Breathing Rate Complexity Features for "In-the-Wild" Stress and Anxiety Measurement

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***Abstract*—Features extracted from respiratory activity signals have been shown to carry information about mental states such as anxiety and mental stress. Such findings, however, are based on studies conducted mostly in controlled laboratory environments with artificially-induced psychological responses. While this assures that high quality data are collected, the amount of data is limited and the transferability of the findings to more ecologically-appropriate natural settings (i.e., "in-the-wild") remains unknown. In this paper, we propose new non-linear complexity measures computed from four different respiration activity time series (i.e., inter-breath interval, inhale-to-exhale ratio, inhale/exhale amplitude envelope, and inter-breath difference) and show their discriminatory power for anxiety and stress monitoring in the workplace. The new features are tested on a dataset collected from 200 hospital workers (nurses and staff) during their normal work shifts. The proposed features are shown to be complementary to conventional measures of breathing rate and depth.**

I. Introduction

Advances in battery and sensing technologies for wearable devices have enabled long-term, unobtrusive and continuous acquisition of biomedical data. Respiration is an easy modality to be monitored by smart-garment based devices such as smart-shirts. Typically, breathing rate based measures have been used as correlates of mental states such as anxiety, amusement, and boredom [1]. When combined with cardiovascular activity monitoring, it has been shown that improved stress and anxiety measurement can be obtained [2], [3].

Respiration can be considered as a mixture of two processes of metabolic and behavioral breathing originating from different parts of the brain [4], with the latter being affected by internal and external stimuli. Usually, these changes are observable in two different aspects of breathing, namely (i) respiration or breathing rate and (ii) tidal volume or breathing depth. Mental stress has been shown to increase both respiration rate and breathing depth [5]. Similarly, anticipatory anxiety is associated with an increase in respiration rate [6]. This respiratory variability has been quantified with simple statistical functionals, such as mean, coefficient of variation and auto-correlation [7]. Notwithstanding, the inter-breath interval series (e.g., as shown in Fig. 1) exhibits a complex fractal behavior similar to inter-beat interval (RR) series of cardiac activity and shows similar degradation with aging [8]. These complex behaviors in the time series can be better quantified by using non-linear measures, as previously shown for cardiac activity [9]. One such measure, called the permutation entropy (PE), has shown to also be robust to artifacts, as it deals with structures and shapes of the time series, and not on magnitude values themselves [10]. The sample entropy ($SampEn$) measure, in turn, provides a simple way of measuring the complexity of a time series and has been extensively used in physiology monitoring [11]. Fractal exponents can be further quantified by using the correlation dimension [12]. Moreover, respiration has been known to be a strong modulator of heart rate dynamics [13], with inhale-to-exhale duration ratios and guided breathing leading to increased relaxation, stress reduction, and mindfulness [14]. Breathing has also shown to modulate cardiac activity in a way that alters the heart rate variability and reduces anxiety [15].

The majority of existing studies have manipulated stress and anxiety in laboratory settings, thus it is unclear how such measures behave in highly ecological settings of natural human behavior (such as in a workplace) where movement artifacts could be highly detrimental. In this work, we propose several new breathing and breathing-cardiac coupling measures for "in-the-wild" assessment of stress and anxiety. Specifically, we propose to extract complexity measures from four time series: (1) inter-breath interval, (2) inhale-exhale ratio, (3) inhale/exhale amplitude envelopes, and (4) absolute first difference of the inter-breath interval. The latter is inspired by work in cardiac series analysis, which showed difference heart rate series as exhibiting interesting non-linear properties [16]. Next, we propose to quantify cardio-respiratory interaction using a new modulation coupling parameter. We show that the proposed features rank highly for the task at hand and provide complementary information to conventional features.

The remainder of this paper is organized as follows. Section II covers the details of data collection, benchmark and proposed features, and the experimental setup. Section III presents the experimental results and a discussion. Lastly, Section IV provides the conclusions.

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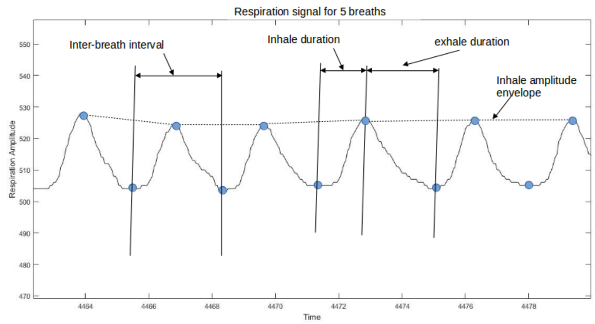

Figure 1. Respiration signal for 5 complete breaths

II. Materials and Methods

A. Participants

Data were collected from 200 participants (66 male, age 38.6 ± 9.8 years) from a pool of employees (nurses and staff) of a large urban hospital in California. Two-thirds of the participants were nurses while one-third were hospital staff. Data were collected for a duration of 10 weeks. Participants consented to participate in the study, which received ethical board approval from the affiliated institutions. Participants carried out their work day as usual but were asked to fill a brief phone-based daily survey that included information on levels of anxiety and stress on a 5-point scale.

B. Wearable Sensors

Participants were outfitted with multiple wearable sensors to collect a variety of biometric data, including audio features, heart rate, respiratory rate, and sleep quality. A custom audiometric badge was used, as detailed in [17], along with a Fitbit Charge 2 and an OMsignal smartshirt. In this paper, only the respiration information measured by the OMsignal smartshirt is used, along with the inter-beat heart rate series, also provided by the garment. The garment provides information about inhale and exhale peaks and the time when these peaks occur.

C. Feature Extraction - Conventional Features

A complete list of conventional and proposed measures can be found in the Table I. Further details about the features are given in the subsections below. Here, the features provided by the OMSignal garment are used as benchmarks and are provided every 5-minute interval. These correspond to the mean and standard deviation of the instantaneous breathing rate (f_R) and the breathing depth (b_D). These features have been shown in the literature to correlate with stress [6] and anxiety [5].

D. Feature Extraction - Proposed Features

Features are extracted from four different time series. These are listed below for each series.

Table I
DIFFERENT GROUPS OF BREATHING FEATURES EXTRACTED

Feature Groups	Features
Benchmark	mean and std of f_R, mean and std of b_D
Inhale-to-exhale ratio	mean, std and CoV, $SampEn$ and PE, d_{cor}, mod_{mn}, mod_{std}
Inter-breath interval	mean, std and CoV, d_{cor}, $SampEn$, and PE for $ibri$ and d_ibri
Amplitude envelope	mean, std and CoV for Inh_{Am} and Exh_{Am}

1) Inhale and Exhale Amplitude Envelope Series: Instead of considering the total breathing depth, which could be sensitive to movement artifacts, we propose to extract features from the inhale and exhale amplitude envelopes (Inh_{Am} and Exh_{Am}, respectively) instead. The inhale amplitude envelope can be seen in Fig. 1. From the two envelopes, we calculate the mean, standard deviation (std) and coefficient of variation (CoV).

2) Inhale-to-Exhale Ratio Series: The inhale-to-exhale ratio series, $ier(n)$, is created from the respiration signal, where n represents a given respiration cycle, as:

$$ier(n) = \frac{inh_{dur}(n)}{exh_{dur}(n)}, \tag{1}$$

where $inh_{dur}(n)$ and $exh_{dur}(n)$ are the duration of inhale and exhale times, as shown in Fig. 1. To quantify the properties of this series and how it modulates heart rate variability, the following features are proposed:

- Statistical features: The mean, standard deviation and coefficient of variation of ier;
- Non-linear features: Permutation entropy (PE), Sample Entropy ($SampEn$), and correlation dimension (d_{cor}) are calculated for ier. The permutation entropy quantifies the occurrence of motifs in the series. Motifs are defined as recurring patterns in the time series with a degree η and lag λ. Based on the rank ordering of the motif pattern we assign it a specific symbol j. Representative motifs of degree 3 and lag 1 are shown in Fig. 2. The permutation entropy is then calculated as:

$$PE = -\sum_{j}^{\eta!} p(j) \cdot \log(p(j)), \tag{2}$$

where $p(j)$ is the relative frequency of the motif pattern represented by j.
Sample entropy, in turn, is the negative natural logarithm of an estimate of the conditional probability that if two sets of vectors ($X_m(i)$ and $X_m(j)$) of

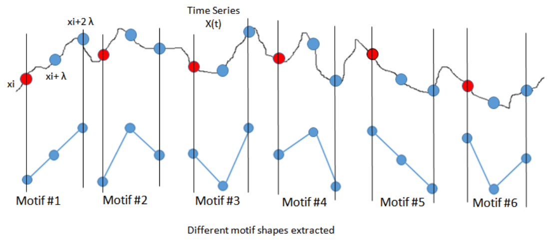

Figure 2. All motifs of degree $\eta = 3$ appearing in a time series

length m have a distance $< r$, then two sets of vectors ($X_{m+1}(i)$ and $X_{m+1}(j)$) of length $m+1$ also have a distance $< r$, based on some distance metric $d_m(X, Y)$. It is formally defined as:

$$SampEn = -\log \frac{N_{m+1}}{N_m}, \tag{3}$$

where N_m is number of vector pairs with $d_m(X_m(i), X_m(j)) < r$ and N_{m+1} is number of vector pairs with $d_m(X_{m+1}(i), X_{m+1}(j)) < r$. Next, the correlation dimension (d_{cor}) is proposed to measure the fractal dimension of the series. It is defined using the correlation integral given by:

$$C(\epsilon) = \lim_{N \to \infty} \sum_{i,j=1}^{\infty} H(\epsilon - |x_i - x_j|), \tag{4}$$

where H is the Heaviside step function. As such, the correlation dimension is defined as:

$$d_{cor} = \lim_{\epsilon, \epsilon' \to 0^+} \frac{\ln[\frac{C(\epsilon)}{C(\epsilon')}]}{\ln(\frac{\epsilon}{\epsilon'})}. \tag{5}$$

- Cardiac-respiration coupling: To quantify the interaction between the inter-beat interval (RR) cardiac series and the ier, two features are proposed:

$$mod_{mn}(n) = \frac{\text{mean}(ier)}{\text{mean}(rr)}, \tag{6}$$

$$mod_{std}(n) = \frac{\text{std}(ier)}{\text{std}(rr)}, \tag{7}$$

where mod_{mn} and mod_{std} represent how the breathing modulates the means and the standard deviation of the RR series, respectively.

3) Inter-breath Interval Series and Difference series: From the inter-breath interval duration series ($ibri$) and the magnitude difference of the $ibri$ series (referred as d_ibri), the following features are computed:

1) Statistical features: The mean, standard deviation and coefficient of variation.
2) Non-linear features: PE, $SampEn$ and d_{cor}.

Overall, a total of 25 features are computed, corresponding to 4 conventional features and the 21 proposed features. These 25 features were extracted over 5-minute long windows and are further aggregated over an entire day using the following statistical functionals: mean, standard deviation, coefficient of variation, median, min, max, 1st and 3rd quartile, skewness and kurtosis. After computing these 10 functionals, a total of 250 features are available for analysis (40 standard and 210 proposed features).

E. Feature Ranking, Classification and Figures-of-Merit

Training classifiers with a large feature set may lead to overfitting and many features may be highly correlated. As such, recursive feature elimination was performed with a step size of 10 using the Extra Trees Classifier. The top 40 features are then selected for classification at each cross validation step. Feature selection and classification are performed on benchmark features alone, the proposed features alone, and a combined set to explore the complementarity of the two sets.

A five fold cross-validation setup was performed with feature selection taking place for the top 40 features at each fold. Forty features were selected as this corresponds to the dimension of the benchmark feature set. Classification was then performed on subject-wise binarized high/low stress and anxiety levels. This subject-wise binarization helps reduce data unbalance and remove subject bais in the ratings. A support vector machine (SVM) classifier with an RBF kernel and a 'balanced' setting is explored, which uses the target value to automatically adjust weights inversely proportional to class frequencies in the input data [18]. As the data is unbalanced, F1-score, balanced accuracy (BACC), sensitivity (Sens), and specificity (Spec) are used as classifier performance figures-of-merit.

III. Experimental Results and Discussion

Classification results for stress and anxiety are shown in Tables II and III, respectively. As can be seen, the proposed breathing features outperform the benchmark ones across most figures-of-merit used, with the only exception being sensitivity for anxiety prediction. For example, for stress, the proposed features resulted in a 4.56 % BACC improvement, and a 2.99% increase for anxiety monitoring. Moreover, feature fusion showed further improvements for anxiety prediction (4.03%). These findings suggest that the proposed features may be more relevant for "in-the-wild" assessment of mental states and to provide complementary information to widely used benchmark breathing measures.

Moreover, to further explore the importance of the proposed features within the combined feature pool, an in-depth analysis on the features ranked highly across all five cross-validation trials was performed. It could be seen that for stress prediction, 15 of the top 18 consistent

Table II
PERFORMANCE COMPARISON FOR ANXIETY PREDICTION

Features	Anxiety			
	BACC	F1-score	Sens	Spec
Benchmark	0.5836	0.5228	0.6264	0.5408
Proposed	0.6135	0.5329	0.5756	0.6514
Fusion	0.6239	0.5497	0.6120	0.6359

Table III
PERFORMANCE COMPARISON FOR STRESS PREDICTION

Features	Stress			
	BACC	F1-score	Sens	Spec
Benchmark	0.5549	0.5360	0.5571	0.5528
Proposed	0.6005	0.5774	0.5891	0.6122
Fusion	0.5955	0.5696	0.5770	0.6141

features were from the new proposed feature set with eight features extracted from the inhale-to-exhale ratio series, six from the inter-breath interval series and one from the inhale/exhale amplitude envelopes. Moreover, both cardiac-respiration coupling features and the inter-breath interval difference series features were present. One benchmark feature, mean of b_D, was not among the top feature set.

For anxiety, in turn, 10 of the top 14 consistent features corresponded to newly proposed ones, with six features extracted from the inhale-exhale ratio series, one feature from the inter-breath interval series and three from the inhale/exhale amplitude envelopes. Moreover, both cardiac-respiration coupling features were present As can be seen, the proposed features convey better discriminatory information for the task at hand.

IV. CONCLUSION

In this paper, we proposed several innovations for "in-the-wild" anxiety and stress measurement using data from wearable devices used in a hospital workplace setting. More specifically, we proposed several new non-linear respiration complexity and cardio-respiratory coupling features. Overall, the proposed features are found to be complementary to basic breathing rate measures and to improve anxiety and stress prediction.

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