Stress Classification by Separation of Respiratory Modulations in Heart Rate Variability using Orthogonal Subspace Projection*

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Abstract— **The influence of respiration on the heart rate is a phenomenon known as respiratory sinus arrhythmia. However, effects of respiration are often ignored in studies of heart rate variability. In this paper, we take respiratory influences into account by separating the tachogram in two components, one related to respiration and one residual component, using orthogonal subspace projection. We demonstrate that it is important to remove respiratory influences during classification of rest and mental stress. Using merely the original tachogram, the classification accuracy is 57.13%, while the use of the residual tachogram results in an almost perfect classification (accuracy = 97.88%).**

I. INTRODUCTION

The variability of the heart rate (HRV) is widely studied as it is a simple and noninvasive tool to assess the activity of the autonomic nervous system (ANS). From the tachogram, several measures, such as spectral indices, that quantify HRV are defined [1]. The power in the low frequency (LF) band, defined from 0.04 to 0.15 Hz, is linked to both sympathetic and parasympathetic activity, while the high frequency (HF) power, ranging from 0.15 to 0.40 Hz, is believed to contain only parasympathetic influences. The latter is often used as an index of respiratory sinus arrhythmia (RSA), the well-known phenomenon that the heart rate modulates in phase with respiration [2]. However, many studies show that the magnitude of RSA changes with the respiratory frequency and tidal volume, independently of changes in vagal control [3], [4]. This makes that the interpretation of HRV measures is questioned. Several remedies are proposed to deal with this issue, e.g. the use of alternative measures of RSA [3], [5], but so far, no agreement has been reached about a valid alternative for the conventional RSA definition.

In this study, we aim to show that it is not only important to take respiratory influences on HRV into account to make correct interpretations of ANS activity, but that respiration should also be included in HRV analyses because differences in the HRV, unrelated to respiration, might be masked by differing respiratory parameters such as frequency and tidal volume. We will demonstrate the latter in the application of stress monitoring. We will show this by separating the tachogram (RR_{orig}) in two components, i.e. one related to respiration (RR_{resp}) and one residual component (RR_{res}) that contains all variations in the heart rate that are unrelated to respiration. The separation will be conducted using orthogonal subspace projection (OSP). Next, spectral HRV measures are computed from both the residual tachogram and RR_{resp}, and the performance is assessed by classification of rest and stress.

II. METHODS

A. Data

The data used in this research were measured at the Department of Psychology of the KU Leuven (Leuven, Belgium) in the context of a broader study [6], [7]. The electrocardiogram (ECG, sampling frequency f_s = 200 Hz) and respiration (f_s = 50 Hz) of 43 healthy students (age: 18-22 years) were recorded using the LifeShirt System (Vivometrics Inc., Ventura, CA). Respiration was recorded using respiratory inductive plethysmography around the abdomen and the ribcage. Based on these two signals, the tidal volume is computed. This volume will further be considered as the respiratory signal (RESP).

The participants were instructed to perform two tasks. A first task was a nonstressful attention task during which the students had to indicate the highest number on a computer. The second task was designed to induce mental stress using arithmetic equations. The full protocol consists of baseline recording, one attention task (AT) and two mental stress tasks (MT1 and MT2), each followed by a resting period. Each task had a duration of 6 minutes. For this study, only two randomly chosen resting periods and the two mental stress tasks of 40 students are used. The experiment was approved by the Ethics Committees of the Department of Psychology and of the Faculty of Medical Sciences.

B. Preprocessing

look up Pan-Tomkins

The tachogram is constructed from the detected R peaks in the ECG using the Pan-Tompkins algorithm. All detections are manually verified and corrected where needed. Next, the tachogram and respiratory signal are resampled at 4 Hz using

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cubic spline interpolation and the respiratory signal is high-pass filtered with a cut-off frequency of 0.05 Hz to remove baseline wander.

In order to increase the number of signals in the dataset, each period of 6 minutes is divided in segments of two minutes, with one minute overlap. This procedure results in 10 segments of rest and 10 segments of stress for each subject.

All processing steps of the data are performed in MATLAB R2012a (MathWorks, Natick, MA).

C. *Orthogonal Subspace Projection*

Orthogonal subspace projection decomposes a signal in two independent components using a given reference, in this case the respiratory signal [8], [9].

Consider X the basis that is constructed of the respiratory signal. The projection matrix P is then defined as

$$P = X(X^T X)^{-1} X \tag{1}$$

and is used to project a signal, i.e. RR_{orig}, onto the respiratory basis X via (2), yielding the respiratory component RR_{resp} of the tachogram

$$RR_{\text{resp}} = P\ RR_{\text{orig}}. \tag{2}$$

Consider Q the orthogonal complement of P, then the residual component RR_{res} is determined by

$$RR_{\text{res}} = Q\ RR_{\text{orig}} \tag{3}$$

or

$$RR_{\text{res}} = RR_{\text{orig}} - RR_{\text{resp}}. \tag{4}$$

The basis X that defines the respiratory subspace is constructed using the detail signals of the wavelet decomposition of the respiratory signal. The Daubechies 4 wavelet (db4) is taken as mother wavelet and the decomposition is performed up to level 4. The approximation signal is not enclosed in the basis. In order to take the effect of previous samples into account, delays of the respiration up to 3 seconds (12 samples) are included. The use of both the wavelet decomposition and delays result in a respiratory basis X that consists of 48 components.

D. *Classifier Design*

The added value of separating respiratory influences from the tachogram in HRV analyses is assessed by classification of rest and stress segments. A least squares support vector machines (LS-SVM) classifier is trained using a radial basis function (RBF) kernel and 5-fold cross-validation to avoid overfitting [10]. The data of 32 randomly chosen subjects are used in the training set and the performance is tested on the remaining 8 subjects. This setup results in subject-independent classifiers.

Consider stress as the positive class and rest as the negative one, then the performance of each classifier is assessed by means of the sensitivity (S^+), specificity (S^-), positive prediction value (PPV), negative prediction value (NPV), the accuracy (acc) and the area under the ROC (receiver operating characteristic) curve (AUC).

The features used to classify the data segments are spectral indices of each tachogram (RR_{orig}, RR_{res} and RR_{resp}). The power in the low (LF) and high frequency (HF) band are computed via Welch's method, using a 1024 point fast Fourier transform (FFT), a periodic Hamming window of a length such that eight equal sections of the tachogram are obtained, and an overlap of 50%. Furthermore, $LFnu = \frac{LF}{LF+HF}$ (normalized units), $HFnu = \frac{HF}{LF+HF}$, the ratio LF/HF and the power in the total frequency band $TF = LF + TF$ are considered. These spectral indices are computed for three classifiers using RR_{orig}, RR_{res} and RR_{resp} separately. Another classifier that combines RR_{res} and RR_{resp} is constructed.

In addition, a classifier that includes respiratory information in the original tachogram is implemented in order to make a fair comparison with the residual tachogram, because RR_{res} is obtained using additional respiratory information. Therefore, a last classifier that uses the recorded respiratory signal (ref) is created using three new features: $LFnu_{\text{ref}}$, $HFnu_{\text{ref}}$ and $LFnu/HFnu_{\text{ref}}$. These features employ the normalized power as the respiratory signal is in arbitrary units. The following classifiers are considered:

- **RR**$_{\text{orig}}$: LF_{orig}, HF_{orig}, $LFnu_{\text{orig}}$, $HFnu_{\text{orig}}$, LF/HF_{orig}, TF_{orig}
- **RR**$_{\text{orig}}$**+RESP**: LF_{orig}, HF_{orig}, $LFnu_{\text{orig}}$, $HFnu_{\text{orig}}$, LF/HF_{orig}, TF_{orig}, $LFnu_{\text{ref}}$, $HFnu_{\text{ref}}$, $LFnu/HFnu_{\text{ref}}$
- **RR**$_{\text{res}}$: LF_{res}, HF_{res}, $LFnu_{\text{res}}$, $HFnu_{\text{res}}$, LF/HF_{res}, TF_{res}
- **RR**$_{\text{resp}}$: LF_{resp}, HF_{resp}, $LFnu_{\text{resp}}$, $HFnu_{\text{resp}}$, LF/HF_{resp}, TF_{resp}
- **RR**$_{\text{res}}$**+RR**$_{\text{resp}}$: LF_{res}, HF_{res}, $LFnu_{\text{res}}$, $HFnu_{\text{res}}$, LF/HF_{res}, TF_{res}, LF_{resp}, HF_{resp}, $LFnu_{\text{resp}}$, $HFnu_{\text{resp}}$, LF/HF_{resp}, TF_{resp}, $TFnu_{\text{res}} = TF_{\text{res}}/(TF_{\text{res}}+TF_{\text{resp}})$, $TFnu_{\text{resp}} = TF_{\text{resp}}/(TF_{\text{res}}+TF_{\text{resp}})$, $TF_{\text{res}}/TF_{\text{resp}}$.

The most important features of each classifier are determined by 5-fold application of automatic relevance determination (ARD) [10] using different training and test sets. The performance measures of all classifiers are averaged over these 5 runs.

III. RESULTS AND DISCUSSION

A. *Orthogonal Subspace Projection*

Fig. 1 shows an example of the time signals and corresponding spectra after application of OSP. The original tachogram is clearly influenced by respiration. This respiratory influence is contained in RR_{resp} while the modulations in the residual tachogram are not related to respiration. The power spectra report the same conclusion; the power in the HF band of RR_{orig} is mainly related to respiration. After separation, this is captured in the spectrum of RR_{resp}. Remark that the residual tachogram still contains power in the HF band as well as at the main respiratory frequency.

OSP is chosen as a suitable method to separate the tachogram in two independent components as it combines

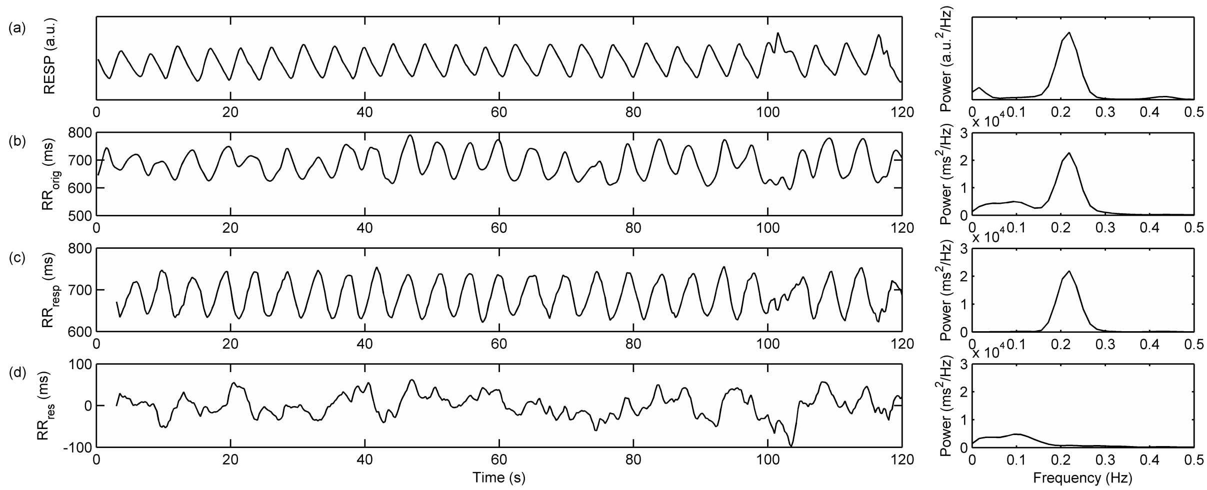

Fig. 1. An example of the obtained signals after application of OSP. The tachograms originate from subject 3 during the first two minutes of rest. The corresponding power spectra are shown on the right. (a) respiratory signal RESP; (b) original tachogran RR_{orig}; (c) respiratory component of the tachogram RR_{resp}; (d) residual tachogram RR_{res}

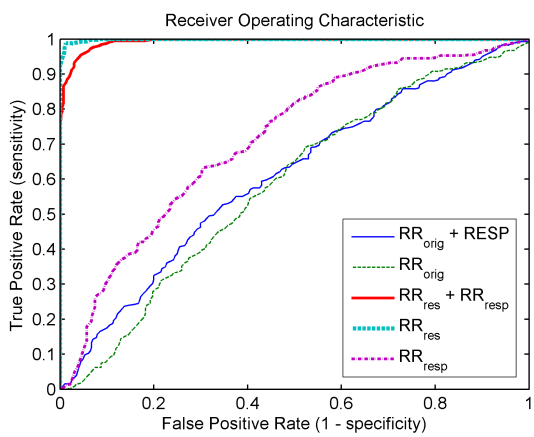

Fig. 2. ROC curves of all classifiers

TABLE I
PERFORMANCE MEASURES OF EACH CLASSIFIER (IN %)

	RR_{orig}	RR_{orig} + RESP	RR_{res}	RR_{resp}	RR_{res} + RR_{resp}
S^+	63.75	60.75	97.00	75.00	91.00
S^-	50.50	55.00	98.75	57.00	98.25
PPV	56.29	57.45	98.73	63.56	98.11
NPV	58.21	58.36	97.05	69.51	91.61
acc	57.13	57.88	97.88	66.00	94.62
AUC	58.24	60.63	99.89	71.19	99.33

S^+: sensitivity; S^-: specificity; PPV: positive predictive value; NPV: negative predictive value; acc: accuracy; AUC: area under the ROC curve

the advantages of two techniques that successfully proved their efficiency to separate respiratory influences from the tachogram. The first technique uses an autoregressive moving average with exogenous inputs (ARMAX) model to assess the respiratory component RR_{resp} as a weighted sum of previous respiratory samples. Similar as in OSP, the least squares solution was used, with the difference that the basis X only consists of delayed respiratory signals [11]. The second technique uses multiscale principal component analysis (MSPCA) to estimate RR_{resp} using projections between the respiratory signal and the original tachogram in several frequency bands via their wavelet decomposition [12]. Note that a preliminary study revealed that OSP is more efficient than ARMAX and MSPCA to separate the tachogram in two components. Model-based approaches to decompose the power spectrum of the tachogram in partial spectra are also presented in the literature, with even the inclusion of blood pressure measurements [13]. Future research should focus on including blood pressure information, as well as an extensive comparison between the different methods.

B. Classification in Rest and Stress

Table I and Fig. 2 show the mean performance of each classifier. We hypothesized that the original tachogram contains modulations from respiration and non-respiration related variations, and that separation of both will reveal new information and lead to an increased performance when rest and stress are classified. This study confirms the postulated hypothesis; based on the original tachogram, classification in rest and stress is almost random (accuracy = 57.13%). Even when respiratory information is added, the performance of the classifier does not improve. This indicates that although respiration is influenced by stress, it is not an important marker to classify stress. Possibly, the chosen features to represent the respiratory pattern are too simple. Other features might improve the performance of the classifier. This observation is confirmed when classification is carried out using only RR_{resp}; the performance is better than with the original tachogram, but the accuracy is barely 66%. An apparent improvement is found when RR_{res} is used, yielding an almost perfect classification (accuracy = 97.88%). Interestingly, combining RR_{res} and RR_{resp} does not lead to an increased performance, on the contrary.

From these observations we can deduce that respiration not only leads to false interpretation about ANS activity, but the effect of respiration on the tachogram might disguise differences in HRV due to differing respiratory patterns. This study shows that the original tachogram contains HR variations, unrelated to respiration, that seem to be very important to distinguish stress from rest, but these variations are masked by the dominant respiratory influence on the heart rate.

In order to determine the most relevant features for each classifier, automatic relevance determination is applied. The features that are at least three times indicated in the 5-fold iteration are indicated below:

- $\mathbf{RR}_{\text{orig}}$: LF_{orig} (3), $HFnu_{\text{orig}}$ (3)
- $\mathbf{RR}_{\text{orig}}$+**RESP**: LF_{orig} (3), HF_{orig}(3), TF_{orig} (5), $LFnu_{\text{ref}}$ (4)
- $\mathbf{RR}_{\text{res}}$: $LFnu_{\text{res}}$ (5), $HFnu_{\text{res}}$ (5)
- $\mathbf{RR}_{\text{resp}}$: HF_{resp} (5), LF/HF_{resp} (3), TF_{resp} (4)
- $\mathbf{RR}_{\text{res}}$+$\mathbf{RR}_{\text{resp}}$: LF_{res} (4), HF_{res} (4), $LFnu_{\text{res}}$ (5), $HFnu_{\text{res}}$ (5), TF_{res} (5), LF_{resp} (5), HF_{resp} (5), $LFnu_{\text{resp}}$ (4), $HFnu_{\text{resp}}$ (4), LF/HF_{resp} (4), TF_{resp} (5).

A resemblance between the selected relevant features and the performance of each classifier can be observed as the inferior performing classifiers do not have consistently important features. RR_{res} on the other hand has two key features while the remaining features are never selected by ARD. Fig. 3 demonstrates the importance of $LFnu_{\text{res}} = LF_{\text{res}}/TF_{\text{res}}$ in the classification of rest and stress. An almost perfect separation is obtained. Moreover, the results indicate that for the same LF_{res}, HF_{res} is lower during stress than during rest as TF_{res} is higher in rest. This means that, as expected, the parasympathetic activity is reduced during stress.

Another important advantage of the followed methodology is that the classification is subject-independent. In most cases, stress has been considered as a subject-dependent phenomenon and classification was performed in a subject-specific manner, as in [11]. The use of subject-independent classifiers might also explain why inclusion of respiratory information does not lead to an improvement of the performance of the classifier. It has been demonstrated that stress influences the respiratory pattern, but these conclusions are deduced from within-subject comparisons [6], [14]. On a subject-independent level, this information seems to be insignificant.

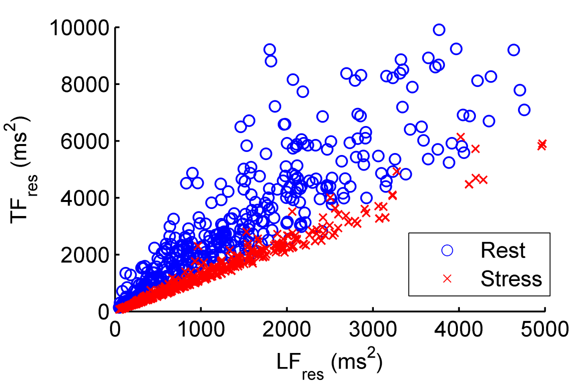

Fig. 3. The importance of $LFnu_{\text{res}} = LF_{\text{res}}/TF_{\text{res}}$ in the classification of rest and stress is shown: LF_{res} versus TF_{res}

IV. CONCLUSIONS

This study demonstrated the importance and the use of separating respiratory influences from the tachogram in the application of stress monitoring. The residual tachogram contains valuable information, that is otherwise masked by respiratory influences, to distinguish a resting state from a stress condition. Other applications should confirm the added value of the proposed technique and extensions to multiclass situations should be made.

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