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A regression approach based on separability maximization for modeling a continuous-valued stress index from electrocardiogram data

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ABSTRACT

In this work we propose a regression approach based on separability maximization (RASMa) for modeling a continuous-valued estimate of the stress level (we called it stress index) using some features extracted from electrocardiogram (ECG) data.

Since no objective measure of the actual stress level (output) is available, finding the stress index cannot be addressed as a classical regression problem. Instead, the proposed approach finds the linear combination of features that maximizes the separability of stress index values for non-stress and stress events. In short, RASMa combines linear discriminant analysis with the Bhattacharyya distance, embedded in a leave-one-subject-out cross-validation scheme.

A 26-case pilot study using 17 heart rate variability (HRV) features was conducted as a proof of concept. A near real-time application tool for monitoring stress level over time was also implemented based on the model obtained from the pilot study.

1. Introduction

Stress is commonly present in several professions. However, reaching high levels of mental stress for long periods of time has a negative impact on professionals' health [1–3], and on their cognitive performance [4,5], increasing the probability of making mistakes. It may become critical in some professions: first responders, air traffic controllers, airline pilots, to name but a few. Hence the importance of real-time monitoring and detection of high stress levels for efficient team management in the theatre of operations.

Several studies in the literature have shown an association between heart rate variability (HRV) features extracted from electrocardiogram (ECG) data and stress (cf. Section 2), pointing in the direction of developing a stress estimate based on HRV features. In addition, recent developments in wearable technology have made it possible to acquire ECG data in a non-invasive and non-obtrusive way, allowing individuals to normally do their jobs.

In this paper we propose a regression approach based on separability maximization (RASMa) for modeling a continuous-valued estimate of the stress level (we called it stress index) using some features extracted from electrocardiogram (ECG) data.

A 26-case pilot study using 17 features was conducted as a proof of concept. A near real-time application tool for monitoring stress level over time was also implemented based on the model obtained from the pilot study.

The paper is organized as follows. In Section 2, other methods for inferring stress levels using HRV features are reviewed. Section 3 details the proposed approach (RASMa) and also describes how the dataset for the pilot study was acquired. The results from the pilot study are presented and discussed in Section 4 and conclusions are drawn in Section 5. Refer to Appendix A for a discussion on normality assumption in our dataset. And, refer to Appendix B for a brief note on measuring separability between two normal distributions.

2. Related work

There is an extensive literature about the effects of mental stress on different heart rate variability (HRV) features – see [6], and references therein, for a review about the impact of stress on linear HRV features. In addition, a review about the impact of stress on non-linear HRV features is presented in [7]. However, in terms of identifying stress levels given some HRV features, the problem becomes much more challenging and the literature is more scarce.

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In a commercial application [8], the ratio of the low-frequency band power to the high-frequency band power in the RR intervals (*LF/HF* ratio) is used as a simple estimate of stress. The rationale behind it is that a higher *LF/HF* ratio indicates a lower balance between the sympathetic and parasympathetic autonomic nervous system which is associated to a higher level of stress [8,9]. Nonetheless, as the *LF/HF* ratio sometimes increases and other times decreases under stress conditions [6], the use of *LF/HF* ratio alone is not enough to distinguish between stress and non-stress events.

In another commercial application [10], it is proposed a technology to measure the stress levels based on the idea that heart rhythm exhibits a coherent pattern (in opposition to a chaotic pattern) when someone is not stressed [11,12]. Mathematically, the spectrum of the heart rate signal is computed and, then, a coherence score given by $(P_p/(P_T - P_p))^2$ is calculated, where P_T is the total power of the spectrum and P_p is the power around the highest peak [10]. Nevertheless, to our knowledge, the lack of statistical analysis of stress versus non-stress samples makes it difficult to assess the potential of this approach.

Other methods proposed in the literature tackle the problem of identifying stress events as a binary classification problem, labeling each interval as stress or non-stress, instead of providing a continuous-valued estimate of the stress level.

In [13], the authors propose a classification method based on support vector machines. This method is a follow-up version of ideas presented in [14]. Several HRV parameters (both in time and frequency) were used together with some respiration features. On field data (collected from 20 participants), a median accuracy of 72% is reported. A ranking of features is also presented, showing that the 80th percentile and average of RR intervals had the highest contribution to stress detection. Note, however, that the authors used a 1-minute time window which is not long enough to compute the frequency domain HRV features, according to [15].

In [16], support vector machines were also employed on binarized data (stress/non-stress) from 22 subjects (both HRV and respiration features were used). In that work, the authors address a pertinent issue: should stress inference from physiological measurements be based on a personalized model rather than a population-level model? A precision increase from 56% to 62% at 80% recall is reported when the personalized model is used.

Melillo et al. [17] proposed a linear discriminant classifier to label an interval as stress or non-stress. Although a total of thirteen non-linear HRV features was taken into consideration, the best classification performance was achieved using only three: an entropy-based measure and both standard deviations of Poincaré plot. A sensitivity and specificity of 86% and 95%, respectively, was reported in an experiment with 42 students during academic examination and after holidays. And in [18], for the same data, they used a tree-based classifier with linear HRV features, reporting a sensitivity and specificity of 83% and 90%, respectively.

As opposed to the previously mentioned methodologies where either physical movement is not taken into account or the corresponding data is excluded from analysis, in [19] an algorithm that combines heart rate with physical movement is presented. Additional heart rate (AHR) is the name of the algorithm for detecting increases in heart rate that are not related to changes in physical activity. The physical movement is estimated from the acceleration signals provided by a thigh-located and a chest-located accelerometer and the algorithm yields a stress-arousal estimate (see [20] for implementation details). Notwithstanding, the results are preliminary and the algorithm performance depends on some heuristic parameters [20].

Lastly, Sun et al. [21] also combined features from an accelerometer on a waist belt together with linear HRV and galvanic skin response features in a study with 20 participants. Both stress and non-stress events were recorded in three different physical activity conditions: seated, standing and walking position. Three types of classifiers – decision trees (DT), Bayesian networks (BN), and support vector machines (SVM) – were investigated. They report that, for a personalized model, DT had the best performance with an accuracy of 92.4% and, for a between-subject model (population-level model), SVM had the best performance with an accuracy of 80.9%.

Although most methods proposed in the literature tackle the problem of identifying stress events as a binary classification problem, labeling each interval as stress or non-stress, in this paper we propose a regression approach for modeling a continuous-valued estimate of the stress level (we called it stress index). In fact, stress level, by its very nature, is a continuous-valued variable and not a binary variable. Hence, it is not appropriate to simply binarize the stress levels when we what to quantitatively assess how much the stress level increased or decreased over time.

3. Materials and methods

Modeling a continuous-valued estimate of stress level cannot be addressed as a classical regression problem since no objective measure of the actual stress level (output) is available to directly train a regression model. Instead, to obtain a continuous-valued stress index, we developed an approach for finding the linear combination of features that maximizes the separability of the stress index values for non-stress and stress events, according to some assumption discussed next.

Another important point mentioned in the previous section is the development of a personalized model versus a population-level model. Although the former achieved better results according to some research work (e.g. [16,21],), which sounds intuitive since we are creating a specific model for each individual, in practice it would be very difficult and time-consuming to implement such personalized models in a large scale. In fact, we would need to run a non-stress/stress experimental procedure to find the parameters of the model whenever we wanted to monitor the stress levels of a new person. Thus, in this work, our goal was to develop a stress index approach based on population-level models.

Fig. 1 depicts the block diagram of the proposed framework. After computing the features for all time samples, the proposed regression approach based on separability maximization (RASMa) can be divided into two main stages. Firstly, a leave-one-subject-out cross-validation scheme is implemented to select the subset of features that best generalize our model. Note a key purpose of cross-validation is to assess how our model will behave on unseen samples in order to mitigate overfitting when selecting the subset of features. Secondly, the coefficients of the final model are computed on all available samples using the previously selected subset of features. Each block in Fig. 1 is explained in the section therein mentioned.

3.1. Participants and data acquisition

A pilot study with 26 subjects (average age ± standard deviation: 36.2 ± 11.5; 5 females) was conducted to test the proposed framework. In the first stage, each participant was at rest in a sit position for about 10 min and the collected ECG data was used as non-stress samples. In another stage, each participant underwent the Trier social stress test (TSST), lasting about 10–13 min, and the collected ECG data was used as stress samples. TSST is a laboratory procedure commonly used to induce stress in participants [22]. It includes a public presentation followed by a mental arithmetic task, during which the participant is asked to count backwards from 1022 in steps of 13. All participants provided written informed con-