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A stress recognition system using HRV parameters and machine learning techniques

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***Abstract*—In this study, we investigate reliable heart rate variability (HRV) parameters in order to recognize stress. An experiment protocol was established including different stressors which correspond to a range of everyday life conditions. A personalized baseline was formulated for each participant in order to eliminate inter-subject variability and to normalize data providing a common reference for the whole dataset. The extracted HRV features were transformed accordingly using the pairwise transformation in order to take into account the personalized baseline of each phase in constructing the stress model. The most robust features were selected using the minimum Redundancy Maximum Relevance (mRMR) selection algorithm. The selected features fed machine learning systems achieving a classification accuracy of 84.4% using 10-fold cross-validation.**

***Keywords*—stress, HRV, heart rate, ECG, pairwise transformation, stress classification**

I. Introduction

In recent years, there is increasing research interest in the area stress recognition and its reliable automatic estimation. Although there is a common sense on stress experience, however, it constitutes a difficult task to categorize efficiently and to estimate objectively one's stress levels. The problem becomes more complex considering the variety of the existing stress types or stress manifestations which greatly vary. Besides, people sometimes make efforts to hide their stress experience as a result of defence mechanisms to avoid the embarrassing situations it causes.

Therefore, there is the need to develop stress detection methods which are based on semi-voluntary or involuntary measures where it is difficult to be affected by the user behaviour. In this direction, physiological signals can provide useful information about the bodily stress response [1]. Common measures that are used in order to analyze stress are Heart Rate Variability (HRV) parameters, Electrodermal Activity (EDA), Breath rate, Electromyogram (EMG), Electroencephalogram (EEG), etc. However, due to the fact that stress is considered a complex of cognitive, affective, psychological factors, the research question in many studies is the identification of the optimal combination of physiological patterns that lead to the emotional state under investigation.

When a person perceives an upcoming threat, a cascade of physiological processes occurs which constitute the term "*stress response*". Heart activity is modulated by two neuromodulatory receptors types (acetylcholine and norepinephrine) of heart cells corresponding to the Parasympathetic (PNS) and Sympathetic (SNS) nervous system respectively. Stress leads to the activation of the SNS, resulting in the increase of heart rate and its force of contraction. As a result, the amount of blood circulates faster through the body in order to deliver immediate more oxygen to the organs as an attempt to eliminate the stressor.

Various studies exist in the literature employing HRV parameters in order to study stress states [2-6]. However, most of the studies use only a subset of features (e.g. only HR, SDNN) without providing information on which are the most relevant HRV parameters on stress response or provide just statistical evidence on their reasoning. On the other hand, the investigation of all HRV measures provides a more complete picture of heart activity in SNS/PNS activation during stress conditions [5].

In this study, the optimal combination of HRV parameters in detecting specific stress types induced in experimental conditions is investigated. These parameters feed a machine learning system in order to discriminate efficiently between stress and neutral states. The proposed methodology validation was performed establishing a thorough experimental protocol recording facial videos/ECG signals towards developing a reliable stress recognition system.

TABLE I EXPERIMENTAL TASKS AND CONDITIONS OF THIS STUDY.

	Experimental phase	Affective State	Duration (min)
Social Exposure			
1.1	Neutral (reference)	N	1
1.2	Interview (self-describing)	S	1
Stressful event recall			
2.1	Neutral (reference)	N	1
2.2	Recall anxious event	S	1
2.3	Recall stressful event	S	1
Cognitive load			
3.1	Neutral/stressful images	S	2
3.2	Stroop Colour Word Task	S	2
Stressful videos			
4.1	Neutral (reference)	N	1
4.2	Relaxing video	R	2
4.3	Adventure video	S	2
4.4	Psychological pressure video	S	2

Note: Intended affective state (N:neutral,S:stress,R:relaxed).

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II. EXPERIMENTAL PROCEDURE AND DATASET

A. Experimental procedure

In order to investigate the effects of stress conditions, stressors were induced to the participants designed to simulate a wide range of everyday life conditions. The different stressors categorized in 4 phases (social exposure, stressful event recall, cognitive load, stressful videos) aiming to cover the underlying stress types they may cause. The experimental procedure (for more details about the procedure please read [4]) with tasks description, duration and their corresponding affective state is presented in Table I.

B. Dataset of the study

The population of this study was 24 participants (7 women, 17 men) with age 47.3±9.3 years. The study was approved by the North-West Tuscany ESTAV (Regional Health Service, Agency for the Technical-Administrative Services of Wide Area) Ethical Committee. The dataset was collected during the second data acquisition campaign (SRD'15) of a research project related to a computational platform monitoring cardio-metabolic risk [7].

III. METHODS

A. ECG recording and preprocessing

For the ECG recording, the patient's skin was prepared using prepping gel and conductive paste. Two Ag/AgCl electrodes were placed in symmetric position of the chest corresponding to the leads V1 and V2 which they are considered as the most appropriate in order to acquire bipolar ECG recording [8].

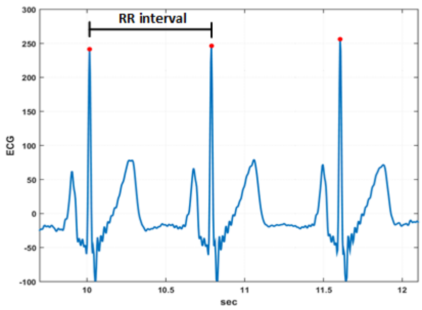

Fig. 2. An example of preprocessed ECG signal from this study, R peaks (red markers) and RR interval determination.

The signal was detrended by subtracting time series polynomial fit and bandpass filtered. Spikes and artifacts (due to the subject's activity/body movements, etc) were also suppressed with proper filters. A typical preprocessed ECG signal acquired during this study is presented in Fig. 2. The R components of the QRS complex were detected and the RR Intervals (RRI) were calculated (Fig. 2). The ectopic heartbeats (irregular heartbeats deviated from normal) were also detected and excluded by adopting the HRV signal approach [9]. (percentage change of 40% over the averaged previous 5 heartbeats). The RRI time series were interpolated to a frequency of $f_{\text{in}\,trp} = 10Hz$.

B. HRV parameters extraction

After the RRI extraction, temporal and spectral HRV parameters were calculated. Temporal HRV parameters were directly computed from RRI [10], whereas the spectral HRV parameters were estimated from the time-frequency representation (TFR) of the RRI timeseries. The TFR (Fig. 1) was estimated using a time-varying autoregressive model [11]. The signal *x(t)* can be expressed as

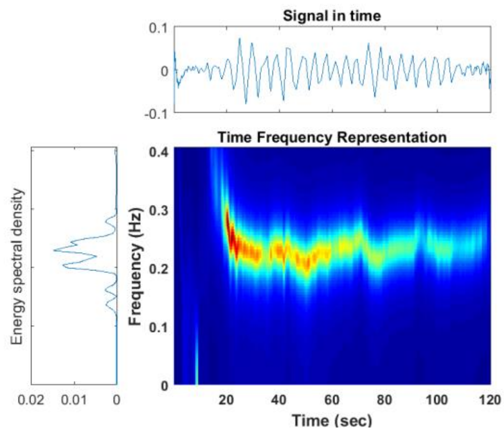

Fig. 1. Time-frequency representation of RR intervals which is used for the estimation of spectral HRV parameters.

$$x(t) = \sum_{k=1}^{p} a_k(t)x(t-k) + e(t) \quad (1)$$

where $\alpha_\kappa(t)$ are the time-varying autoregressive (*TVAR*) coefficients, p is the model order, and $e(t)$ is Gaussian noise with zero mean and variance σ_n^2 . The model order was selected using the Akaike criterion (AIC) and determined at order 18 leading to normalized spectral indices. The temporal update and evolution of (AR) coefficients were estimated using a Kalman filter algorithm [11] which is an optimal estimator in the mean-square sense. The adaptive time-varying estimation of spectrum achieves enhanced spectral resolution compared to FFT-based spectrum [11], thus enabling reliable estimates even for shorter time periods. The produced spectrogram *S(t,f)* is discretized into resels (resolution elements) integrating the time interval of each overlapping moving window Δt [12].

The HRV parameters that investigated in this study divided into time and frequency domain as follows:

Time Domain: RR, SDNN, HR_m, HR_{std}, RMSSD, NN50, pNN50, HRV triangular index, ECG envelope
Frequency Domain: Total power, LF, HF, LF/HF, LF_{norm}, HF_{norm}, LF peak, HF peak

All of them form the feature matrix $X \in \mathbb{R}^2$ with dimensions *NxM* representing *N* samples and *M* features (e.g. a specific sample is provided as an *M*-dimensional vector $X(t_i) = [\, f_1(t_i), f_2(t_i), ..., f_M(t_i)]$) and $Y \in \mathbb{N}$ is the class vector (class 1: no stress, class 2: stress).

C. Baseline removal and pairwise transformation

For each participant, a relaxed period was established which carefully took into account when designing the research experiment. This period corresponds to each subject's baseline which is removed from all subsequent feature analyses. This transformation generates a common reference across subjects providing data normalization [4].

The problem of stress detection can be viewed as a ranking problem where the input is the feature matrix *X* and the class vector *Y* described in section IIB. In order to transform into a 2-class (classes: no stress, stress) classification problem, the pairwise transformation was used as introduced in [13]

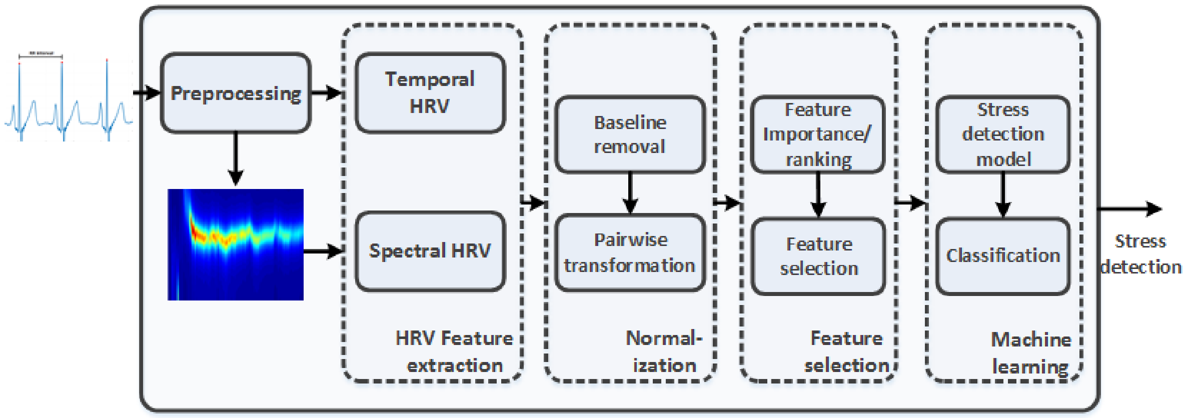

Fig. 3. Architecture of the ECG stress recognition system comprising of 5 subsystems: (a) preprocessing, (b) HRV feature extraction, (c) normalization, (d) feature selection, (e) machine learning.

$$T: \begin{array}{l} X' = X(t_i) - X(t_j) \\ Y' = sign\{Y(t_i) - Y(t_j)\} \end{array}, \forall \text{corresponding } i, j$$

where *i,j* refer to the temporal indices of non-stress and stress periods respectively with all possible pairs of a specific case of the feature matrix. The pairwise transformation creates preference pairs of feature vectors and their labels $sign(Y(t_i)-Y(t_j))$. If $Y(t_i) > Y(t_j)$ then $X(t_i) \succ X(t_j)$ and this preference pair is a positive instance, otherwise, it is a negative instance ($X(t_i) \prec X(t_j)$). The preference pairs and their corresponding labels after transformation can be considered as instances and labels in a new classification problem which then can be performed with traditional classification schemes.

D. Feature selection

The most relevant and important HRV features are investigated and selected in order to improve the performance of stress anticipation. The ranking of feature importance was performed using the minimum Redundancy Maximum Relevance (mRMR) selection algorithm [14]. This algorithm evaluates the features' importance ranking based on maximal relevance and minimum redundancy optimizing in terms of the Mutual Information Quotient (MIQ) criterion.

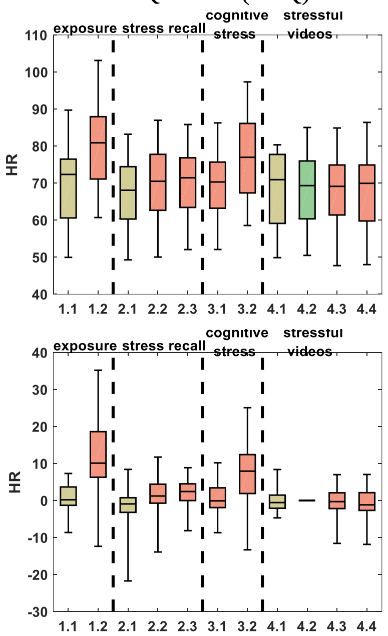

Fig. 4. An example of baseline (relaxed task) removal providing a common reference and unveiling effects of stress that were hidden due to great inter-subject variability.

IV. Results

The architecture of the proposed stress recognition system is presented in Fig. 3. Its input is the ECG signal and the output is the automatic decision on the 2 emotional states under investigation (stress, no stress classes).

C. Feature evaluation

The HRV parameters were evaluated for significant differences between neutral and stress states for the different tasks of the experiment. Comparisons among tasks for each phase was performed using as control state the neutral recording at the beginning of each phase. There are some HRV parameters with discriminative ability between the two states, however their behaviour is not present and consistent across all tasks. Specifically, the most consistent HRV features are HR_m, HR_{std}, total power, LF/HF, LF_{norm} which significantly increase and the features SDNN, RMSSD, NN50, pNN50 which significantly decrease in specific experimental tasks making them possible efficient features for stress anticipation.

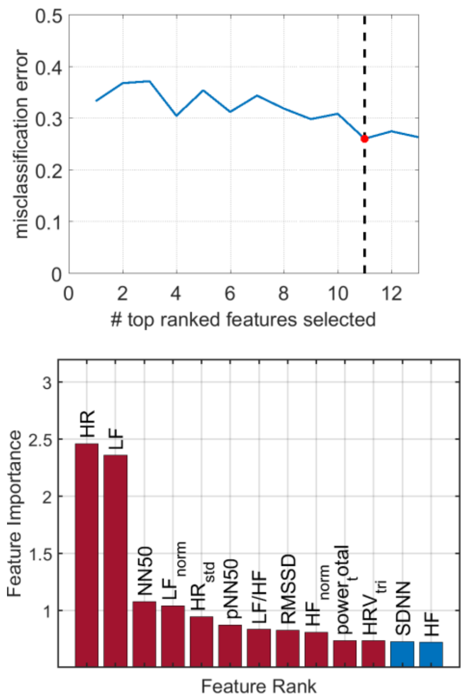

Fig. 5. (Upper graph) Misclassification error (SVM, 10-fold cross validation) as a function of number of selected features and the selected number (11) of features. (Lower graph) Feature importance ranking according to RF and the selection of the most important 11 features (denoted with red columns).

TABLE IV CLASSIFIERS PERFORMANCES OF DISCRIMINATION ACCURACY FOR THE SELECTED TOP-RANKED HRV FEATURES

Classifier	Sample basis Accuracy (%)	After pairwise transform Accuracy (%)
KNN	66.7	73.8
GLM	56.2	76.2
NVB	61.5	64.9
LDA	65.6	69.9
SVM	73.6	**84.4**
RF	**75.1**	70.0

A significant consideration in order to reveal the effects of stress was the careful determination of a relaxed period in the experiment so as the subsequent features analyses are referred to this baseline. This is very important to eliminate the great inter-subject variability on stress response providing a common reference to each feature across subjects ensuring data normalization. The effects of this procedure on the mean HR (HR_m) is presented in Fig. 4.

After the baseline was removed and the feature matrix was transformed using the pairwise transformation (see section III.C) in order to transform the ranking problem into a 2-class [no stress, stress] classification problem. The mRMR feature selection algorithm (section III.D) was employed in order to estimate each feature's importance ranking and to select a robust subset of top-ranked features. The algorithm minimizes the misclassification error of the 10-fold SVM discrimination accuracy between the 2 classes (no stress, stress) (Fig. 5, upper graph) yielding the selection of 11 top ranked features. The 11-most important features (HR_m, LF, NN50, LF_{norm}, HR_{std}, pNN50, LF/HF, RMSSD, HF_{norm}, total power, HRV_{tri}) were selected for the problem under investigation (Fig. 5, lower graph).

Then, the top-ranked selected features were evaluated in terms of their ability to discriminate between the two classes (no stress, stress). A 10-fold cross-validation scheme on sample basis was used with the KNN, Generalized Linear Model (GLM), Naïve Bayes (NVB), Linear Discriminant Analysis (LDA), Support Vector Machines (SVM), Random Forest (RF) classifiers. The results are shown in Table IV where RF outperforms all other classification schemes with a classification accuracy of 75.1%. Then, the system's performance was investigated on the pairwise transformed selected features where the system's performance improved noticeably reaching a classification accuracy of 84.4% using SVM. The performance results are presented in Table IV.

V. DISCUSSION

This study investigates the stress effects on HRV parameters and pursuits to identify the optimal combination of HRV features being able to detect reliably stress conditions. The HRV features were ranked in terms of their significance and relevance to stress anticipation leading to the selection of the 11 top-ranked features (HR_m, LF, NN50, LF_{norm}, HR_{std}, pNN50, LF/HF, RMSSD, HF_{norm}, total power, HRV_{tri}).

The proposed system was evaluated on 24 participants and 11 tasks performing a research protocol for about 45 min. Despite the fact that a bigger sample would enhance the generalizability of the results, the number of tasks (11 in total) increased the available data for each participant. Besides, the proposed pairwise transformation enhance the dataset and it is an efficient way to address this kind of problems making the dataset proper for feeding traditional classification systems.

The best performance achieved in the proposed stress recognition system only utilizing HRV parameters is 84.4% classification accuracy in a 10-fold approach. These results are promising as only ECG signal was used. Considering that stress is a complex state that can use information from multimodal sources in order to assess reliable stress levels, this accuracy could, under circumstances, be increased using other modalities in parallel.

The interest of the scientific community on the usage of only one ECG channel makes these methods appropriate, as they can be conveniently used through wearable devices in daily monitoring. Further studies and increased sample size would increase the model's reliability, accuracy as well as to estimate the importance of the involved HRV parameters. Even though cardiac signals contain limited information, this study indicates that the usage of only ECG recordings could serve efficiently in stress detection.

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