Objective measurement of stress resilience: Is RSA a possible indicator?

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Abstract. Mental and physical health are interlinked. While there are many objective measurement methods and diagnostic tools for physical disorders, the factors influencing mental health are wide-ranging and very subjective. As a result, there is a need for an objective method for assessing stress and stress resilience. The main parameter used today is heart rate variability, which unfortunately varies according to age, gender and physical health. In this paper, we analyze the effects of respiratory sinus arrhythmia (RSA) on stress and promote RSA as a possible new and advanced parameter for stress resilience. In an evaluation we recorded the heart rate of 20 subjects via a PPG finger sensor and a rPPG method utilising only a webcam. Based on the recorded heart rate data we demonstrate RSA variation and define an RSA parameter that can be assessed remotely without physical contact using computer vision and a standard webcam.

Keywords: respiration · RSA · respiratory sinus arrhythmia · non contact · vital data recognition · stress.

1 Introduction

Stress resilience, defined as the ability to adapt and recover from stressors, plays a crucial role in maintaining mental and physical well-being. It has even been shown to slow the effects of aging [10]. As the demands of modern life continue to increase, there is a growing interest in developing objective methods to assess stress resilience [18]. Since hypertension and increased heart rate are associated with stress, heart beat parameters are used to assess the effects of stress, but these have so far been very unspecific. One promising avenue of investigation is the study of respiratory sinus arrhythmia (RSA), a phenomenon characterized by the natural variation in heart rate that occurs during the breathing cycle.

RSA reflects the dynamic interplay between the respiratory system and the autonomic nervous system, specifically the parasympathetic branch. During inhalation, heart rate tends to increase, while during exhalation, it tends to decrease. This rhythmic fluctuation in heart rate is believed to be an adaptive response, facilitating oxygen exchange and optimizing physiological functioning [25]. Importantly, alterations in RSA patterns have been associated with various stress-related conditions, including anxiety disorders, depression, and cardiovascular diseases [29].

Given the potential link between RSA and stress resilience, there is growing interest in exploring RSA as an objective measure of an individual's ability to cope with and recover from stress. By quantifying and analyzing RSA patterns, it may be possible to identify individuals with higher levels of stress resilience, as they might exhibit more efficient regulation of heart rate in response to stressors.

This paper aims to critically examine existing methods for the measurement of stress and stress resilience. After which a new way of measuring stress via a novel RSA parameter is introduced. To this end we conduct our own study to create a database of heart rate measurements, as well as a questionnaire about the stress levels of the participants. The database is then used to extract a novel parameter for the quantification of RSA. Lastly we aim to then link this newfound parameter to the occurrence of stress in our study.

Ultimately, understanding the potential of RSA as an objective measure of stress resilience could have significant implications for both research and clinical practice. By identifying individuals with lower stress resilience early on, appropriate interventions and strategies can be implemented to enhance their ability to cope with stress and promote overall well-being.

2 Related Work

Stress can be defined as a physiological and psychological response to external or internal pressures, often referred to as stressors, that challenge an individual's ability to cope [19]. It is a natural and adaptive response that helps us navigate demanding situations. Stress can manifest in various forms, including physical, emotional, or cognitive, and can have both short-term and long-term effects on overall well-being. It can also be divided into two general categories, distress and eustress.

Distress refers to a negative or unpleasant form of stress that exceeds an individual's ability to cope effectively. It is often associated with feelings of anxiety, sadness, and an overall sense of being overwhelmed [32]. Distress can have detrimental effects on physical and mental health if prolonged or left unmanaged. Examples of distressing events or circumstances may include traumatic experiences, chronic illness, or significant life changes.

Eustress is a positive form of stress that is typically associated with beneficial or exciting experiences. It is characterized by feelings of motivation, excitement, and a sense of fulfillment [3]. Eustress can arise from situations such as starting a new job, getting married, or participating in challenging activities that provide a sense of accomplishment. Unlike distress, eustress is believed to have a positive impact on performance, personal growth, and overall well-being.

It is important to note that the distinction between distress and eustress lies mainly in the individual's perception and interpretation of the stressor, which in turn is highly dependent on the resource state of the individual. If the individual has the ability and resources to manage the stressor, it will be perceived more positively as a challenge. If not, it will be perceived as a hindrance. Hence, what may be distressing for one person can be perceived as eustressful by another, depending on their subjective appraisal and ability to cope with the given situation [5].

2.1 Subjective Stress Determination

The assessment and evaluation of stress often requires a combination of different methods in order to be able to evaluate stress comprehensively. Each method has its strengths and limitations, and the choice of assessment method depends on the research or clinical objectives, context, and available resources.

Some stress monitoring methods are performed by the users itself or other observers. These assessment methods are highly subjective and might include a high variability and fuzziness.

Self-Report Measures Self-report measures involve individuals providing subjective information about their perceived stress levels, symptoms, and psychological well-being. This can be done through questionnaires, surveys, or rating scales specifically designed to assess stress [9]. Examples of self-report measures include the Perceived Stress Scale (PSS) and the Holmes and Rahe Stress Scale [22]. These measures provide insights into individuals' subjective experiences of stress but may be influenced by factors such as self-report bias and individual differences in introspection.

Behavioral observation Behavioral observation involves direct observation and assessment of behavioral indicators of stress. This can include changes in facial expressions, body language, vocal tone, or observable signs of agitation or distress. Behavioral observation can provide valuable insights into stress responses, especially in social or interactive contexts [31]. However, it may be subjective and influenced by the observer's interpretation and biases.

Psychometric Assessments Psychometric assessments are standardized tests or inventories that measure specific aspects related to stress, such as coping strategies, resilience, or specific stress-related symptoms. These assessments provide quantitative data and can help identify individual differences in stress-related constructs. Examples include the Coping Strategies Inventory (CSI) and the Connor-Davidson Resilience Scale (CD-RISC) [7].

2.2 Objective Stress Determination

Objective assessment methods are independent by the observer but may also be error-prone because of indirect measurement and the individual feeling of the persons. Their advantage is reproducibility and objectivity.

Physiological Measures Physiological measures assess stress by monitoring changes in the body's physiological responses to stressors. Common physiological measures include heart rate [12], blood pressure [28], body or skin temperature [11], and skin conductance [21]. These measures can indicate the activation of the autonomic nervous system and the body's stress response. Physiological measures are objective and can provide insights into the body's acute or chronic stress responses. However, they may not capture the full complexity of stress experiences and can be influenced by various factors such as environmental conditions and individual variability.

Biomarkers Biomarkers are objective physiological or biochemical indicators of stress that can be measured in biological samples such as blood, saliva, or urine. These biomarkers can include cortisol, adrenaline, and inflammatory markers [4]. Biomarker analysis can provide insights into the body's stress response at a molecular level. However, biomarker assessments may require specialized laboratory analysis and may not be feasible for routine stress assessment in certain settings.

2.3 Respiratory Sinus Arrhythmia

Respiratory sinus arrhythmia (RSA) is a normal variation in heart rate that occurs in sync with the respiratory cycle. During inhalation, the heart rate increases, and during exhalation, it decreases. This rhythmic fluctuation is believed to be caused by the parasympathetic nervous system (PNS), which is mostly controlled by the vagus nerve [17]. The presence of a pronounced RSA in a subjects heart rate is considered as an indicator of good cardiovascular health, as well as psychological well-being [33] [34].

3 Application of RSA

Measuring RSA is an established procedure to check for the function of the autonomic nervous system, autonomic balance and specifically the activity of the parasympathetic system as well. It is also generally relevant in infant research [1], risk assessment for patients with cardiac issues [13] and diabetes patients [6].

3.1 Applications in Cardiovascular Medicine

RSA can be used as an indicator of cardiovascular health. RSA reflects the heart's ability to adapt to changes in physiological demands and is often measured during cardiac health assessments to evaluate the autonomic nervous system's control over heart rate. When the RSA is present, it typically indicates good cardiovascular health [27].

3.2 Applications in Psychophysiological Medicine

RSA is used in psychophysiological medicine to assess emotional regulation and stress response. It is often used to evaluate how the nervous system responds to stress and relaxation, and can be an indicator of psychological resilience and emotional well-being. In more detail, a study of RSA-based biofeedback training (RSA-BF) on managers by Munafò et al. [20] indicated that higher RSA values are associated with increased vagal control. Also, RSA-BF decreased sympathetic arousal and lowered emotional interference and hence reduced negative psychophysiological outcomes of stress. In a similar study on healthy adults with increased stress levels by Sherlin et al. [26], RSA-BF had a carryover effect that reduced HR reactions to a repeated stressor, thus lowering stress reactivity. Given these insights, the RSA indeed seems to be indicative for stress reactivity and thus how good individuals cope with stressful events which is closely connected to the concept of stress resilience, further highlighting the need for an easily applicable RSA parameter.

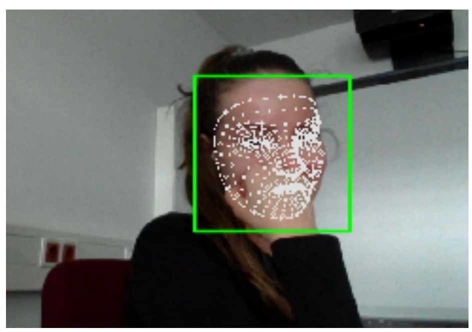

Fig. 1. Non contact heart rate detection during controlled respiration.

3.3 Problems in the Application

RSA is already widely applied, both in science and in clinical contexts. However, its use still brings issues with it, which have not been completely solved at this point in time.

RSA is a special characteristic of the variability of heartbeats. Unfortunately, heart rate variability (HRV) is not a single parameter, but is described by many, including in the time and frequency domain [23]. With expert knowledge one might be able to estimate the quality of RSA from multiple HRV parameters, however it would be much simpler if RSA could be described by a single parameter, that is also understandable with only surface level knowledge of the topic.

There is even some parameters, which aim to describe RSA directly, as shown by e.g. Lewis et al. [15]. However, these largely suffer from the same problems as other HRV parameters, as in that they are either not intuitive, don't communicate the magnitude of RSA well or require additional information about the breathing frequency. While information about respiration would be helpful for determining RSA, the focus in this paper is on heart rate data only which makes our approach more widely applicable even in scenarios where only a heart rate sensor is available.

The question therefore arises as to whether stress or stress resilience can be described by a new RSA parameter that is easy to record, use and understand, but still precise. To this end we created an evaluation to calculate a diverse range of HRV parameters and develop a suitable RSA parameter from those.

4 Evaluation of RSA

This section's goal is to evaluate a range of diverse HRV parameters and their potential link to RSA. The motivation behind this evaluation is that these parameters and the gained understanding of their relation to RSA can then be used later for the development of a new and more sophisticated RSA parameter.

In order to properly evaluate RSA as a possible measure for stress and stress resilience we have conducted our own study with a size of 20 subjects for that very purpose. The mean age of the subjects was 35 with a standard deviation of 12.4 years. 18 of the subjects were male and 2 female. All subjects were healthy, did not have a history of heart related diseases and gave written, informed consent prior to the experiment.

During the study each participant's heart rate was recorded for six minutes with two measuring methods. The first one being a standard PPG-sensor (Pulox PO-300) and the second one a system for remotely measuring the heart rate via a webcam (CareCam), which can be seen in operation in Figure 1. The PPG-Sensor is a finger sensor that measures the pulse wave with a sampling rate of 60 Hz. The CareCam [14] is a technology that retrieves the pulse rate of the subject by analysing the chromatic change of the skin that is caused by every heart beat because of the varying blood flow at the forehead of the subject. The webcam (standard VGA resolution) records the videosignal with 30 fps.

The six minute experiment time was divided into three phases with a length of two minutes each in order satisfy common recommendations for cardiovascular science [24]. During the first phase, the resting phase, the participants were asked to sit in an upright position and to breathe freely. During the second phase, the reactivity phase, the participants were asked to match their breathing to on-screen instructions, in the form of a breathing cycle, which matched a breathing frequency of about 6 bpm (breaths per minute) in order to maximize the occurrence of RSA. During the last phase, the recovery phase, the participants were asked to breathe freely again. These three phases and the effect they have on the RSA-related heart rate are illustrated below in Figure 2.

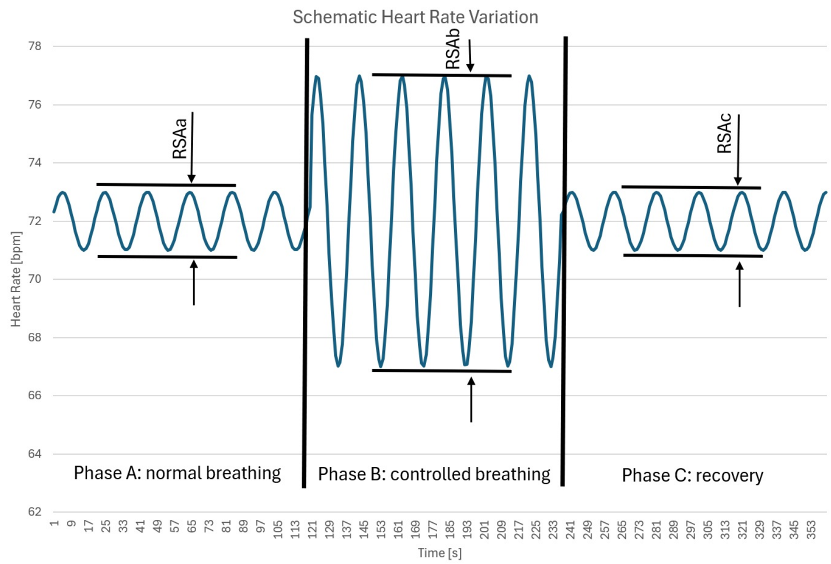

Fig. 2. Phases of the evaluation, resting phase A, reactivity phase B, recovery phase C.

After the experiment was completed, every subject answered a brief questionnaire in order to get additional contextual information about the measurement and the stress of the subject before, after and during the experiment. The most relevant contents of the questionnaire were as follows:

1. Did you feel stressed at the beginning of the experiment?
   – scale of 1 (not stressed) to 5 (very stressed)
2. Do you feel less stressed after the experiment?
   – scale of 1 (not stressed) to 5 (very stressed)
3. Did the breathing exercise have a relaxing effect on you?
   – scale of 1 (very stressful) to 5 (very relaxing)
4. Did you have air problems during the breathing exercise?
   – scale of 1 (no problems) to 5 (respiratory distress)

After all experiments of the study are done, there are now two largely similar, but still distinct, heart rate datasets. One is from the PPG-sensor recordings and one from the CareCam recordings. The general quality of the recorded data is mostly similar between the two, as can be seen when comparing Figures 3 and 4. The two figures demonstrate that the fluctuations in the heart rate caused by RSA can be captured by both methods. A more in-depth comparison of the two methods and the results they each produce would surely be interesting and worthwhile. However, it would take too much of the limited space available for the paper and also distract further from the main goal of developing a parameter for the assessment of stress. So in order to remain concise, the data obtained from the PPG-sensor is chosen for further processing, since it has the higher sampling rate of 60 Hz, as compared to the CareCam's 30 Hz. A higher sampling rate makes the calculation of heart rate parameters, especially time-based ones, more precise.

4.1 Annotation

After the experiment, peak detection [8] was performed on the raw ppg-waveform and from the intervals between the detected peaks the heart rate was then calculated. This was performed with the Python package *Neurokit 2* with version 0.2.7. The result of this is then a graph for each subject's heart rate in bpm (beats per minute) over the six minutes of the experiment. Those six minutes are then divided into windows with a length of 40 s each, so there are nine windows per experiment. After windowing, each window is manually annotated, according to how strong RSA is visible in that window. More specifically, each window gets assigned a score from 0 to 5, depending on the magnitude of RSA in the heart rate. RSA in this case is interpreted as a sinus-shaped waveform in the heart rate graph, which matches a possible breathing frequency, i.e. is between a frequency of 0.08 and 0.5 Hz. The criteria for the annotation scoring are as follows:

- 0: Heart rate is constant, with no variations.
- 1: Slight variations in the heart rate of up to 5 bpm, but not necessarily in a shape matching RSA.
- 2: Variations in the heart rate from 5 up to 10 bpm, matching the shape of RSA.
- 3: Variations in the heart rate from 10 up to 15 bpm, matching the shape of RSA.
- 4: Variations in the heart rate from 15 up to 20 bpm, matching the shape of RSA.
- 5: Variations in the heart rate of over 20 bpm, matching the shape of RSA.

4.2 Metrics

A diverse range of parameters is calculated for each of the 40s windows of recorded heart rate data. For calculating the parameters *Neurokit 2* is used again and a total of 34 different parameters are calculated for each window [16]. The parameters can roughly be partitioned into three distinct categories. 18 of these 34 parameters fall into the first category of *time-based parameters* [4], those being e.g. the mean of the NN-intervals or the pNN50-value. 8 of the 34 parameters are from the second category of *frequency-based parameters* [5], those being

[4] https://neuropsychology.github.io/NeuroKit/functions/hrv.html#hrv-time
[5] https://neuropsychology.github.io/NeuroKit/functions/hrv.html#hrv-frequency

e.g. the spectral power in the low-frequency band or the LF/HF-ratio. The remaining 8 parameters belong to the third category, which consists of *RSA-based parameters* [6], i.e. parameters which are already designed to quantify RSA, but might not be suitable for the reasons discussed at the end of section 3.

All 34 parameters are extracted from the heart rate data and then normalized along with the annotation. The *StandardScaler* function from *Scikit-Learn* with version 1.4 was used for normalization. After this, the Pearson correlation coefficient of each of the parameters with the annotation is calculated for each subject. This is done as a way of evaluation and to get an understanding of how well each parameter is able to represent RSA. In practice this means that for every subject and parameter the correlation coefficient with the respective annotation vector is calculated. For example, given a subject x with annotation vector $anno = [1, 1, 1, 5, 5, 5, 1, 1, 1]$, each value represents the annotated RSA value for the respective 40s window and one parameter vector could be $meanNN = [1000, 1000, 1000, 800, 800, 800, 1000, 1000, 1000]$, where again each value represents the calculated parameter for the respective 40s window and the vector as a whole represents one six minute experiment of a subject. The correlation coefficient between the annotation- and parameter-vector would then be $r = -1$. This way of calculating the correlation coefficient is then done for the other 33 parameter-vectors for that subject and then the same is done for every other subject. The result of this is a matrix with the correlation coefficient of every parameter-vector of every subject with their respective annotation-vector.

4.3 Results

In order for a parameter to be regarded as indicative of RSA within a subject it has to achieve a ”moderately strong” correlation with the annotation, i.e. a correlation coefficient of greater than 0.6 or smaller than -0.6 [2]. In order for a parameter to be further regarded indicative of RSA in general, and not only within a subject, it needs to be indicative of RSA within at least half of the subjects, i.e. for 10 or more. With this general criterion in mind, a total of 14 parameters turn out to be indicative of RSA. A brief overview of them can be found in Table 1.

The table displays the mean value of the correlation and also the median p-value for each parameter. Each of them are calculated for the respective parameter and over all subjects. Because of this there are also the correlation values included in the calculation of the mean, which did not meet the threshold of 0.6 or -0.6. This fact in conjunction with the circumstance that there is also a high inter-subject variability leads to some of the correlation mean values in the table to be lower than 0.6, despite still meeting the general criterion defined earlier.

For displaying the p-values of the parameters, their respective median was chosen instead of their mean, as some heavy outliers were significantly skewing the mean value for many of the parameters. Yet still, some of the median p-values do not meet the generally accepted threshold for statistical significance of being

[6] https://neuropsychology.github.io/NeuroKit/functions/hrv.html#hrv-rsa

lower than 0.05. For this however, one has to take into consideration that each p-value is calculated based on a rather small sample size, which vastly increases the influence of random error on the p-value and means that the threshold of 0.05 shouldn't be taken too seriously [30].

Four of those 14 parameters even manage to be indicative of RSA in at least 75% of subjects, i.e. for 15 or more subjects. Those four parameters are *RespPSD, GatesSD, IQRNN* and *LF/HF*. In this context it is also worth mentioning, that for two subjects no single parameter had a moderately strong correlation with the annotation and indeed those subjects' heart rate shows no visible signs of RSA, so it can be expected that there is a significantly lesser degree of correlation between those subjects' parameters with what is essentially "noise", at least in regards to RSA.

To summarize this section, a heart rate dataset was created with the aim of evaluating RSA on its basis, which was then divided into windows and annotated. The dataset was then analyzed by extracting a diverse range of HRV parameters. These parameters were then further evaluated in regards to their potential link with RSA.

Table 1. Overview of HRV parameters that have a link to RSA and the mean of their absolute correlation over all subjects

Parameter	Correlation Mean	P Median
RespPSD: Absolute Power Spectral Density around the common respiratory frequency	0.71	0.02
P2T: Median of the Peak-to-Trough values	0.64	0.08
PB: Porges-Bohrer value	0.54	0.09
GatesSD: Standard Deviation of the Gates values	0.74	<0.01
SDNN: Standard Deviation of NN-Intervals	0.56	0.11
CVNN: Standard Deviation of the NN-Intervals divided by the mean of the NN-Intervals	0.59	0.09
MadNN: Median Absolute Deviation of NN-Intervals	0.60	0.04
MCVNN: Median Absolute Deviation of the NN-Intervals divided by the median of the NN-Intervals	0.64	0.02
IQRNN: Interquartile Range of the NN-Intervals	0.76	<0.01
Prc20NN: 20th percentile of the NN-Intervals	0.65	0.03
HTI: Total Number of NN-Intervals divided by the height of the NN-Intervals histogram	0.58	0.07
LF: Power Spectral Density of the Low Frequency Band (0.04 to 0.15 Hz)	0.67	0.04
LFn: Normalized PSD of the Low Frequency Band	0.60	0.04
LF/HF: Ratio of Low Frequency Band to High Frequency Band PSD	0.63	0.06

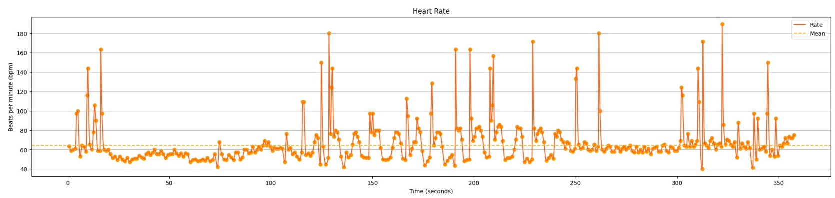

Fig. 3. Finger sensing of RSA.

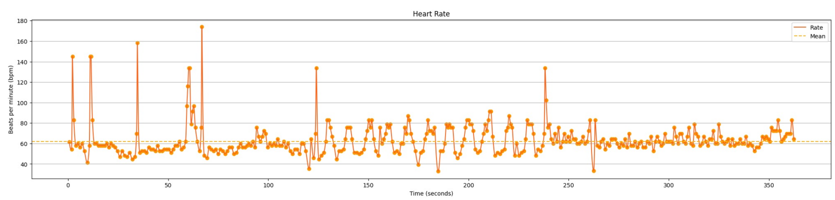

Fig. 4. Non contact RSA measurement.

5 New Qualitative Estimate for RSA

In the previous section, multiple parameters were found to be strongly indicative of RSA. However, none of these give an intuitive understanding of RSA. This means that, given a value, it is difficult to have an immediate understanding of how the heart rate looks like in regards to RSA. However, such a parameter has already been introduced in the context of this paper in the form of the annotation, which gives a very concise estimate of RSA from an intuitive standpoint from "nonexistent (0)" over "moderate(3)" to "strongly present (5)".

It would then be useful to have an application or model, which takes some piece of heart rate data, calculates the diverse parameters from the previous section and then gives an intuitive value based on the parameters, that is directly representative of the RSA occurring in the heart rate data similar to the scale used during the annotation. In addition it would also be interesting to get insight into the decision making process of the model, i.e. to see how the model reaches its result. The implementation of this model and its relevance then for stress detection is described in the following section.

5.1 Implementation

The objective in the calculation of an estimate for RSA is twofold. Firstly, to create a model, that takes the parameters derived from the heart rate and gives an estimate of RSA that is as accurate as possible. Secondly, to get an idea of how the model got to its estimate.

For each subject there are nine 40-second windows and the study includes twenty subjects in total, which leads to a number of 180 instances in the dataset. Since that is not a lot of data, a deep-learning approach seems ill-suited. From the more classical machine-learning methods the Decision-Tree-Algorithm seems the most promising, due to the relatively high number of parameters in the dataset and the circumstance that decision trees are easy to visualize and understand, if they don't get too complex. This means, that in order to understand how the model determines the value for the RSA parameter, one can simply look at the visualization of a decision-tree model with an acceptable performance. Once that model has been created it can then be optimized beyond it's purpose of visualization to achieve the best performance possible. For the implementation and evaluation of all models the Python package *Scikit-Learn* is used.

For the first model, the objective is to get a decision tree model, which is small and has acceptable performance, it doesn't need to be outstandingly accurate, but humanly understandable instead. In order to keep the decision tree small, certain parameters are restricted, namely the maximum depth of the tree and the minimum amount of samples needed to form a leaf. To find the optimal combination of these parameters within the restrictions, hyperparameter-tuning via Grid-Search is used with the resulting maximum depth having a value of 6 and the minimum number of samples needed to form a leaf being 10. It is also worth noting, that the decision tree has been created as a regressor, not a classifier, since the value it is trying to predict can be interpreted as being an element of a real-valued interval-scale. This model has then been evaluated by utilising a test-set, with a test-split size of 0.2. Calculating the Root-Mean-Square-Error (RMSE) on it gives a result of $RMSE = 1.14$. This result isn't too great, but also not bad, considering that the range of possible values is from 0 to 5.

When observing the tree, which is displayed in Figure 5, one interesting piece of information arising is that the error largely comes from samples with a RSA-value in the middle range, i.e. somewhere around 2 to 3. But with RSA-values that are closer to either extreme, i.e. values around 1 or 5, the decision tress has significantly less trouble. To optimize the model AdaBoost should be a good approach, since the AdaBoost algorithm puts emphasis on samples that produce a larger error. So this algorithm should work well in order to teach the model how to handle samples with RSA-values in the middle range as well.

Again, Grid-Search is used to find the best hyperparameters for the optimized model, which in this case results in a value of 2 for the learning rate and a value of 25 for the number of estimators. The base estimator is a Decision-Tree-Regressor, similar to the simple model. The optimized model is then also evaluated on the same test-set, that was used previously in order to have a better understanding of how this model performs relative to the previous one. The evaluation leads to a result of $RMSE = 0.83$, which means a significant improvement compared to the simple model. The remaining error can, at least in part, be attributed to measuring errors during the experiment, e.g. sudden peaks of over 160 bpm in the heart rate data, as well as human error during the annotation. It could be possible to achieve an even better performance with a deep-learning approach, however, due to the low amount of data this doesn't seem sensible to try for now.

In summary, theses two models demonstrate two different things. The more sophisticated model made with the AdaBoost algorithm shows that it is generally possible to get a qualitative estimate of RSA only from heart-rate data, which is suitably accurate. Meanwhile, the simpler model gives a rough understanding of how one can infer RSA from heart-rate data. The next step now is to try to link that qualitative value of RSA to stress.

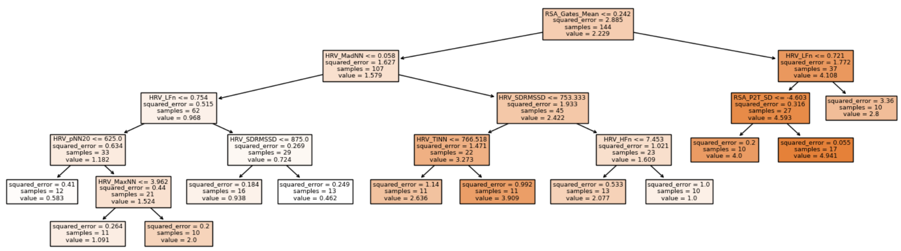

Fig. 5. Visualisation of the simple Decision Tree without optimization.

5.2 Relevance for Stress-Detection

In order to now show the relevance of this new RSA parameter in regards to stress it would make sense to compare the RSA values from the study, described in section 4, to the stress values in the questionnaire from the study. This turns out to be difficult however, since the dataset from the study is unbalanced, as almost none of the participants reported that they feel stressed either before or after the experiment. In total only two participants reported they were at least moderately stressed (3 or greater on the scale) before the experiment and three participants reported so after the experiment. The mean of the stress level across all participants lies at 1.55 both before and after the experiment. Meanwhile the mean value of RSA during the reactivity phase of the experiment lies at 3.97. So in general one could say that stress levels in the study are generally low while RSA levels are generally high, which is indeed in accordance with the current state of the art. These observations also demonstrate that the design of the study succeeded in its goal of eliciting a strong RSA response from the subjects. However, at the same time it is unfortunately not possible to test whether the inverted assumption, that high stress leads to a low RSA value, also holds true, which would have been closer to the actual objective of the paper.

So in summary, while the developed RSA parameter so far works in accordance with the current state of the art, it is not possible to infer a relevant link between this RSA-parameter and stress yet, due to a lack of suitable data, that is representative for stress. It is thus left open to future work to conduct another study in which more stress is induced in participants using established methods, e.g., the Trier Social Stress Test, the Stroop Color Word Test or the Serial Seven Test, where participants have to count backwards.

6 Discussion

In this paper we introduced a new parameter for the quantification of RSA, which can potentially be used as a factor to detect stress and assess the stress resilience of a person. This new parameter is better suited for stress detection than other HRV parameters, as those tend to be more age-dependent. In addition, since RSA is strongly related to the activity of the parasympathetic nervous system, it is also a more direct indicator for the neurological effects of stress. Other than for stress measuring, the new RSA parameter can also be applied in physiological medicine, as RSA is a significant indicator for cardiac health in general and also specifically for mortality in patients who suffered myocardial infarction. However, in order to asses the newly developed parameter's usefulness in the context of physiological medicine, a separate evaluation on a more suitable clinical dataset would have to be conducted.

Looking a bit closer on the study, more specifically on the Peak-to-Trough (P2T) parameter, which describes the difference between the maximum heart rate during inhalation and the minimum heart rate during exhalation. The evaluation of the mean P2T value for each phase and over all subjects shows values of $P2Ta = 6.84 \pm \sigma = 5.35, P2Tb = 12.3 \pm \sigma = 7.49,$ and $P2Tc = 7.92 \pm \sigma = 6.32$, each value is given in beats per minute. This shows that the subjects were more relaxed at the end of the evaluation in comparison to the start. It is worth mentioning however that during the study there were no ground truth measurements of respiration and thus the respiration signal for the calculation of the P2T values was derived from the heart rate. This means that those values are not fully reliable, but nevertheless provide a good estimation about the overall range of RSA. Indeed, these findings are further underlined when looking at the mean annotation values over the three phases: $ANNOa = 6.05 \pm \sigma = 4.75, ANNOb = 19.8 \pm \sigma = 6.75,$ and $ANNOc = 8.75 \pm \sigma = 6.3$, again each values is in beats per minute. These observations also demonstrate that the design of the study succeeded in its goal of eliciting a strong RSA response in the subjects.

During the study we also showed that RSA measurement can also be achieved by a contactless assessment using the CareCam technology. This enables a continuous monitoring, e.g. during office work, and supports the idea of an unobtrusive stress assistance in the application field of occupational health. A deeper look into the data obtained via the CareCam would be worthwhile, since only some of the data was compared to the ground truth in the context of this paper. Through a deeper evaluation it could be possible to evaluate, if methods like the

CareCam could potentially also be used to obtain ground truth data and if so, under which circumstances.

Other potential avenues for the application of the RSA parameter, as a parameter of stress and stress resilience, lie in estimating the efficiency of traditional stress training courses. While many coaching methods are costly and might be ineffective, RSA provides a promising new approach for educating individuals or treating patients, potentially including younger populations as well. It would be particularly interesting to explore how soldiers, who undergo significant behavioral changes during their service, are affected by intense training programs, such as boot camps or even a deployment both before and after their completion.

7 Conclusion and Outlook

In this paper a new method to objectively and unobtrusively measure a persons stress and stress resilience was developed. For this purpose a study was conducted with a focus on obtaining heart rate data, that had both pronounced RSA, as well as comparative baseline values. Additionally, the subjects' stress was also recorded via a questionnaire. Heart rate data was obtained in two ways. The first one being a PPG-sensor, attached to the finger of the subject and the second one a contactless method, working only with a RGB-video of the subject, called CareCam. It was demonstrated that both methods can achieve comparable quality in their results.

After data acquisition and annotation, a diverse range of HRV related parameters were extracted from the dataset. These parameters were then evaluated as to how strong their connection to RSA is. This was done by calculating each of their correlation coefficient with the RSA annotation, with the result being, that many of them have a moderate degree of connection and a few even have a strong connection. It was also found however, that none of the evaluated parameters give an intuitive understanding of the magnitude of RSA present in a given instance of heart rate data.

Thus a new parameter was introduced that is directly and intuitively communicating the degree of RSA present and is calculated on the basis of the evaluated HRV parameters. For this purpose a classical machine-learning approach has been applied, consisting of the Decision Tree and AdaBoost algorithms. The resulting model has then been evaluated on a test set with good results.

After calculating the newly developed RSA parameter it was then attempted to demonstrate its link with the stress related data from the questionnaire. This was unfortunately not possible in this way, since almost none of the subjects were even moderately stressed before or after the study. Meaning that the RSA parameter could not be linked to stress, due to a lack of data representative for stress in the study. This however does not contradict the concept of the RSA parameter, since the results in general are still in accordance with the state of research in this area, i.e. stress values were generally low and RSA values were generally high.

For continuing research it would definitely be advisable to conduct another study with a stressor built into its design in order to elicit a measurable stress response in the subjects, so it can be compared to the data acquired in this papers study. It would also be interesting to have a more in depth comparison between the two heart rate measuring methods, as especially the unobtrusiveness of the CareCam offers an advantage over more classical methods like PPG or ECG.

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