Autonomic Modulation During a Cognitive Task Using a Wearable Device

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Abstract. Heart-brain interaction is by nature bidirectional, and then, it is sensible to expect the heart, via the autonomic nervous system (ANS), to induce changes in the brain. Respiration can originate differentiated ANS states reflected by HRV. In this work, we measured the changes in performance during a cognitive task due to four autonomic states originated by breath control: at normal breathing (NB), fast breathing (FB), slow breathing (SB) and control phases. ANS states were characterized by temporal (SDNN) and spectral (LF and HF power) HRV markers. Cognitive performance was measured by the response time (RT) and the success rate (SR). HRV parameters were acquired with the wristband Empatica E4. Classification was accomplished, firstly, to find the best ANS variables that discriminated the breathing phases (BPH) and secondly, to find whether ANS parameters were associated to changes in RT and SR. In order to compensate for possible bias of the test sets, 1000 classification iterations were run. The ANS parameters that better separated the four BPH were LF and HF power, with changes about 300% from controls and an average classification rate of 59.9%, a 34.9% more than random. LF and HF explained RT separation for every BPH pair, and so was HF for SR separation. The best RT classification was 63.88% at NB vs SB phases, while SR provided a 73.39% at SB vs NB phases. Results suggest that breath control could show a relation with the efficiency of certain cognitive tasks. For this goal the Empatica wristband together with the proposed methodology could help to clarify this hypothesis.

Keywords: ANS · HRV · Response time · Cognition

1 Introduction

Brain-heart interactions have been a focus of attention for more than 150 years, with the pioneer work of Claude Bernard, whose suggestions and intuitive framework was strengthened recently, relying on solid physiological backgrounds. Cerebral arousal and autonomic control over the cardiovascular system are bidirectionally linked. Then, modifying one will affect the other, and vice versa. For instance, a growing body of evidence suggests that heart rate variability (HRV) reflects emotion regulation and autonomic responses in the body [11]. Furthermore, there exist a model, the neurovisceral integration model, that use HRV to monitor the activity of a neural network regulating physiological, cognitive, and emotional responses [4,5].

On the other hand, it has also been known that breathing frequency influences amplitude of heart rate variability [2,3], evidencing a maximum heart rate oscillation at a 0.1 Hz (5.5 breaths per minute) respiratory frequency. Indeed, it is in this frequency that heart rate oscillates in phase with respiration, taking place a maximum respiratory sinus arrhythmia (RSA) and the most efficient gas exchange. Practices in slow breathing have shown beneficial effects in many psychological or physiological conditions such as pain and anxiety [6], stress and hypertension [8], coronary artery disease [13] and even in sports [1].

In parallel, wearable devices have widely spread in the last decade and measuring HRV indirectly from photoplethysmography (PPG) has gained increasing attention due to its portability, low cost and flexibility [9]. The pulse rate variability (PRV), however, may lack of accuracy due to measurement errors and/or physiological factors such as transmission of the pulse wave through the tissues or EMG artifacts obscuring the signal. In the recent past, a number of studies have indicated a reasonable agreement between HRV and PRV, encouraging the use of PPG as an indirect measure of HRV [14].

Although great efforts were made on identifying the connections of the neural-autonomic drive of the heart, the system has been extensively studied along one direction; from brain to heart. Moreover, most of the research has focused on emotions, but not on cognitive processes. Thus, experimental paradigms are usually designed to induce emotions and measure their reflex on the HRV. In this work, the feasibility of the Empatica wristband for measuring ANS states has been proved by designing an experiment to investigate to what extent a local cardiovascular autonomic state can afferently change cortical activity. To pursue this, an autonomic procedure was designed based on breath control that directly affects the autonomic drive in the heart. Then, ANS-induced cardiovascular changes were measured to check whether this affected the response times and hit rate in a cognitive task.

2 Materials and Methods

Study Population and Experimental Paradigm. Twenty one young healthy subjects were enrolled aged 34.4 ± 7.2 years old (12 male). From this population, two subjects were discarded due to noisy respiratory phases and two subjects due to invalid recordings in the cognitive task.

Groups were defined according to three respiratory frequencies; normal breathing at about 12 breaths per minute (NB), fast breathing at about 20 breaths per minute (FB) and slow breathing, below 6 breaths per minute (SB). In addition, a control group without breath control was included. During respiratory phases NB, FB and SB, subjects were asked to close their eyes, except for control, where remained with their eyes opened. All experiments were accomplished in the morning, in the same room. Blood volume pulse (BVP) was obtained from photoplethysmography (PPG) using the wearable device E4 Empatica wristband [10].

After the control period and every breathing phase, subjects were asked to complete a cognitive task consisting in the N-Back task with $N = 2$. From these tests, two variables describing performance were recorded, the time to answer, called Response Time (RT) and the hit rate, denominated as Success Rate (SR). The order of the respiratory sessions was randomized to avoid bias due to training.

Autonomic Assessment. Maxima of blood volume pressure waveform were detected, and the n-th pulse-to-pulse interval (PPI) was measured as the temporal distance between the n-th and (n+1)-th blood pulse maxima. From these PPI series, NN series were constructed by concatenating normal PP intervals ignoring the gaps in the time domain, while for frequency-domain analysis, gaps were filled out with artificial PP intervals obtained by linear interpolation. Recordings lasted from one to five minutes, from which sections free of noise and missing beats were cropped and used for analysis. The temporal HRV index chosen was the standard deviation of the NN series (SDNN). Prior to frequency domain analysis, the time series were preprocessed by lowpass filtering at 2 Hz (zero-phase Butterworth filter, order 4th) and subtracting the mean value. Then, resampling at 4 Hz by cubic splines interpolation was accomplished to obtain evenly spaced samples. Afterwards, the periodogram was carried out to estimate the power spectrum of the interpolated NN series. Spectral power of the low frequency band around 0.04–0.15 Hz (LF) and that of the high frequency band around 0.15–0.4 Hz (HF) were computed.

Statistical Analysis and Classification. Kruskal-Wallis ANOVA was used to compare within and between group comparisons, followed by Mann-Whitney post-hoc comparisons. Statistical significance was defined for $p < 0.05$.

A classification step has been performed in order to prove the plausibility of estimating breathing phase (BPH), RT and SR, taking into account the set of measured variables: HR, SDNN, LF and HF. For performance evaluation a test set about (20%) was used and min-max normalization was performed over each variable. As the number of samples is very low, 17 subjects for four experiments make a total of 68 samples, test sets are biased, not being representative of the whole population, therefore, the performance has been evaluated over 1000 classification iterations to evaluate its distribution. For each iteration, the training and test sets have been chosen randomly. A multi-layer perceptron has been used for classification with a L2 regularization term $\alpha = 1\mathrm{e}{-5}$.

The classification process has been split into three stages. First, feature ranking was carried out using recursive feature elimination technique in order to select the best two features for the task of estimating the BPH, resulting in the selection of LF and HF variables. Second, estimation of RT was accomplished by the discretization of the values around the mean, that is, greater values were labeled as 1 and lower ones as 0. With the same feature ranking method, the best two variables have been used for the following classifications: NB versus FB, NB versus SB and FB versus SB. Analogously, estimation of SR implemented SR discretization around its mean and followed the classification processes as for the RT variable.

3 Results

Figure 1 shows a representative example of the heart rate (HR), power spectral density (PSD) and blood volume pressure signal (Bvp) for a subject at Control, NB, FB and SB groups (from top to bottom, respectively). Notice the strong oscillations in the HR and in the Bvp for the slow breathing group, product of the resonance of the respiratory frequency with baroreflex activity.

Figure 2, on the other hand, shows the boxplot distributions expressed as percentages of control values of the low frequency and high frequency energy for the different respiratory groups. Notice that the LF band produced two increases in the order of 300% with respect to control at NB ($p = 2\mathrm{e}{-4}$) and SB ($p = 8\mathrm{e}{-6}$) groups, while in the HF band, only the NB group showed an increased activity in the order of 200% with respect to control ($p = 0.001$) and FB ($p = 0.001$). This evidences a significant increase in autonomic activity from eyes opened to eyes closed, suggesting a modulation of this effect over the remaining respiratory groups. In FB, however, there is a supression of autonomic activity, while a marked increase appears in the SB group at the LF band, reflecting the shift of the respiratory peak, usually centered about 0.25 Hz in the HF band to frequencies below 0.15 Hz, in the LF band. The latter is compatible with cardiac coherence and biofeedback techniques.

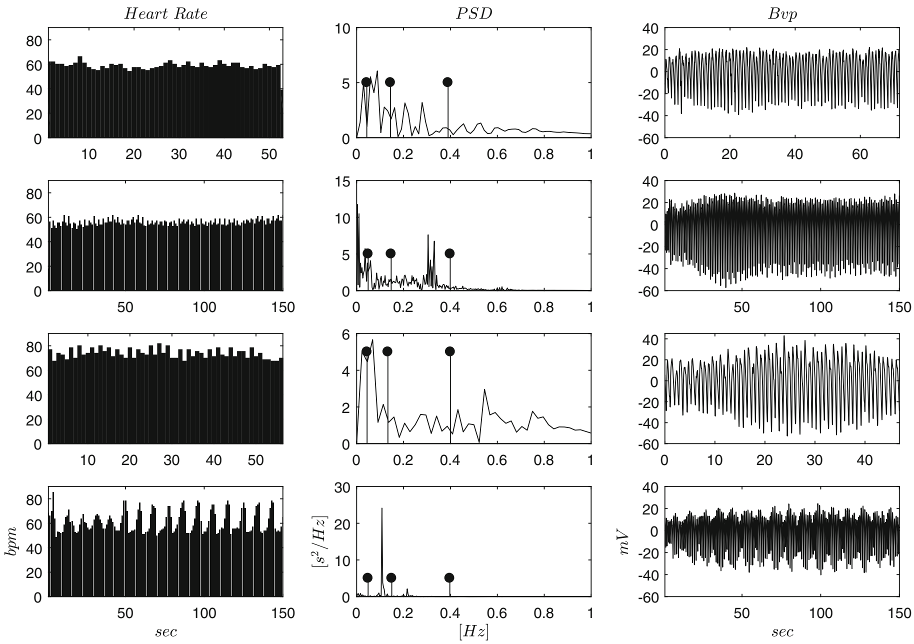


Fig. 1. HRV signals. Tachogram, PSD and Bvp signals for a representative subject at the three breathing phases (NB, FB and SB, from top to bottom) and control. Notice the HR greatest variability evidenced as marked oscillations in the tachogram as well as the Bvp signal at SB and its respective shift in frequency of the breath peak, as observed in the PSD. Stems mark the limits of the LF (0.04–0.15 Hz) and HF (0.15–0.4 Hz) frequency bands.

Analogously, Fig. 3 shows the mean heart rate (HR), SDNN, response time (RT) and success rate (SR) for the different respiratory groups. Even though not significant, RT was uptrended for SB and downtrended for FB, while SDNN produced the highest value at SB. Accordingly, SR showed a trend for the highest CR at SB with the lowest dispersion. HR, on the other hand, was lower than control and FB at NB, although no statistical significance was achieved.

For the classification process, Fig. 4a shows the performance distribution of 1000 classifications for estimating the BPH, where the chance is 25% for the four cases: Control, NB, FB and SB. Results shown that on average the classifiers perform the estimation with a $59.9 \pm 12.48\%$ of accuracy. In Fig. 4b three cases are taken into account: NB, FB and SB. For this case, the mean average performance is $83.52\% \pm 10.23$. Therefore, LF and HF are suitable features for the estimation of the BPH. On the other hand, the classification process has been performed for binary cases on both RT and SR features. For a better comparison, mean accuracy performances are shown in Table 1.

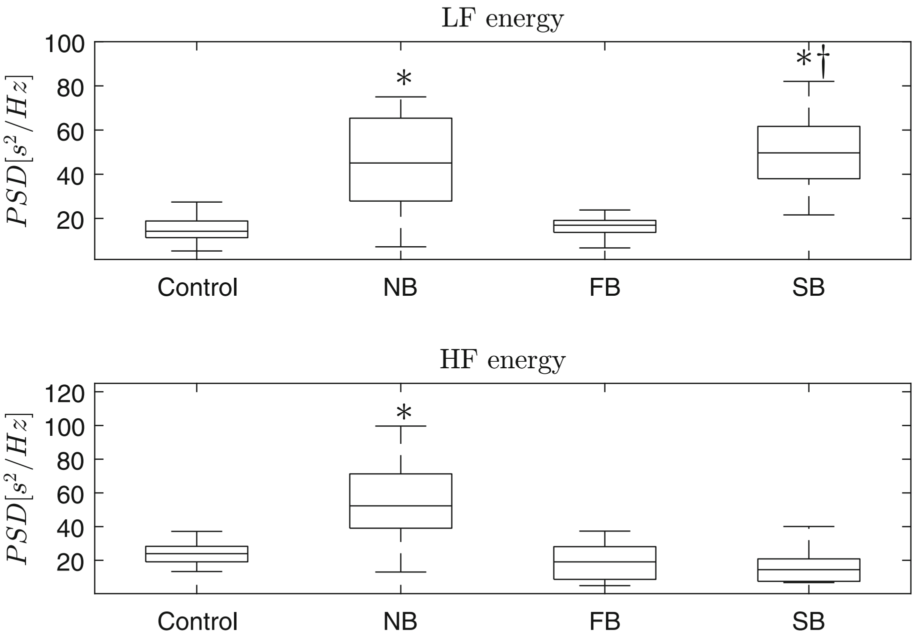


Fig. 2. HRV spectral parameters. Boxplot representations for LF energy (top) and HF energy (bottom) at NB, FB, SB and control for the entire population. Variables were normalized to control values. Notice the remarkable increase of LF at SB, which is not accompanied by a HF increase. $^{*}p < 0.0005$ vs control, $^{\dagger} < 0.0005$ vs FB.

Table 1. Obtained estimation performances on RT and CR variables.

Classification	Label	Average accuracy	Selected features
FB vs SB	RT	$52.61\% \pm 15.56$	HF, LF
FB vs NB	RT	$52.38\% \pm 16.68$	HF, LF
SB vs NB	RT	$63.88\% \pm 17.18$	HF, LF
FB vs SB	SR	$66.97\% \pm 15.64$	HR, HF
FB vs NB	SR	$49.30\% \pm 16.46$	SDNN, HF
SB vs NB	SR	**$73.39\% \pm 14.65$**	SDNN, HF

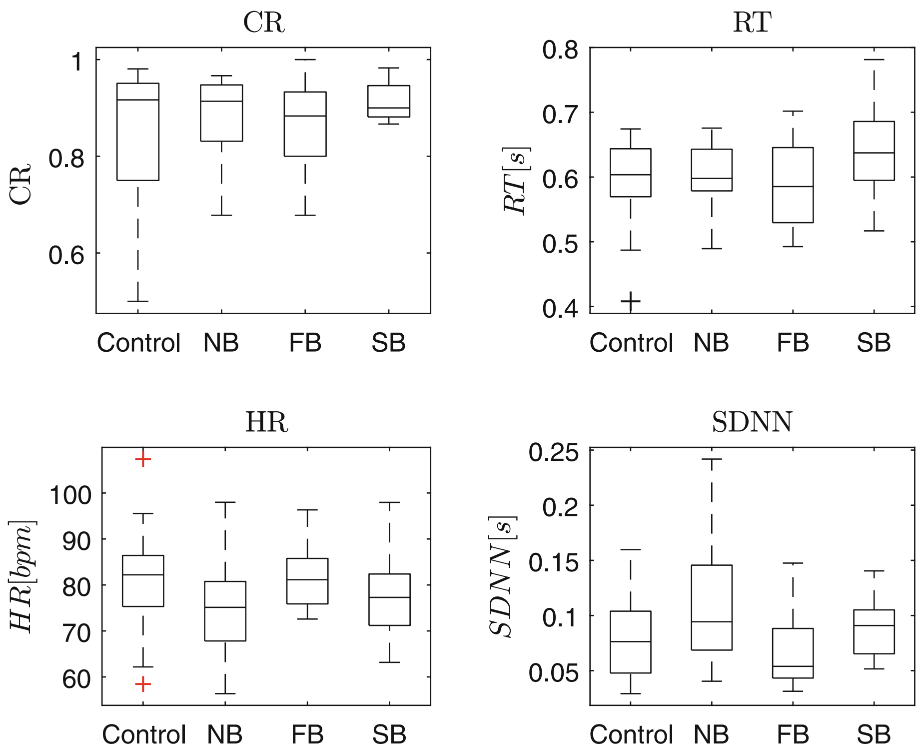
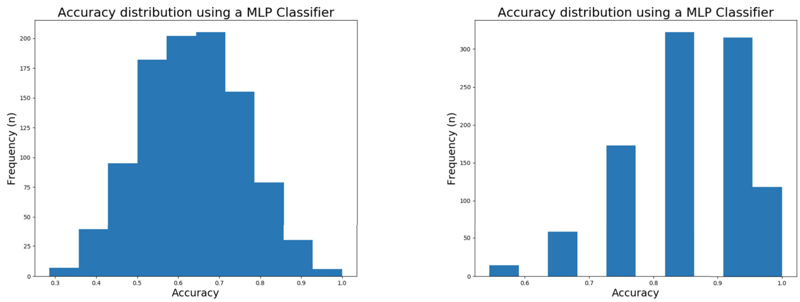


Fig. 3. Trend for cardiovascular and cognitive parameters. Boxplot representation of Heart Rate (HR), SDNN, reaction times (RT) and success rates (SR). Variables were normalized to control values.



(a) (b)

Fig. 4. Accuracy distributions. (a) Classification performance using HF and LF features on the BPH with four experiments: control, NB, FB and SB. (b) Classification performance using HF and LF features on the BPH with three experiments: NB, FB and SB.

4 Discussion and Conclusions

The spectral HRV parameters (LF and HF) significantly changed throughout the breathing phase. Findings related to such parameters are consistent with the literature, particularly for the SB phase, where a state of cardiac coherence was achieved, evidenced by large HR oscillations and maximum HRV power [3]. Accordingly to our results, a higher SDNN, LF power and LF/HF ratio, and no significant differences in HF power was found in [7,15] for all paced breathing sessions as compared to the control condition (spontaneous breathing). Moreover, HRV transitions through respiratory phases were presented, allowing for a complete description between respiratory frequency and ANS system.

Regarding the cognitive parameters, they failed to produce statistical significance although a trend for a higher response time and higher hit rate for the slow breathing phase can be appreciated in Fig. 3. Moreover, the neural networks classification confirmed the trend, with both SR and RT differentiating SB from NB, producing performances of 73.39% and 63.88% respectively. These results suggest a relation between HRV and cognitive parameters at least during SB and NB.

According to RT and SR changes, it could be inferred that SB induces a relaxation state that slows down the reactivity but enhances efficiency. These findings partially agree with Maman et al., who found significant decreases in the response time of basketball players together with significant increases in the shooting performance [12]. A possible explanation of this difference in RT could be attributed to the time elapsed between the breathing session and the task, which is immediate, while due to a long-term effect in the basketball players. It is also worth noting that in order to avoid for training bias, we have changed the order of the breathing phases throughout subjects, so that NB, FB and SB had a roughly balanced amount of sessions in the last trial. Then, the better efficiency in the congruence rate at SB should not be attributed to training but to slow breathing per se.

Finally, from this work, the following findings could be derived: (1) the wristband Empatica E4 was accurate enough to allow for HRV analysis from the Blood Volume Pressure (Bvp) signal without significant loss for about 5 min. (2) From all the BPH analyzed, the slow breathing phase produced the clearest ANS change. And (3) This SB-induced ANS change produced the distribution with less variance around the highest mean SR. This suggests that breath control could influence the efficiency of certain cognitive tasks, although a greater number of experiments should confirm this.

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