [6].

F. Method

Our aim is to define a heartbeat probability model with the help of R-R interval and relate that to the stress and other given parameters in the dataset. We make an assumption that, in a time interval of $(0, T]$, there are K spikes occurring and we record those spikes in such a way from the ECG that $0 < u_1 < u_2 <, ..., < u_k <, ..., < u_K \leq T, K$.
Also, our assumption is that within consecutive $R - R$ intervals, the time length before next spike obeys an history-dependent inverse Gaussian probability density model, which can be represented by $f(t|H_k, \theta)$, H_k is the history dependent function over R-R interval till u_k. The history function can be described using the Eq. (3) and Eq. (4).

$$H_k = \{u_k, w_k, w_{k-1}, w_{k-p+1}\} \tag{3}$$

$$w_k = u_k - u_{k-1} \tag{4}$$

The mean μ is represented by $\mu(H_k, \theta) = \theta_0 + \sum_{j=1}^{p} \theta_j w_{k-j+1}$, where θ is the model parameter vector. The model is defined as,

$$\begin{aligned} f(t|H_k, \theta) = \left[\frac{\theta_{p+1}}{\pi(t-u_k)^3}\right]^{\frac{1}{2}} \\ \exp\left\{-\frac{1}{2}\frac{\theta_{p+1}\left[t-u_k-\mu(H_k,\theta)\right]^2}{\mu(H_k,\theta)^2(t-u_k)}\right\} \end{aligned} \tag{5}$$

Eq.(5) obeys the stochastic nature of the R-R wave interval. It represents the probability of occurring a spike given the history of previous spikes.
If we make an assumption that R-R intervals are independent, then from the definition of p, $p = 0$. If we apply our assumption to the Eq.(5), we can derive $\mu(H_k, \theta) = \theta_0, f(t|H_k, \theta) = f(t|u_k, \theta_0, \theta_1)$ and our model equation in Eq.(5) transfers into a simple renewal inverse Gaussian model.
The mean and standard deviation of R-R probability model in Eq (5). are,

$$\mu_{\mathrm{RR}} = \mu(H_k, \theta) \tag{6}$$

$$\sigma_{\mathrm{RR}} = \left[\mu(H_k, \theta)^3 \theta_{p+1}^{-1}\right]^{\frac{1}{2}} \tag{7}$$

Barbieri and Brown [15] [16], developed a stochastic state point process filter (SSPPF) for estimating a linear Gaussian state process for point process observations. As θ is a time varying parameter, it can be represented by a state space model. To design the state space model, we divide the time T into small J time intervals, such that $\Delta = T/J$, where Δ is the width of the time interval. Δ needs to be chosen so that there should be maximum of one spike per time interval. The estimated value θ is updated at $j\Delta$, where $j = 1, 2, ..., J$ and θ can defined as

$$\theta_j = \theta_{j-1} + \varepsilon_j \tag{8}$$

where ε_j is a Gaussian noise having zero mean and W_ε is the covariance matrix.
With the probability model in Eq. (5), conditional intensity function (CIF) has been defined as

$$\lambda(j\Delta|H_j, \theta_{j\Delta}) = \frac{f(j\Delta|H_j, \theta_{j\Delta})}{1 - \int_{u_j}^{j\Delta} f(u|H_j, \theta_u)du} \tag{9}$$

Here, the conditional intensity function defines the probability of occurrence of a spike between time interval $(j-1)\Delta, j\Delta$. The steps in the recursive algorithm update both the θ parameters and the variance by using first and second order instantaneous gradients of the conditional intensity function. With the state model in Eq.(8) and the conditional intensity function in Eq.(9), the adaptive filter can be defined as below,

$$Prediction \begin{cases} \theta_{j|j-1} = \theta_{j-1|j-1} \\ W_{j|j-1} = W_{j-1|j-1} + W_\varepsilon \end{cases} \tag{10}$$

The update equation can be written as,

$$\theta_{j|j} = \theta_{j|j-1} + W_{j|j-1}(\nabla \log \lambda_j)[n_j - \lambda_j \Delta] \tag{11}$$

$$\begin{aligned} W_{j|j} = \Big[W_{j|j-1}^{-1} - (\nabla^2 \log \lambda_j)[n_j - \lambda_j \Delta] \\ -(\nabla \log \lambda_j)[\nabla \lambda_j \Delta]'\Big]^{-1} \end{aligned} \tag{12}$$

Here, λ_j is defined as the conditional intensity function in Eq. (9) and ∇, ∇^2 defines the first and second derivative of a function with respect to θ where $j = 1, 2, ..., J$ respectively.
The update and prediction steps are same as given in Kalman filter. In the above equations, a recursive Gaussian approximation has been used for estimating hidden state w.r.t a point process, which in this case, θ_j can be defined as the hidden state and the point process can be defined as the heartbeat [11].

III. Results

In order to test our algorithm to check how best it can track the changes, we start the algorithm with $p = 9$ and initialize the values of model parameters $\theta_0, \theta_1, ..., \theta_{p+1}$ with constant values. We initialize the covariance matrix W_ε to be a diagonal matrix with values of 3x10^{-7} for θ_0 and 4x10^{-13} for the autoregressive parameters. Using the point process adaptive filter, average RR interval was computed for all 21 individuals from the SWELL dataset under all the different conditions. Fig. 4 shows an example of the result of our algorithm tracking the mean RR interval from the ECG data. Evidently, the Kalman filter does a good job at tracking, but there is an obvious DC shift included as well. The cause of this DC shift is currently unknown, but it is assumed that due to the change in the time-varying parameters a tiny DC shift is accumulated over each iteration. In order to continue with our analysis we remove the DC shift by adding an offset value to our μ values.

Standard deviation of the RR intervals was computed from the mean RR intervals using equations .

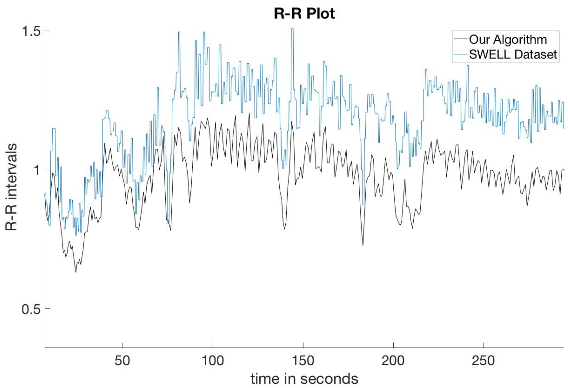
$$\mu_{\mathrm{RR}}(j\Delta) = \mu(H_j, \theta_{j|j}) \tag{13}$$

$$\sigma_{\mathrm{RR}}(j\Delta) = \left[\mu(H_j, \theta_{j|j})^3 \theta_{p+1,j|j}^{-1}\right]^{\frac{1}{2}} \tag{14}$$

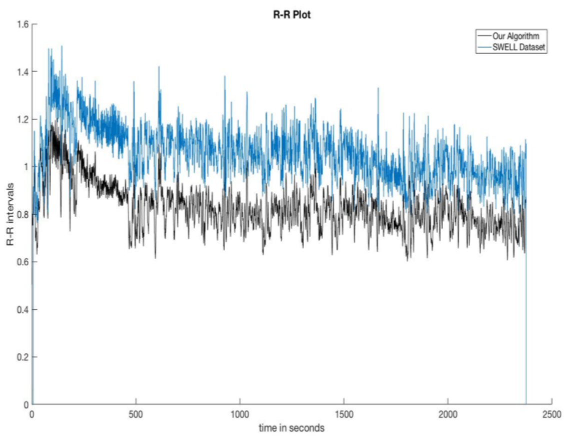
The mean and standard deviation of heart rate were calculated using the following equations.

$$\mu_{\mathrm{HR}}(j\Delta) = \mu^*(H_j, \theta_{j|j})^{-1} + \theta_{p+1,j|j}^{*}{}^{-1} \tag{15}$$

$$\sigma_{\mathrm{HR}}(j\Delta) = \left[\frac{2\mu^*(H_j, \theta_{j|j}) + \theta_{p+1,j|j}^*}{\mu^*(H_j, \theta_{j|j}) \cdot \theta_{p+1,j|j}^{*}{}^{2}}\right]^{\frac{1}{2}} \tag{16}$$



(a)



(b)

Fig. 4: This figure shows the ability of our algorithm to track the changes. For fitting the model better, we chose the model parameter p as 9 and initialize $p+2$ values of θ.

It can be observed from Fig. 5 that the standard deviation of the RR intervals and the Heart rate tend to follow the same curve as their mean counterparts. This is due to the fact that the parameters of the model converge rather quickly (after a few 1000 iterations) and becomes a constant. Hence, the standard deviation values are only linearly dependent on the mean values.

A. Linear Regression

In order to compute the relationship between heart rate variability and stress with inferential statistics, a linear regression model was developed with the mean heart rate as the explanatory variable and stress as the response variable. The overall p-value for this model was 0.8266 (which is way greater than 0.05) indicating that there is no dependence between the heart rate values and the stress value whatsoever.

B. Pearson Correlation Test

Additionally, all the variables present in the dataset were compared to the average heart rate value using the Pearson Correlation test. Fig. 6 depicts the Pearson correlation coefficient of all the variables when compared with the mean RR interval. As we can see in the figure, the correlation coefficients of any variables are not close to 1, indicating no significant relationship between the variables and mean RR interval. The apparent independency of Stress and Heart Rate from the analyses can be attributed to the fact that the stress data was subjective. It was collected based on how the subjects were feeling personally which leads to a different scale metric for each participant.

C. Comparison of HRV under all three conditions

Physiological literature tells us that stress and heart rate (or HRV) are in fact positively correlated. To test this aspect, the focus was shifted to just analyzing the HRV under different conditions. Fig. 7 shows the line plot of the mean heart rate variability (HRV) of all the three conditions for every subject. Visually, one can say that the mean HRV in the Neutral condition is mostly lower than that in the Interruptions or Time Pressure conditions. This does not make sense as it is expected that a person in the baseline condition (Neutral) will experience less stress and therefore have a lower heart rate as opposed to the other conditions. One reason for this maybe that since every patient was always asked to perform the tasks under Neutral condition first, they were probably more stressed out at the beginning than they were for either of the other two conditions.

D. T-tests

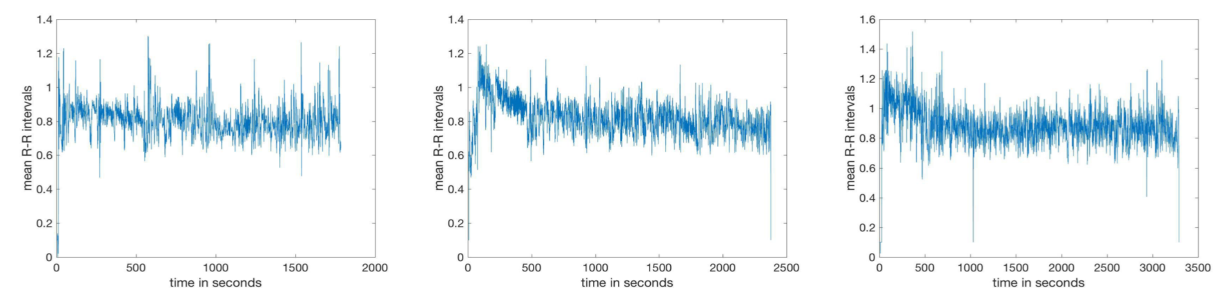
It is vital to learn whether the observations of mean RR intervals for all three conditions, namely Neutral, Time Pressure and Interruptions are all coming from the same population or not. In order to do so, two sample t-tests were run on the mean RR of each in one condition vs the other. Table II, III and IV show the corresponding results. In all the cases the p-value reported is much higher than 0.05 which leads us to conclude that there is a strong possibility of all the mean RR values to be from the same distribution.

TABLE II: T-test for mean R-R intervals in Interrupt vs Neutral condition

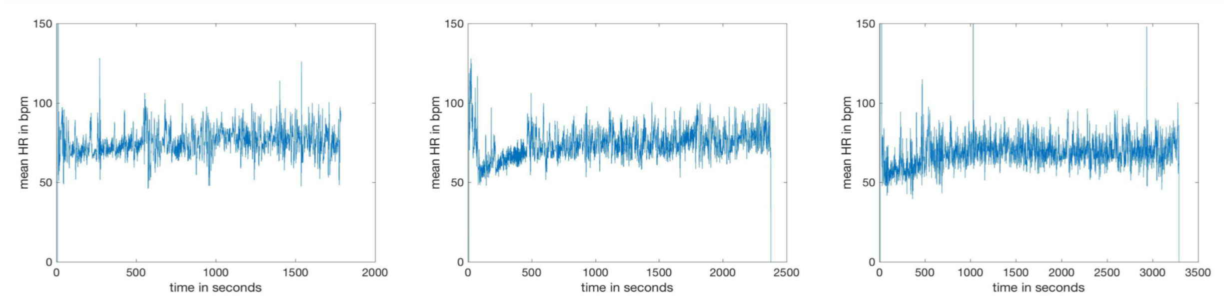
T-test for mean R-R intervals in Interrupt vs Neutral condition
data:Mean.RR.I and Mean.RR.N
t = 1.5849, df = 38.031, p-value = 0.1213
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
-0.01553464,0.12759200
sample estimates:
mean of x mean of y
0.8596520 0.8036233

E. AIC Evaluation and KS plots for Model Selection

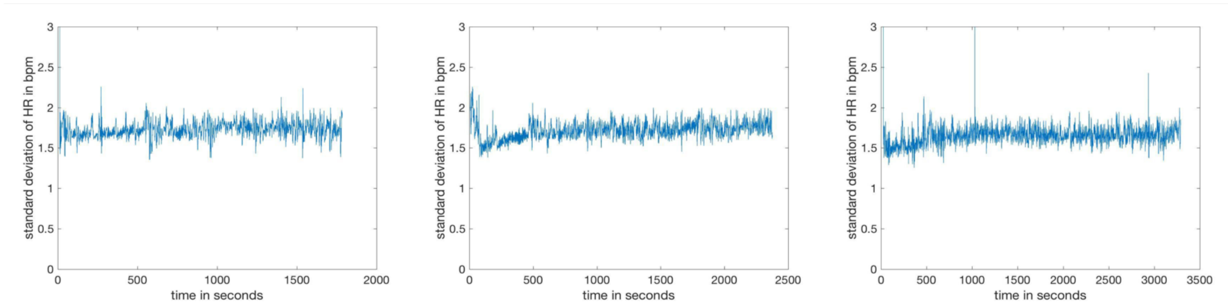
In order to select the right model with the right number of parameters, Akaike Information Criteria (AIC) formulation is used on the MLE algorithm developed by Barbieri et al [15]. As expected, each file has a different best model with different number of parameters. Tables V, VI and VII show the AIC weights and ΔAIC values corresponding to model



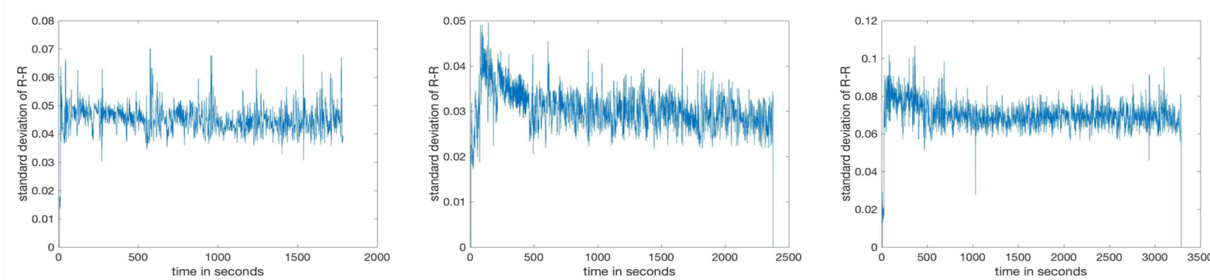
(a) This figure shows the plot of the mean RR interval for subject 7 under Neutral, Time pressure and Interruption conditions respectively.



(b) This figure shows the plot of the hear rate in bpm for subject 7 under Neutral, Time pressure and Interruption conditions respectively.



(c) This figure shows the plot of the SD of the heart rate for subject 7 under Neutral, Time pressure and Interruption conditions respectively.



(d)This figure shows the plot of the SD of the RR interval for subject 7 under Neutral, Time pressure and Interruption conditions respectively.

Fig. 5: From this figure, we can conclude that the heart rate is higher for subject 7 under neutral condition than the other two conditions and as the values of θ converges quickly the standard deviation is linearly dependent of the mean value and the trends of these two plot are quite similar.

parameters ranging from 2 to 9.

The AIC weights determine the probability of that model to be a best fit. From the tabular data one can see that all models except the best model have very low probability to be the best model for a given file. Goodness-of- fit was assessed by looking at KS plots of the different models. Fig. 8 shows that the hard-coded value of 9 is not the best fit for all the files.

IV. Conclusion

The inconclusive results achieved using the user defined inputs can be attributed to the fact that these parameters are subjective in nature and do not adhere to any evaluation metric whatsoever. However, physiologically or biologically, it makes sense that when a person is experiencing stress, his/her

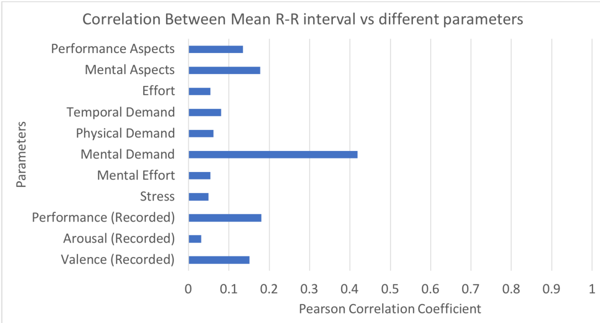


Fig. 6: Comparison of the Pearson's correlation coefficient for different parameters given in the dataset with the mean R-R interval has been plotted. From the figure, we can define that there is no relation present between mean R-R interval with different parameters other than mental demand, though the relation is not strong enough.

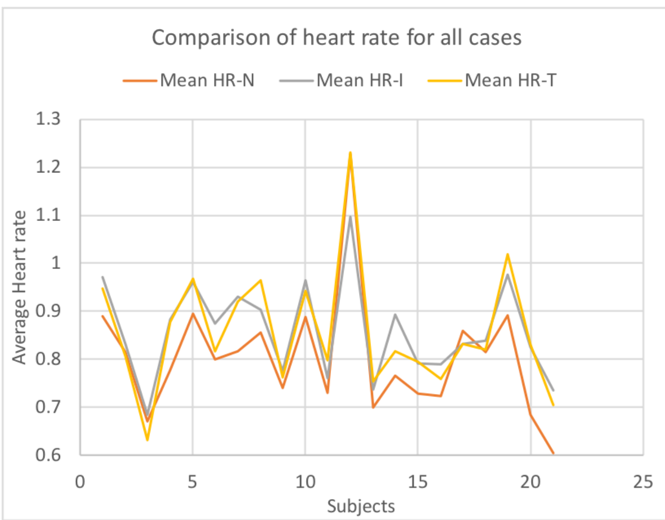


Fig. 7: Comparison of mean heart rate for 21 participants under three different conditions (neutral, interrupt and time-pressure) under which they worked. Visually, we can infer that the mean heart rate is least for most of the participant when they did the task under the neutral condition. Mean heart rate increases for interrupt and time-pressure condition.

TABLE III: T-test for mean R-R intervals in Time Pressure vs Neutral condition

T-test for mean R-R intervals in Time Pressure vs Neutral condition
data: Mean.RR.T and Mean.RR.N
t = 1.3603, df = 39.997, p-value = 0.1813
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
-0.02599318 0.13302568
sample estimates:
mean of x mean of y
0.8571395 0.8036233

heart rate is bound to increase. Therefore, it is important that the stress variables be recorded in such a way that they follow a standard metric and are not subject-evaluated. Results from t-tests also indicate that the mean heart rate during Neutral(baseline) condition is higher than during Time Pressure or Interruptions. Again, according to literature we know that this is not true. Therefore, SWELL dataset is not an ideal dataset to compare Heart rate with Stress factors.

TABLE IV: T-test for mean R-R intervals in Interrupt vs Time Pressure condition

T-test for mean R-R intervals in Interrupt vs Time Pressure condition
data:Mean.RR.I and Mean.RR.T
t = 0.070688, df = 37.893, p-value = 0.944
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
-0.06944623 0.07447109
sample estimates:
mean of x mean of y
0.8596520 0.8571395

REFERENCES

[1] X. Fei and L. Bing, "A study on work stress of real estate industry knowledge workers on the basis of psychological contract," in *Management Science and Engineering (ICMSE), 2012 International Conference on*. IEEE, 2012, pp. 1272–1280.

[2] H. Selye, *The stress of life*, 1956.

[3] L. D. Van de Kar and M. L. Blair, "Forebrain pathways mediating stress-induced hormone secretion," *Frontiers in neuroendocrinology*, vol. 20, no. 1, pp. 1–48, 1999.

[4] L. Bernardi, J. Wdowczyk-Szulc, C. Valenti, S. Castoldi, C. Passino, G. Spadacini, and P. Sleight, "Effects of controlled breathing, mental activity and mental stress with or without verbalization on heart rate variability," *Journal of the American College of Cardiology*, vol. 35, no. 6, pp. 1462–1469, 2000.

[5] C. Tennant, "Work-related stress and depressive disorders," *Journal of psychosomatic research*, vol. 51, no. 5, pp. 697–704, 2001.

[6] S. Koldijk, M. Sappelli, S. Verberne, M. A. Neerincx, and W. Kraaij, "The swell knowledge work dataset for stress and user modeling research," in *Proceedings of the 16th International Conference on Multimodal Interaction*. ACM, 2014, pp. 291–298.

[7] T. Theorell, G. Ahlberg-Hulten, M. Jodko, F. Sigala, and B. De La Torre, "Influence of job strain and emotion on blood pressure in female hospital personnel during workhours," *Scandinavian journal of work, environment & health*, pp. 313–318, 1993.

[8] M. Horsten, M. Erigson, A. Perski, S. P. Wamala, K. Schenck-Gustafsson, and K. Orth-Gomér, "Psychosocial factors and heart rate variability in healthy women," *Psychosomatic Medicine*, vol. 61, no. 1, pp. 49–57, 1999.

[9] N. Hjortskov, D. Rissén, A. K. Blangsted, N. Fallentin, U. Lundberg, and K. Søgaard, "The effect of mental stress on heart rate variability and blood pressure during computer work," *European journal of applied physiology*, vol. 92, no. 1-2, pp. 84–89, 2004.

[10] A. J. Camm, M. Malik, J. Bigger, G. Breithardt, S. Cerutti, R. J. Cohen, P. Coumel, E. L. Fallen, H. L. Kennedy, R. Kleiger *et al.*, "Heart rate variability. standards of measurement, physiological interpretation, and clinical use," *European heart journal*, vol. 17, no. 3, pp. 354–381, 1996.

[11] S. Akselrod, D. Gordon, F. A. Ubel, D. C. Shannon, A. Berger, and R. J. Cohen, "Power spectrum analysis of heart rate fluctuation: a quantitative probe of beat-to-beat cardiovascular control," *science*, vol. 213, no. 4504, pp. 220–222, 1981.

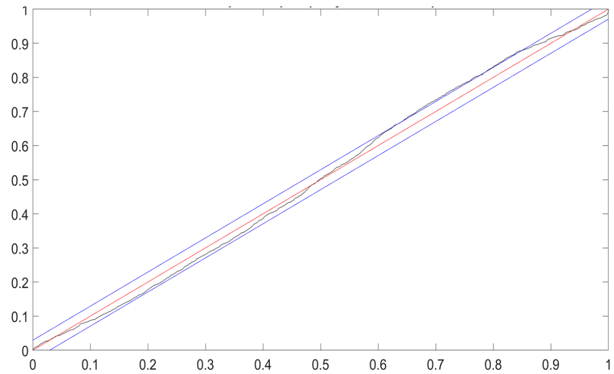
[12] N. Montano, A. Porta, C. Cogliati, G. Costantino, E. Tobaldini, K. R. Casali, and F. Iellamo, "Heart rate variability explored in the frequency domain: a tool to investigate the link between heart and behavior," *Neuroscience & Biobehavioral Reviews*, vol. 33, no. 2, pp. 71–80, 2009.

[13] N. Y. Belova, S. V. Mihaylov, and B. G. Piryova, "Wavelet transform: A better approach for the evaluation of instantaneous changes in heart rate variability," *Autonomic Neuroscience: Basic and Clinical*, vol. 131, no. 1, pp. 107–122, 2007.

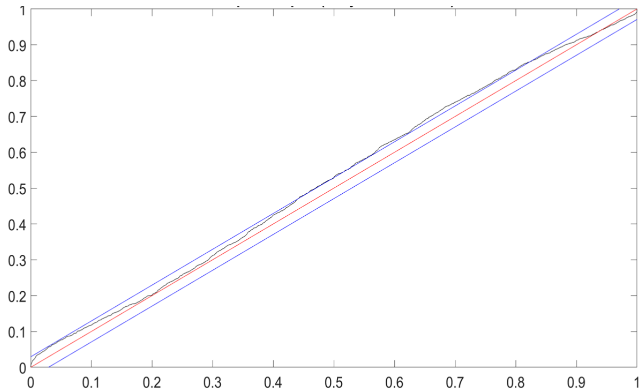
[14] A. Voss, S. Schulz, R. Schroeder, M. Baumert, and P. Caminal, "Methods derived from nonlinear dynamics for analysing heart rate variability," *Philosophical Transactions of the Royal Society of London A: Mathematical, Physical and Engineering Sciences*, vol. 367, no. 1887, pp. 277–296, 2009.

[15] R. Barbieri, E. C. Matten, A. A. Alabi, and E. N. Brown, "A point-process model of human heartbeat intervals: new definitions of heart rate and heart rate variability," *American Journal of Physiology-Heart and Circulatory Physiology*, vol. 288, no. 1, pp. H424–H435, 2005.

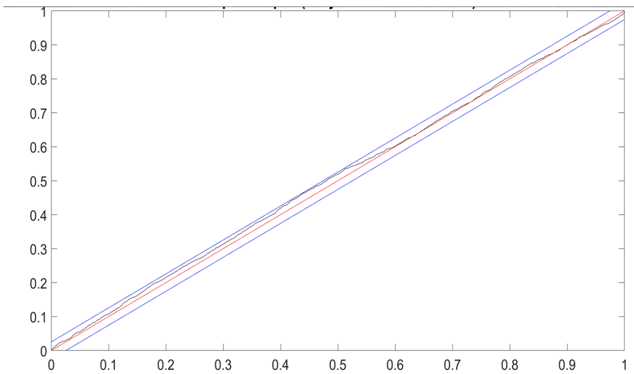
[16] R. Barbieri and E. N. Brown, "Analysis of heartbeat dynamics by point process adaptive filtering," *IEEE transactions on BioMedical Engineering*, vol. 53, no. 1, pp. 4–12, 2006.



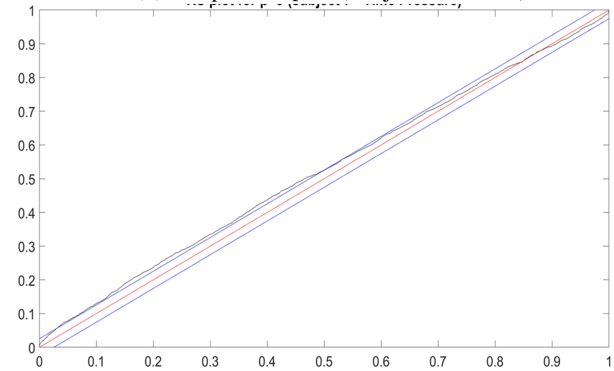
(a) KS-plot for p=2 (Subject 7-Neutral)



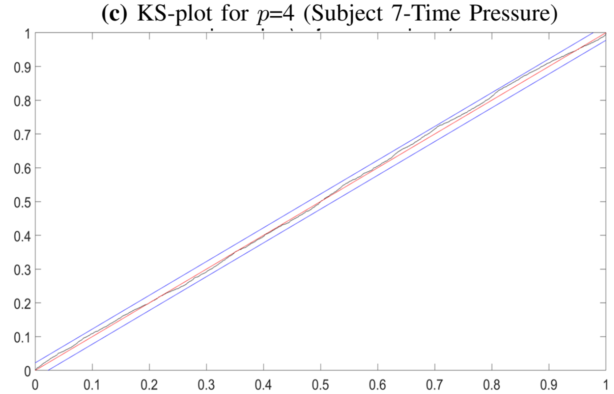
(b) KS-plot for p=9 (Subject 7-Neutral)



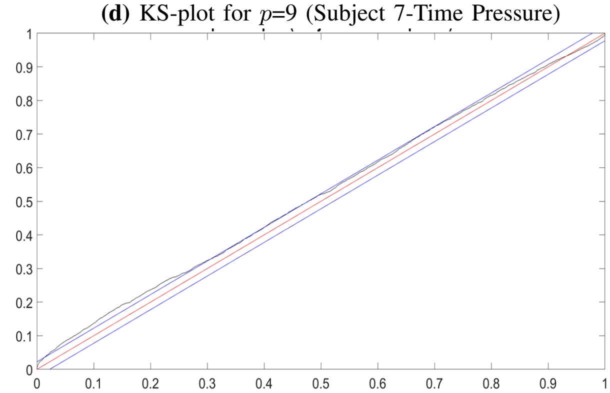
(c) KS-plot for p=4 (Subject 7-Time Pressure)



(d) KS-plot for p=9 (Subject 7-Time Pressure)



(e) KS-plot for p=3 (Subject 7-Interruptions)



(f) KS-plot for p=3 (Subject 7-Interruptions)

Fig. 8: Using the AIC, the best fitted model has been found for each condition and each subject and we plot KS-plot using the measured value in fig.(a), (c) and (e). We ran the same KS-plot when the number of parameters are fixed with 9 for all the conditions and subjects (figure (b), (d), (f)). We found that when we use the number of parameters with the measured values from the AIC, we get a better result.

TABLE V: AIC-Neutral Condition

Subject 7 - Neutral						
Mu(RR-intervals)	**No. of parameters**	**Mu (MLE)**	**RSS**	**AIC**	**△ AIC**	**AIC Weights**
0.7994	2	0.7997	4.563401206	-13825.04275	0	1
	3	0.7999	4.826953397	-13697.66588	127.3768716	2.19E-28
	4	0.7997	4.907999866	-13658.4842	166.5585493	6.80E-37
	5	0.7998	4.978339159	-13624.70898	200.333768	3.15E-44
	6	0.7993	4.987094111	-13618.78546	206.2572929	1.63E-45
	7	0.7987	5.124959011	-13555.89349	269.149259	3.59E-59
	8	0.7986	5.230911889	-13508.19941	316.843346	1.58E-69
	9	0.7988	5.363711363	-13450.2169	374.8258478	4.05E-82
	10	0.7987	5.854463642	-13252.7217	572.3210499	5.27E-125
	11	0.7985	6.118438637	-13152.2407	672.8020512	8.00E-147

[17] A. Garde, B. Laursen, A. Jørgensen, and B. Jensen, “Effects of mental and physical demands on heart rate variability during computer work,” *European journal of applied physiology*, vol. 87, no. 4-5, pp. 456–461, 2002.

TABLE VI: AIC-Time Pressure Condition

Subject 7 - Time Pressure						
Mu(RR-intervals)	**No. of parameters**	**Mu (MLE)**	**RSS**	**AIC**	**△ AIC**	**AIC Weights**
0.817	2	0.818	4.969178895	-18518.30599	73.04973547	1.07E-16
	3	0.8179	4.875707165	-18571.50835	19.84737303	3.81E-05
	4	0.8177	4.839201449	-18591.35572	0	7.78E-01
	5	0.8183	4.840060028	-18588.84	2.515718871	2.21E-01
	6	0.8181	4.858406205	-18575.84189	15.5138292	3.33E-04
	7	0.8174	4.92381276	-18534.96734	56.38838101	4.43E-13
	8	0.8174	5.037730883	-18466.47676	124.8789632	5.94E-28
	9	0.8174	5.17404193	-18386.86443	204.4912952	3.07E-45
	10	0.8173	5.296918466	-18316.63411	274.7216153	1.72E-60
	11	0.8171	5.444247691	-18234.88245	356.4732759	3.05E-78

TABLE VII: AIC-Interruptions Condition

Subject 7 - Interruptions						
Mu(RR-intervals)	**No. of parameters**	**Mu (MLE)**	**RSS**	**AIC**	**△ AIC**	**AIC Weights**
0.875	2	0.8755	12.11168305	-21543.94406	34.10452131	3.93E-08
	3	0.8748	11.99581736	-21578.04858	0	1
	4	0.8756	14.18422919	-20946.64555	631.40303	7.81E-138
	5	0.8757	14.71344735	-20807.05901	770.9895691	3.82E-168
	6	0.8752	15.20229616	-20682.29558	895.7529954	3.09E-195
	7	0.8745	14.59166756	-20834.27592	743.7726623	3.10E-162
	8	0.8745	15.59512819	-20582.47217	995.5764065	6.51E-217
	9	0.875	Inf	Inf	Inf	0
	10	0.8741	16.84362221	-20289.20942	1288.839156	1.36E-280
	11	-8.36E+179	Inf	Inf	Inf	0

[18] J. Wahlström, M. Hagberg, P. Johnson, J. Svensson, and D. Rempel, "Influence of time pressure and verbal provocation on physiological and psychological reactions during work with a computer mouse," *European journal of applied physiology*, vol. 87, no. 3, pp. 257–263, 2002.

[19] L. Salahuddin, M. G. Jeong, D. Kim, S.-K. Lim, K. Won, and J.-M. Woo, "Dependence of heart rate variability on stress factors of stress response inventory," in *e-Health Networking, Application and Services, 2007 9th International Conference on*. IEEE, 2007, pp. 236–239.

[20] B. Cinaz, B. Arnrich, R. La Marca, and G. Tröster, "Monitoring of mental workload levels during an everyday life office-work scenario," *Personal and ubiquitous computing*, vol. 17, no. 2, pp. 229–239, 2013.

[21] H.-K. Yang, J.-W. Lee, K.-H. Lee, Y.-J. Lee, K.-S. Kim, H.-J. Choi, and D.-J. Kim, "Application for the wearable heart activity monitoring system: analysis of the autonomic function of hrv," in *Engineering in Medicine and Biology Society, 2008. EMBS 2008. 30th Annual International Conference of the IEEE*. IEEE, 2008, pp. 1258–1261.

[22] U. T. Eden, "Point process adaptive filters for neural data analysis: Theory and applications," in *Decision and Control, 2007 46th IEEE Conference on*. IEEE, 2007, pp. 5818–5825.

[23] U. T. Eden, L. M. Frank, R. Barbieri, V. Solo, and E. N. Brown, "Dynamic analysis of neural encoding by point process adaptive filtering," *Neural computation*, vol. 16, no. 5, pp. 971–998, 2004.

[24] R. Barbieri and E. N. Brown, "Application of dynamic point process models to cardiovascular control," *Biosystems*, vol. 93, no. 1-2, pp. 120–125, 2008.

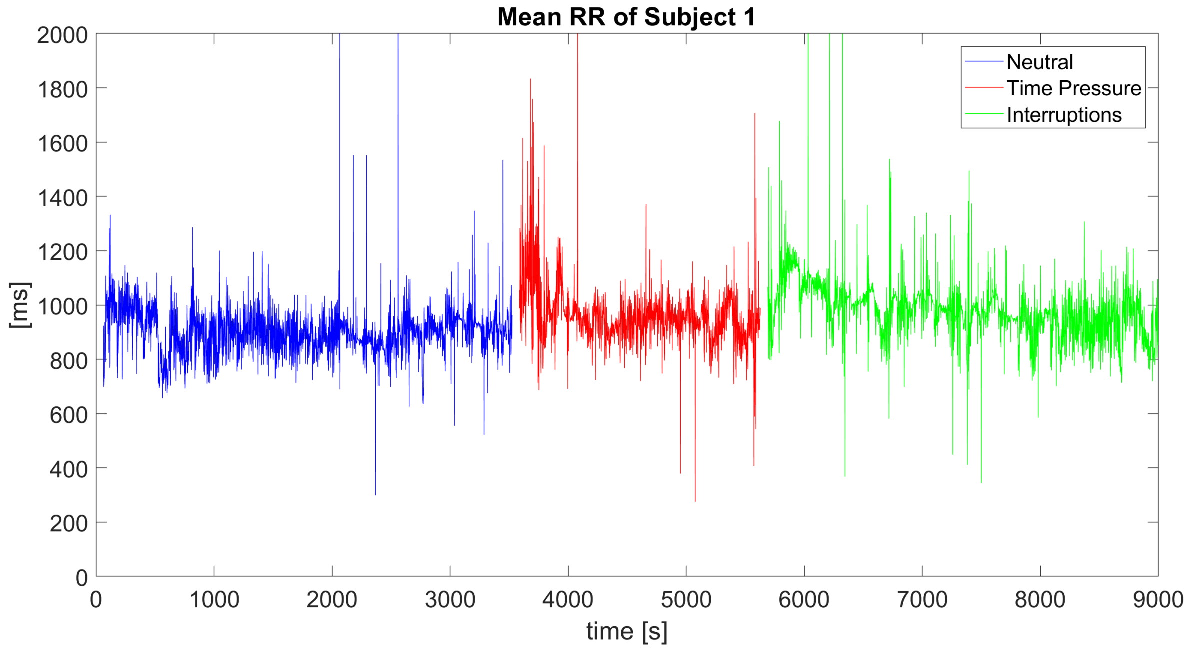
[25] J. E. Hall, *Guyton and Hall textbook of medical physiology e-Book*. Elsevier Health Sciences, 2015.

[26] K. E. Barrett, S. M. Barman, S. Boitano, and H. Brooks, "Ganong's review of medical physiology. 23," *NY: McGraw-Hill Medical*, 2009.

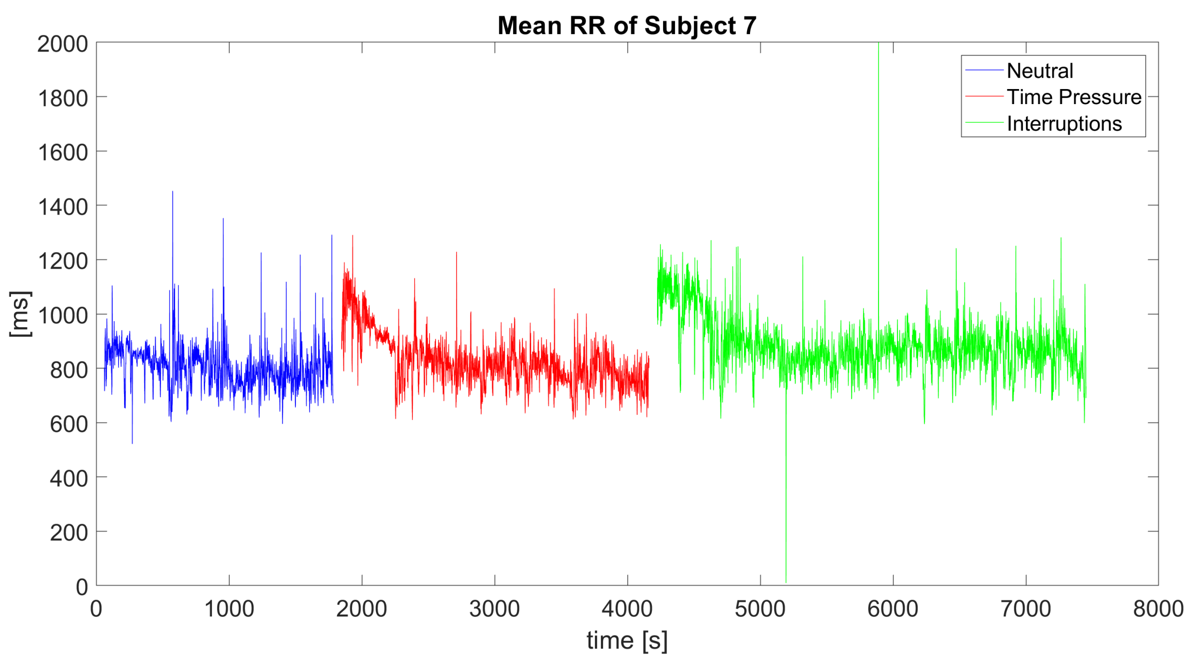
[27] M. Lunt, "Introduction to statistical modelling: linear regression," *Rheumatology*, vol. 54, no. 7, pp. 1137–1140, 2013.

[28] J. Neter, M. H. Kutner, C. J. Nachtsheim, and W. Wasserman, *Applied linear statistical models*. Irwin Chicago, 1996, vol. 4.

APPENDIX



Mean RR of Subject 1
[ms]
time [s]
Neutral
Time Pressure
Interruptions
0
200
400
600
800
1000
1200
1400
1600
1800
2000
0
1000
2000
3000
4000
5000
6000
7000
8000
9000



Mean RR of Subject 7
[ms]
time [s]
Neutral
Time Pressure
Interruptions
0
200
400
600
800
1000
1200
1400
1600
1800
2000
0
1000
2000
3000
4000
5000
6000
7000
8000