Heart Rate Variability for Stress Detection with Autistic Young Adults

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Abstract. Physiology, such as heart rate viability (HRV), can give meaningful insights about autonomic response to stress. Autism Spectrum Disorder has been linked to atypical physiological responses and poor emotion regulation. Explorations of the differences in physiological response between autistic young adults and neurotypical young adults can provide meaningful information on stress responses in these populations and can be used to create adaptive systems. Stress detection is an important aspect of creating closed-loop systems that can respond and change based on the emotional state of the user. This paper aims to explore HRV as a means of obtaining stress information from physiological data and to explore differences in stress response between autistic young adults and their neurotypical peers using Kubios HRV Premium analysis software during the PASAT-C, a distress tolerance task. Unpaired *t* tests showed statistically significant ($p < .05$) differences in three stress related indexes: the parasympathetic nervous system index, the sympathetic nervous system index, and the stress index. Preliminary results show validity of HRV for stress insight and provides evidence for physiological differences in stress response between the two groups.

Keywords: Stress detection · Heart rate variability · Adaptive systems · Autism

1 Introduction

Physiological data, specifically heart rate variability (HRV), can give important insight to stress responses from the two branches of the autonomic nervous system (ANS), the parasympathetic nervous system (PNS) and the sympathetic nervous system (SNS) [1–3]. HRV, and other physiological measures, are the body's response to the ANS using sensory and motor neurons to operate between various organs and the central nervous system. During a stressful event, the SNS releases several stress hormones, including cortisol, which cause the organs and motor neurons to respond [4]. These responses happen simultaneously with emotions and stress [5]. Physiological responses to stress are involuntary and are especially useful because they are less susceptible to being masked by an individual [6]. In cases of acute stress, the response is immediate [7] and can be measured. Prior to physiology-based stress detection, questionnaires were used to determine stress levels. However, the questionnaires are subjective and often the

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collection of stress data is delayed [8], furthering the need for physiology-based detection. However, current physiology-based stress detection relies on supervised machine learning approaches that require ground truth labels from a trained behavioral expert or relay on task based stress labels [9–11]. Obtaining ground truth labels is labor intensive and cost prohibitive in many cases and level-based labels may not correctly represent an individual's stress level. Many machine learning approaches also rely on additional inputs beyond heart rate data, such as electrodermal activity and electromyogram data that require additional sensors [12–14]. HRV analysis of stress could be a means of obtaining these stress measures without the need for ground truth labels and reduce the number of necessary sensors.

Autism Spectrum Disorder (ASD) is characterized by differences in social communication and social behaviors, as well as difficulties with emotional regulation, including stress management [15, 16]. The prevalence of autism continues to rise, with the CDC estimating that the prevalence has risen from 1 in 150 in 2000 to 1 in 44 as of 2018 [17]. As the prevalence rises, it becomes even more necessary to understand the differences that characterize autism, including emotional regulation and stress to provide support and accommodations for autistic[1] young adults. Atypical physiological reactivity, including differences in heart rate variability (HRV) have been linked to autism [18]. While research on physiological reactivity in autistic individuals exist, much of the current literature is focused on children and gives little insight to how physiological responses may change in adulthood. In particular, how physiological responses can be utilized in inferring stress in autistic adults during human-computer interaction has not been thoroughly explored.

In recent years, learning technologies have expanded to include adaptive systems that can alter their functionality and interaction based on the needs of an individual or group [19]. Initial studies explored how other emotions could be mapped to physiology to create adaptive games [20, 21] and have expanded to apply to learning technologies and intelligent human-computer interactions [10, 22]. Using these concepts, technologies that harness physiological data for stress detection can be used to create a closed loop[2] system that adapts in response to stress. In turn, the closed loop system allows for "flow" learning to be achieved. Flow theory, as introduced by Csikszentmihalyi [23], refers to the state of mind that can lead to deep learning and high satisfaction. To achieve "flow", the activities must be challenging but should not overmatch existing skills or cause distress [23]. In order to achieve and maintain flow in an adaptive system, stress detection is useful.

In this paper, we explore HRV data for stress detection. While it is known that autistic individuals have heighten emotional responses, to our knowledge, there are no studies that explore differences in HRV measures, such as sympathetic and parasympathetic activity, and stress trends during a distress tolerance task between autistic young adults and NT young adults. To address these questions, we specifically look at trends in

[1] Recent surveys with autistic self-advocates suggest a preference for identify first language. In accordance have chosen to adopt identity first (*autistic persons*) language in place of person first (*persons with autism*) language [37].

[2] Closed loop refers to a system in which an operation, process, or mechanism is regulated by feedback [38], in this case the feedback is stress.

HRV based stress between ASD and NT young adults during the Paced Auditory Serial Addition Task (PASAT) [24, 25], a known distress tolerance task using Kubios[3] HRV Premium, a heart rate variability analysis software. In Sect. 2, we detail system design including the methods, and the data analysis using Kubios. Results are presented in Sect. 3 and discussed in Sect. 4.

2 System Design

2.1 Methods

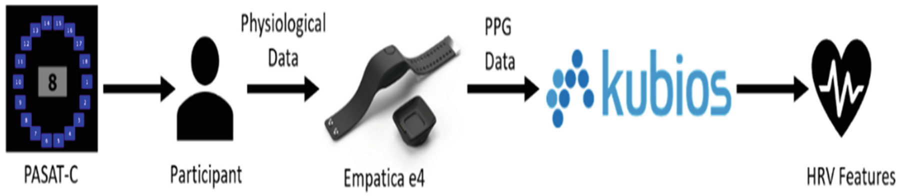

Fig. 1. System design flow

The modified computer version of the PASAT was developed to produce psychological stress in lab settings in a consistent way [25]. Physiological data was collected using the Empatica E4 wristband[4]. The original task code developed by Millisecond Software[5] was adapted in order to add a three-minute baseline and stress self-report between each level. The task presents a single digit that must be added to the digit presented previously. The presentation of the digits can be seen in Fig. 2. The participant is not asked to keep a running total, but instead to only add the last two presented digits. For each incorrect answer, a loud, pitched error sound is played. The task begins with 11 practice trials and proceeds into levels one, two, and three with the time between digits decreasing with each level. Digits are presented every three seconds for three minutes during level one and are presented every two seconds for five minutes during level two. Level three digits are presented in 1.5 s intervals for a duration of 10 min. The Likert self-stress scale is presented between each level.

The Empatica E4 collects blood volume pulse (BVP) data from the photoplethysmogram (PPG) sensor. The PPG uses combined green and red light to maximize the detection of the pulse wave. The green and red LEDs are oriented toward the skin. This allows the light to be absorbed by the blood and then reflected back. The reflected light is measured by the light receiver. The measurements taken during the green light exposure are used to generate the pulse wave and estimate heartbeats. The measurements during the red light exposure are used to create a reference light level that cancels out motion artefacts [26].

[3] www.kubios.com.
[4] www.empatica.com.
[5] www.millisecond.com.

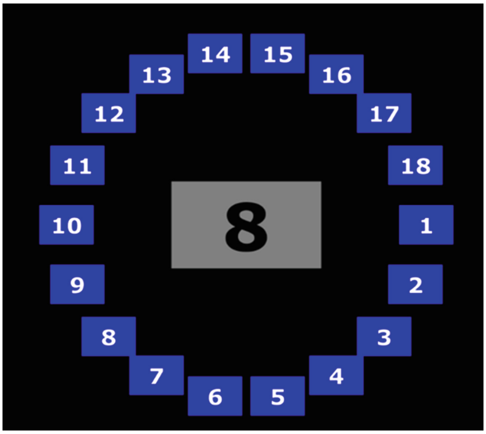

Fig. 2. Presentation of digits for PASAT-C

Prior to the beginning of the task, demographics were collected including gender, height, weight, caffeine intake for the day, and general exercise levels, as these characteristics can affect physiological response and should be taken into account. The E4 was placed on the non-dominant wrist and the participant was asked to reduce motion of that wrist to minimize data loss and noise.

Five autistic young adults (Mean Age = 20.8, SD = 2.5) and five neurotypical young adults (Mean Age = 21, SD = 2.23) completed the task and informed consent was obtained following the approval of the Vanderbilt University Institutional Review Board (IRB). The two groups were age-matched in order to reduce age-related physiological response differences. COVID-19 protocols were followed to reduce exposure including mask usage, social distancing, and disinfecting of all equipment between participants.

2.2 Data Analysis

The BVP obtained from the E4 PPG was analyzed using Kubios HRV Premium. Kubios is a gold-standard heart rate variability software designed to process multiple data formats, including PPG data [27]. Each participant's data were loaded in Kubios along with gender, height, and weight, and segmented into sections based on the timestamps of the baseline and each level, as found from the PASAT-C data, as can be seen in Fig. 3a. While the software does provide automatic noise detection, it was not used as it is generally recommended for long-term ambulatory recordings. As recommended by [2], artefact correction was applied to account for missing, misaligned or extra beat detection and other arrhythmias. A low threshold-based artefact correction algorithm was applied in which each value in a 0.35 s interval is compared to the local average and outliers are replaced with interpolated values using cubic spline interpolation [28]. After artefact correction, several time-domain and frequency domain parameters such as mean time between two successive R-waves (RR interval), root mean square of successive difference between normal heartbeats (RMSSD), low and high frequency peak frequencies, were extracted.

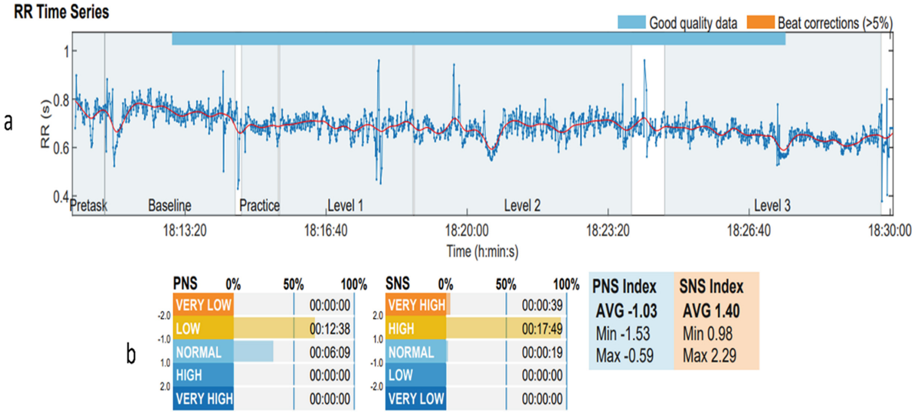

Fig. 3. Kubios output showing a) segmented PPG data based on level and b) PNS and SNS index output for the full duration of the task

The parasympathetic nervous system (PNS) is responsible for "rest and digest" conditions in the body [29] and is known to decrease heart rate by increasing the time interval between successive heart beats, increase changes in RR intervals based on respiration, and decrease the ratio between lower frequency and higher frequency oscillations in the time series [2, 3]. Based on these characteristics, Kubios computes the PNS index based on the mean RR interval, RMSSD, and the Poincaré plot index SD1 in normalized units. A longer mean RR intervals and high RMSSD values both indicate higher PNS activation. The SD1 of the Poincaré plot is linked to RMSSD, the normalized value is used as the third parameter. The parameter values compared to normal population values and then scaled with the standard deviations of normal population before a weighting is applied. A PNS index value of zero means the PNS activity is equal to the normal population average. Positive and negative values show by how many standard deviations are the parameter values above or below the normal population, respectively [30].

The sympathetic nervous system (SNS) drives the "fight or flight" response to stimuli in the body [29], which can be observed by increased heart rate, decreased HRV, and an increased ratio between the lower frequency and the higher frequency oscillations in the HRV data. SNS activation is computed based on mean heartrate interval, Baevsky's stress index [31] and the Poincaré plot index SD2 in normalized units. Kubios calculates a normalized stress index (SI) based on the following equation found in [31]

$$SI = \frac{AMo}{2Mo * MxDMn} \tag{1}$$

where each variable is a mathematical parameter found from a curve of distribution-histogram constructed for variational pulsometry. *Mo* refers to the mode, or the most frequently observed value in the dynamic line of cardio interval while *AMo* is the amplitude of mode that measures the number of cardio intervals appropriate to the mode value in percentage. The variation scope (*MxDMn*) reflects the variability degree of cardio interval values in the dynamic line [31]. In order to make the stress index normally distributed, Kubios takes the square root of the *SI* calculated by Eq. (1). Normalized stress index values between 7 and 12 are considered normal. The Poincaré plot index SD2 is linked to the standard deviation of RR intervals, also known as the SDNN, and correlates with the low frequency/high frequency ratio. Similar to the PNS index, an SNS index of 0 indicates that the three parameters are on average equal to the normal population average. Stress can increase the SNS index to between 5–35 [30].

The PNS index gives valuable insight into how the autonomic nervous system (ANS) recovers after stimuli while the SNS index shows the stress response to stimuli. Comparisons of the overall average PNS index, average SNS index, and stress index per each level were computed to examine group trends during the PASAT-C.

3 Results

Initial results show that the ASD participants, on average, have lower PNS indexes and higher SNS indexes as seen in Fig. 4 when compared to NT participants, showing initial validation of claims that the two groups have varied physiological stress response to the same stimuli.

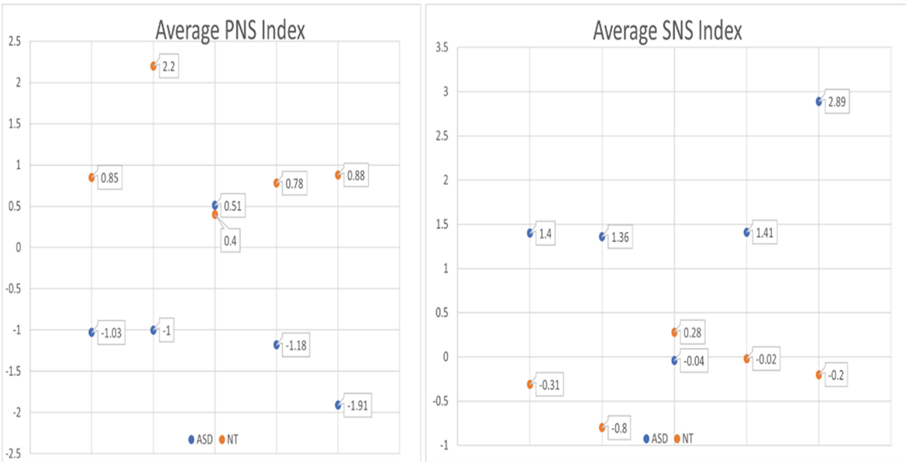

Fig. 4. (a) Average PNS and (b) SNS where each blue dot represents a ASD participant, and each orange dot presents a NT participant

Unpaired two tailed *t* tests were run for the average PNS, SNS, and stress indexes between the two groups and the difference was found to be statistically significant ($p < 0.05$) across all three categories. Results of the unpaired t tests can be seen in Table 1.

Average stress index by level was calculated for each group to explore if similar stress trends emerged based on the level of the PASAT-C. Comparison of these averages are shown in Fig. 5. It can be seen that the autistic group had higher stress averages across all levels of the task, with the practice level being the most stressful. The NT group showed the highest level of stress during level 2.

Table 1. Unpaired t test results for average PNS, SNS, and stress index

	Neurotypical		ASD				
	Mean	*Standard deviation*	*Mean*	*Standard deviation*	*df*	*t*	*p*
PNS index	1.02	0.67	−0.92	0.88	8	3.89	.0046**
SNS index	−0.21	0.39	1.40	1.03	8	3.25	.0117*
Stress index	6.37	1.52	11.82	3.70	8	2.83	0.0218*

* $p < .05$, ** $p < .01$

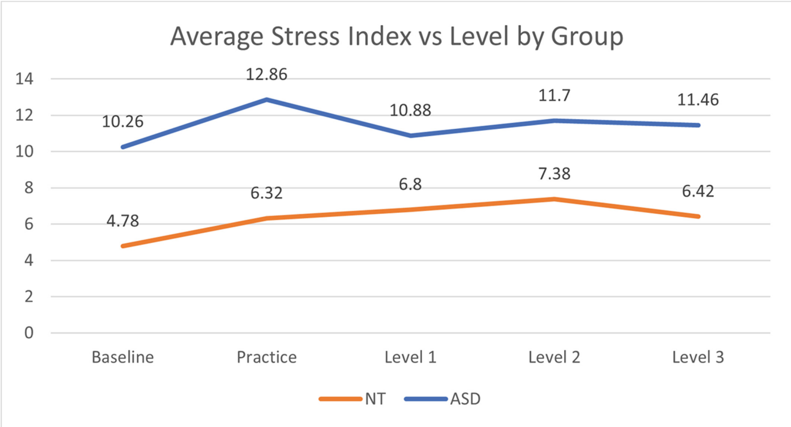

Fig. 5. Average stress index vs level by group

4 Discussion and Conclusion

These results reaffirm that physiological responses to stress varies between the two groups and that autistic young adults are more likely to experience higher levels of stress and lower recovery after a stressful stimulus. This study also proved that HRV alone has the ability to represent these differences. As shown by the unpaired *t* test, there are statistically significant differences in PNS, SNS, and SI during the duration of the PASAT-C. The low PNS activity and high SNS activity of the autistic group during the task is consistent with findings that this group struggles with emotional regulation. While it is expected that SNS activity would rise during a distress tolerance task, such as the PASAT-C, Fig. 4 shows that, when compared to NT peers, the physiological response of ASD young adults is dominated by their "fight or flight" division of autonomic nervous system while the NT young adults' response is dominated by the "rest and digest" division of the autonomic nervous system. These results also show that the PASAT-C did cause a physiological response in both groups when compared to the general population, as shown by the SNS and PNS activity not being zero for either group. Figure 5 indicates that the ASD group was most stressed during the practice round while the NT group was most stressed during the second level, which shows that not only is the overall stress response is distinct between the groups, but that specific portions of the interaction affected each group differently.

One possible application of HRV stress detection is with a virtual reality interview simulator for autistic young adults. Securing a full-time job is one hallmark of successful transition to adulthood for all young adults [32], however, half of autistic young adults are under-or unemployed [33]. The interview process has been identified by autistic self-advocates and their families as one of the largest barriers to employment [32, 34]. In many circumstances, the autistic candidate possesses the necessary skills and relevant experience, however, is unable to perform well in the interview based on "neurotypical standards" [35]. Overcoming stress during the interview process allows autistic individuals more opportunities to obtain employment. Repeated exposure to the interview process is important for successful interviewing [35]. In order to meet this need, we designed Career Interview Readiness in VR (CIRVR) that is detailed in our previous work [36].

In the context of CIRVR, the results of this paper are significant because they reiterate that when designing a closed-loop system specifically for autistic young adults, different considerations must be made than when designing for the general population. To maintain flow, it is beneficial to both track stress response and to know how to effectively adapt the system so that the challenge is still present while stress is reduced. Maintaining flow allows for the most effective learning to be achieved. For autistic young adults, the concept of flow can also be used to aid them in emotion regulation. For example, due to the differences in stress response, a redirection approach, such as using multiple-choice white board questions or moving to a different topic, may be more helpful for the ASD population while rephrasing the question and giving more time to answer would be more appropriate for the NT group. The redirection approach removes the stressor (the question or topic) thus reducing SNS activity while the rephrasing technique gives more time for the PNS to return to baseline. Further exploration of specific adaptation techniques will be investigated in future work.

While this paper focused specifically on the PNS, SNS, and SI indexes, it also opens the door for deeper exploration of additional HRV features that were not discussed. These initial results validate the use of PPG data alone to extract heart rate variability information that gives insight into stress response for autistic young adults. Kubios provides a number of other time-domain, frequency-domain, nonlinear, and time-varying results that are beyond the scope of this paper.

Future work will explore stress-based adaptation within the CIRVR system in order to ensure that the user is adequately challenged without becoming overly stressed by integrating the PNS, SNS, and SI indexes to inform the real-time system of stress levels. This will allow for exploration of stress trends during the interview process. Further exploration will include how additional HRV features may give insight into stress. Knowledge of interview specific stress trends will allow for accommodations to be made that can reduce the barriers to employment that interviews currently present.

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