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Information Dynamics in Cardiorespiratory Time Series during Mental Stress Testing

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***Abstract*— In this study, we assessed the information dynamics of respiration and heart rate variability during mental stress testing by means of the cross-entropy, a measure of cardiorespiratory coupling, and the self-entropy of the tachogram conditioned to the knowledge of respiration. Although stress is related to a reduction in vagal activity, no difference in cardiorespiratory coupling was found when 5 minutes of rest and stress were compared. The conditional self-entropy, on the other hand, showed significantly higher values during stress, indicating a higher predictability of the tachogram. These results show that entropy analyses of cardiorespiratory data reveal new information that could not be obtained with traditional heart rate variability studies.**

I. INTRODUCTION

Mental stress is a psychological condition that has been associated with an increased risk for cardiovascular disorders [1]. In order to study the stress mechanisms that cause this risk, the autonomic control of the cardiac system has been studied by means of heart rate variability (HRV) [2]. It has been observed that mental stress reduces respiratory sinus arrhythmia (RSA), the vagally-mediated phenomenon that the heart rate varies in phase with respiration [3]. However, the influence of respiration is often not taken into account in HRV analyses, even though research found that RSA does not always reflect vagal activity, depending on the respiratory rate and tidal volume, leading possibly to false conclusions of autonomic functioning [4].

In this study, we aim to conduct a combined analysis of the cardiorespiratory system by assessing the information dynamics of HRV and respiration during stress testing. Information theory has proven to be useful to assess directional interactions between cardiorespiratory time series [5], and we hypothesize that information-theoretic measures may reveal altered cardiorespiratory patterns during mental stress.

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II. INFORMATION DECOMPOSITION

Let us consider a system that is composed of two interacting processes X and Y, then we define the predictive information P_Y as a measure of how much information carried by the present sample Y_n can be predicted by the knowledge of the past of all considered processes X and Y, denoted as $\boldsymbol{V}_n^{X,Y}$:

$$P_Y = H(Y_n) - H(Y_n|\boldsymbol{V}_n^{X,Y}), \tag{1}$$

with $H(Y_n) = -\sum p(y_n)\ln\, p(y_n)$ the Shannon entropy.

The predictive information of Y can also be written as the sum of the cross-entropy $C_{X\to Y}$ and the conditional self-entropy $S_{Y|X}$, with

$$C_{X\to Y} = H(Y_n) - H(Y_n|\boldsymbol{V}_n^{X}) \tag{2}$$

$$S_{Y|X} = H(Y_n|\boldsymbol{V}_n^{X}) - H(Y_n|\boldsymbol{V}_n^{X,Y}). \tag{3}$$

The cross-entropy $C_{X\to Y}$ indicates how much information that is carried by Y_n can be predicted by the past of X, and the conditional self-entropy $S_{Y|X}$ quantifies how much of the information carried by Y_n can be predicted by the knowledge of its own past, conditioned to the knowledge of the past of X. Let $X = r$ be the respiratory signal and $Y = R$ be the RR interval series, then $C_{r\to R}$ is an index of cardiorespiratory coupling. Note that assessment of information transfer via the cross-entropy is an alternative approach to the use of the more traditional transfer entropy (defined as $T_{X\to Y} = H(Y_n|\boldsymbol{V}_n^{Y}) - H(Y_n|\boldsymbol{V}_n^{X,Y})$). Here, this approach quantifies information transfer exploiting the knowledge of the unidirectional nature of RSA.

The probability function $p(\cdot)$ is estimated using a nonlinear model-free approach with non-uniform embedding that does not make any prior assumption about the probability distribution of the observed bivariate process. First, the conditioning vector $\boldsymbol{V}_n^{X,Y}$ is progressively built by selecting terms from an initial candidate set $\widehat{\boldsymbol{V}}_n^{X,Y} = [X_{n-1},\ldots,X_{n-L},Y_{n-1},\ldots,Y_{n-L}]$ that includes lags up to L (in this study $L = 10$), that minimize the conditional entropy $H(Y_n|\boldsymbol{V}_n^{X,Y})$ and optimize the description of the target series Y. When there is no significant decrease in conditional entropy, the selection procedure of terms for the conditioning vector terminates. Next, the entropies in Eqs. (1-3) are estimated using the histogram-based method with 6 quantization levels. A more detailed description of this procedure can be found in [5].

III. DATA ACQUISITION AND PROCESSING

The data were recorded at the Faculty of Psychology and Educational Sciences of the KU Leuven (Leuven, Belgium)

in the context of a larger study on mental stress and sustained attention [2], [6]. The electrocardiogram (ECG, sampling frequency f_s = 200 Hz) of 40 healthy students (age: 18-22 years) was recorded using the LifeShirt System (Vivometrics Inc., Ventura, CA). Simultaneously, the tidal volume, taken as the respiratory signal (f_s = 50 Hz), was estimated by means of respiratory inductive plethysmography around the abdomen and the ribcage.

During the protocol, the participants underwent, among others, baseline recording during which they watched a relaxing documentary and a mental arithmetic task to induce mental stress. Both periods had a duration of 6 minutes.

The R peaks in the ECG are detected using the Pan-Tompkins algorithm, and in order to obtain an accuracy of 1 ms to construct the tachogram, parabolic interpolation using the 5 samples surrounding the detected R peak is conducted. Next, the tachogram and respiratory signal are resampled at 2 Hz using cubic spline interpolation and baseline wander of the respiratory signal is removed using a high-pass filter with a cut-off frequency of 0.05 Hz. Finally, only the last 5 minutes of each period are selected for the analysis of information dynamics in order to reduce the transient behaviour and obtain stationary conditions.

After the computation of predictive information, cross- and conditional self-entropy, differences in cardiorespiratory information dynamics between the resting and stress condition are assessed by means of the Wilcoxon signed rank test. Taking the Bonferroni correction for multiple comparisons into account, a significance level of $\alpha = 0.05/3$ was used.

IV. RESULTS AND CONCLUSION

Fig. 1 displays boxplots of predictive information (P_R), cross-entropy ($C_{r\to R}$) and conditional self-entropy ($S_{R|r}$) during rest and stress. We can observe that P_R does not show a significant difference between rest and stress, nor does $C_{r\to R}$. Since the cross-entropy can be considered as a measure of cardiorespiratory coupling, its unaltered distribution may indicate that the reduction in RSA amplitude expected during stress [1], [2] is not directly accompanied by a reduction in cardiorespiratory coupling.

When the conditional self-entropy $S_{R|r}$ during rest and stress is studied, we find significantly higher values during stress. This difference reveals that the RR interval series can be better predicted based on its own past, given the information of respiration, during stress than during rest, and thus points to a more predictible cardiac system when the participants experience mental stress. Given that predictability of the heart rate is typically associated with an unhealthier cardiovascular system that shows reduced flexibility to respond to bodily demands [7], the difference in conditional self-entropy is in line with our hypotheses.

Although the cross-entropy was expected to decrease during stress, the obtained results confirm previous HRV analyses in which respiratory information was taken into account by separating the tachogram into a component that is related to respiration, and a component that is unrelated to it [8]. We found that the tachogram component unrelated to respiration is highly informative to classify periods of rest and stress, while the component related to respiration does not succeed in distinguishing rest and stress. The latter can be linked to the cross-entropy while the component unrelated to respiration can be linked to the conditional self-entropy.

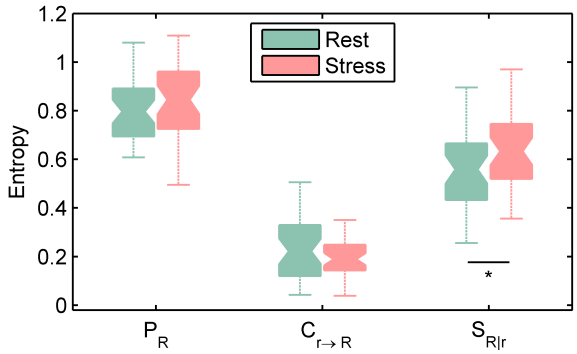


Fig. 1. Boxplots of predictive information (P_R), cross-entropy ($C_{r\to R}$) and conditional self-entropy ($S_{R|r}$) during 5 minutes of rest and stress. Significant differences ($\alpha = 0.05/3$) between rest and stress are indicated by *.

Note that normally a beat-to-beat approach is used to compute information dynamics. Given the substantial difference in maximum HR between rest and stress, where in the latter HR up to 120 bpm are denoted, we opted to resample the tachogram such that lags up to 5 s are always taken into account in the conditioning vector. Increasing the resampling frequency does not change the results, provided that the number of lags L increase accordingly.

We can conclude that during mental stress testing the self-entropy seems to be an informative tool to study the predictability of RR interval series, that moreover takes information of respiration into account. This measure contains new information that could not be obtained with traditional HRV analysis, and demonstrates that inclusion of respiratory information can significantly enhance HRV analyses.

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