Multi-Feature Classification of Physiological Stress in Cardiovascular and Cardiorespiratory Interactions

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***Abstract*— Physiological stress influences cardiovascular (CV) and cardiorespiratory (CR) control mechanisms. Accurate classification methods incorporating multiple features from the CV and CR physiological systems are necessary to better distinguish among different stress states. In this work, a novel multi-feature classification approach based on local information theory was used to differentiate postural and mental stress evoked in 127 healthy young subjects. The results evidenced a better classification performance of postural stress based on CV and CR dynamics, suggesting that these dynamics are affected more strongly by the postural than the mental challenge.**

Keywords—Cardiovascular and Cardiorespiratory Variability, Classification, Information Theory

I. INTRODUCTION

Stress, a ubiquitous component of daily life, can manifest in various forms and intensities, impacting both mental and physical well-being of the individual [1]. Stress can influence several key output variables of physiological control mechanisms, including heart rate, blood pressure, and respiratory rate [1]. The cardiovascular (CV) regulation can be studied through the bivariate interactions between the heart period and the systolic arterial pressure (SAP), descriptive of the baroreflex mechanism buffering blood pressure changes by varying the heart period [2]. Similarly, cardiorespiratory (CR) interactions can be studied assessing bivariate relations between the heart period and respiration (RESP), mainly determined by the respiratory sinus arrhythmia (RSA) modulation of heart rate by respiration [3].

Categorizing the complex effects of physiological stress on CV and CR variability requires sophisticated classification methods able to accurately distinguish between subtly different stress states. In this context, information theory provides flexible frameworks serving the steps of feature selection and classification. Indeed, information theoretic-measures characterizing physiological interactions can be used as classification features reflecting intrinsic mechanisms [4]; machine learning classification algorithms are often based on estimates of local probability density or information content [5], [6]. Combining these aspects, the use of multiple features within classification algorithms is important for enhancing the precision and reliability of stress assessment.

The aim of this work is to implement a multi-feature classification approach based on local information theory, to better discriminate postural and mental stress from CV and CR time series extracted from healthy young subjects.

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II. MATERIALS AND METHODS

A. Experimental protocol

The study involved 127 healthy young volunteers (75 females; age: 18.6 ± 3.3 years), all normotensive and with body mass index in a normal range (BMI: 21.4 ± 2.2). All the participants signed an informed consent to join the experimental study approved by the Ethics Committee of the Jessenius Faculty of Medicine, Comenius University, Martin, Slovakia [7]. For this study, only three different conditions of the experimental protocol, fully described in [7], were considered: (a) REST (resting supine position), (b) HUT (head-up-tilt phase performed by tilting the motorized bed on which the subjects were laid to a 45° upright position to evoke orthostatic stress), (c) MA (non-verbal mental arithmetic task phase in the supine position performed by adding up 3-digit numbers until reaching 1-digit and identifying whether it was even or odd to evoke mental stress). Electrocardiographic, arterial pressure (AP) and respiratory volume signals were simultaneously acquired at a sampling frequency of 1kHz.

B. Time series and Feature extraction

Starting from the acquired signals, 300-beat long RR-interval (RRI), SAP and RESP stationary time series were extracted for each subject and each phase of the protocol and processed following the same procedure outlined in [7], [8]. Conventional CV and CR variability indices belonging to the time, frequency and information domains were extracted, including univariate and bivariate features, respectively reflecting the internal regulation of a given time series and the pairwise interactions between pairs of them. In detail, for each experimental condition, two time-domain indices, i.e., the average value (MEAN) and the standard deviation (STD) were first computed on each time series [7]. Moreover, three information theoretic indices based on bivariate linear parametric analysis were computed to assess physiological interactions. Specifically, the transfer entropy (TE) was calculated to describe causal interactions from SAP to RRI for CV interactions and from RESP to RRI for CR interactions [9]. The conditional self-entropy measure (cSE) assessing the internal dependencies of each process was also taken into account [9]. Finally, the mutual information rate (MIR) that quantifies the information rate shared by bivariate CV and CR interactions per unit of time was calculated [10]. The three measures were computed in the time domain and within the Low Frequency (LF) (0.04-0.15 Hz) and the High Frequency (HF) (0.15-0.4 Hz) spectral bands [9]. Model identification was performed by the least-squares method, setting the order according to the Akaike Information Criterion (AIC) for each subject (with maximum order of 12).

C. *Multi-feature classification based on local information*

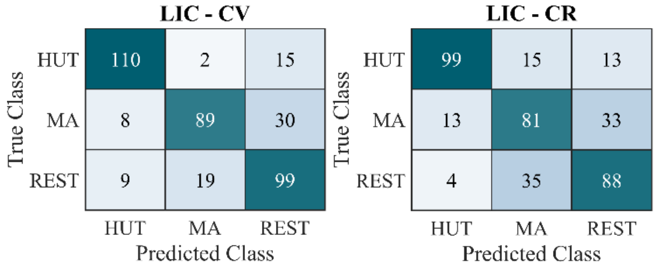
In the scenario of a multi-feature classification task, focused on distinguishing between the rest and the two stress conditions, the extracted features were used as input to the novel Local Information Classifier (LIC) [5]. Specifically, the LIC provides an information-theoretic approach to classification [6] by assigning data points to specific classes through minimization of the information content predicted by the trained model for each class. Leveraging probability densities derived from observed feature data, the classifier computes the local information content as the negative logarithm of the joint probability quantifying the pointwise information contained in a specific outcome of the feature and class vectors [5]. By decomposing the local joint entropy into the local entropy of the features given the class and the local entropy of the class itself, the classifier effectively maximizes the joint probability of features and tested class, implementing an information-theoretic version of the Bayes' rule [11]. The LIC relies on the nearest neighbour estimator, exploiting the intuitive notion that probability density is inversely related to the distance between data observations [5].

To evaluate the predictive performance of the LIC classifier, and considering the limited dataset available, we adopted a 10-fold cross-validation technique. The class balance was ensured since the time series data across the three conditions were of equal length. Subsequently, conventional performance metrics i.e., overall accuracy and per class sensitivity and precision, were computed to assess the effectiveness of the LIC classifier in discriminating the three physiological states with regard to both CV and CR variability analysis.

III. RESULTS AND DISCUSSION

Figure 1 reports the results in terms of the performance metrics of multi-feature classifications, i.e. accuracy, sensitivity and precision in the three experimental phases, computed separately for CV and CR variability using the LIC. As reported, the best overall accuracy is achieved for CV analysis, while the class with the best performance in terms of sensitivity and precision, is the HUT for both CV and CR analysis. As shown by the confusion matrices, the HUT class consistently exhibits the best ranking, achieving higher True Positive values if compared to the other classes.

Physiologically, although the analyzed time series are the same across the three experimental conditions, the patterns of physiological responses prove to be more easily identifiable during postural stress than during mental stress, thus facilitating the classification process. These results are in accordance with previous findings reported in the literature [12] that exhibited a better discrimination of postural stress using traditional statistical analyses. Physiologically this may be due to the stronger autonomic nervous system response during postural stress [12]. More specifically, during the HUT phase changes in AP activate the baroreflex mechanism to modulate heart rate, producing simplified CV dynamics [12]. This mechanism could generate more pronounced patterns of variability than those associated with a MA task. Moreover, for CR interactions, the reduced involvement of the RSA mechanism during postural stress allows a better classification of this type of stress compared to cognitive load [12].



	Accuracy (%)	Sensitivity (%)			Precision (%)		
		REST	*HUT*	*MA*	*REST*	*HUT*	*MA*
CV	78.2	77.9	86.6	70.1	68.7	86.6	80.9
CR	70.3	69.2	77.9	63.8	65.7	85.3	61.8

Fig. 1. (top) Confusion matrices and (down) table with results of the multi-feature classification performance (Accuracy, Sensitivity and Precision) for the cardiovascular (CV) and cardiorespiratory (CR) variability in REST, HUT, and MA experimental phases.

IV. CONCLUSION

The present work highlights the feasibility of multi-feature classification to obtain discrimination of physiological stress based on CV and CR variability indices. Our results document a more accurate classification of the HUT phase probably due to the higher sensitivity of the LIC classifier to physiological patterns and mechanisms that are more peculiar of postural stress.

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