Design of Breathing-states Detector for m-Health Platform using Seismocardiographic Signal

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Abstract—In this work, a seismocardiogram (SCG) based breathing-state measuring method is proposed for m-health applications. The aim of the proposed framework is to assess human respiratory system by identifying degree-of-breathing, such as breathlessness, normal breathing, and long and labored breathing. For this, it is needed to measure cardiac-induced chest-wall vibrations, reflected in the SCG signal. Orthogonal subspace projection is employed to extract the SCG cycles with the help of a concurrent ECG signal. Subsequently, fifteen statistically significant morphological-features are extracted from each of the SCG cycles. These features can efficiently characterize physiological changes due to varying respiratory-rates. Stacked autoencoder (SAE) deep learning architecture is employed for the identification of different respiratory-effort levels. The performance of the proposed method is evaluated and compared with other standard classifiers for 1147 analyzed SCG-beats. The proposed method gives an overall average accuracy of 91.45% in recognizing three different breathing states. The proposed framework has a great potential for different healthcare applications, and it may be commercially fabricated for IoT based remote health-monitoring systems for consumer electronics market.

Index Terms—Seismocardiogram; ECG; Heart cycle; Neural networks; Stacked autoencoder; Respiratory efforts

I. INTRODUCTION

THE development of alarming devices for health monitoring via body area networks (BANs) has been receiving substantial interest recently. An automatic breathing-state assessment system has a large scope in the consumer electronics market, such as apps in the devices like tablets, smart phones, e-whiteboards, smart watches, and health-bands [1]. Recent cardiovascular studies suggest that seismocardiography (SCG) has greater potential to be a diagnostic tool for early prediction of cardiac diseases in wearable healthcare [2], [3]. The SCG signal measures cardiac mechanical events by recording cardiac-induced chest-wall vibrations [4], [5]. These cardiovascular events are opening and closure of heart valves, blood filling and ejection through heart-chambers, and so on. The SCG is found somewhat advantageous over earlier cardiac modalities such as electrocardiography (ECG) and phonocardiography (PCG) [6]. The wearable healthcare appliances integrated with an SCG-based system have a great potential for wireless wearable BANs [2]. Many factors affect the SCG signal morphology, such as body movement, posture, and respiration. This study is mainly focused towards the analysis of SCG morphology under varying respiratory-effort levels.

Long term irregularities in respiratory rhythms often affect the heart and the lung functions. Hence, identification of breathing patterns is an essential task to avoid the related diseases. In medical diagnosis, breathing patterns give important information to detect various life-threatening diseases including cardiovascular diseases like arrhythmias, cardiac arrest and sepsis, and diseases due to lung dysfunctions such as asthma, pneumonia, chronic obstructive pulmonary disease (COPD), hypercarbia and pulmonary embolism [7]. Fear, anxiety and extensive exercises could also produce abnormal breathing symptoms even in healthy individuals. During the breathing inhalation time, the diaphragm contracts and moves down, the chest surface expands, pressure in the intrathoracic cavity reduces, each of the lungs inflates, and the heart moves almost linearly with the displacement of diaphragm [8]. The hemodynamic variations, such as changes in blood volume, turbulence and pressure caused due to decreased intrathoracic pressure affect the morphological structure of the SCG signal [8]. The morphology of an SCG signal is affected by different respiratory conditions, and so, the SCG can not only be used to measure cardiac health, but also to assess lung fitness [3], [9]. In our previous work [9], significant changes in SCG morphologies are shown for different respiratory events. Breathing patterns may be categorized into three states, viz., breathlessness, normal breathing, and long and labored breathing. Sudden shortness of breath, also known as acute/chronic dyspnea, is a serious pathological condition [10]. The severe abnormalities in lung and heart are the major causes of these conditions in most of the cases. It is to be mentioned that the physical examinations cannot always diagnose these conditions [10]. The SCG would be helpful in establishing physiological-relationship for cardiorespiratory, which would also be applicable to cardiopulmonary exercise testing (CPET).

In the existing literature, a few research works have been suggested using ECG or SCG signals for detection of respiratory information, such as extraction of breathing rate sequence and detection of sleep apnea. To identify the respiratory inhale and exhale phases, the SCG signal may also be used [11]–[15]. Zakeri et al. devised an approach to analyze the SCG beats for the recognition of respiratory phases [11]. In this approach, an SCG beat is segmented into identical sized blocks in temporal and spectral domains, and average values from the blocks are used as features. Thereafter, support vector machine (SVM) is used to select an optimal feature-group which gives a higher identification-rate. Another method was proposed...
in this direction, which considers an averaged value of 512 data points of each of the systolic-profiles as a feature, and subsequently, an SVM is used for identification of breathing phases [13]. The aforementioned schemes use R-peaks of temporally concurrent ECG signals for the segmentation of SCG cycles. In [15], it was demonstrated that all SCG cycles can be categorized into inhale and exhale phases with the help of a respiratory signal. In this direction, a frequency-domain SCG signal analysis is suggested by Pandia et al. [12]. The entire frequency range is split into two spectral bins corresponding to 5 and 10 Hz, and discrimination between the inhalation and exhalation phases is statistically done in the 10–40 Hz frequency range. As a preliminary work, we presented a method for characterization of two breathing states by analyzing morphological differences of an SCG waveform [9]. However, the variation of morphological characteristics of the SCG signal due to different respiratory conditions is still needed to be extensively investigated.

The objective of this study is to propose an SCG-based breathing-state detector for m-healthcare applications. The proposed framework is designed to identify different breathing patterns, namely breathlessness, regular/noraml respiration, and long and labored breathing. The labored breathing is an abnormal pattern characterized by a symptom of increased breathing effort. All these patterns are abbreviated as SB, NB, and LB for stopped, normal and long breathing, respectively. The proposed breathing-state detector needs a concurrent ECG signal to extract the SCG cycles. A set of statistical-, amplitude-, time-, and spectral-based features of the SCG signal is extracted. The deep neural networks (DNN) are finally deployed for identification of different breathing levels. In our method, stacked autoencoder (SAE) based deep learning scheme is used to create the DNN architecture. The rest of the paper is organized as follows: Section II presents the proposed methodology. The experimental results are presented in Section III. Finally, conclusions are drawn in Section IV.

II. PROPOSED BREATHING STATE DETECTION METHOD

The SCG beat morphologies can indicate respiratory-effort levels. As shown in Fig. 1 the waveform characteristics of SCG signals changes for SB, NB, and LB breathing conditions. More specifically, SCG signals in breathlessness condition have peaky-distributed beat patterns having almost constant amplitude and regular heart-rhythm, while relatively more variations of amplitude and heart-rhythm are observed during normal breathing. Large amplitude-modulated type beat patterns with varying heart-rates are observed in long breathing conditions. In order to identify different breathing states, the features which can identify and segregate morphological variations of an SCG signal due to different breathing conditions need to be extracted. The overview of the proposed methodology is illustrated in Fig. 2. The proposed work is carried out in three major phases. In Phase-I, signal-database was generated followed by feature extraction in Phase-II. Finally, classification is done to identify the degree of breathing levels (SB, NB and LB).

A. Database Creation

For the breathing level identification purpose, the dorso-ventral SCG and concurrent ECG (Lead-II) signals are acquired from healthy male subjects. Chosen subjects have following demographics, age: 28.75±2.31 yrs, weight: 71.63±7.85 kg, height: 5’7.6”±2.6”, heart-rate: 79.18±10.93 bpm. The signals are recorded in three sessions: normal breathing for 5 minutes (NB), holding breath for 50 s (SB), and long respiration for 2 minutes (LB). So, two breathing conditions, namely breathlessness as well as long- and labored-respiratory data are artificially generated. The signals are sampled at a frequency of 1 kHz. All the signals were recorded using our self built data acquisition system (DAS). The description of the designed DAS is provided in [10]. The recording process was approved by the institutional ethical review board.

B. Feature Extraction

A number of features are extracted from an SCG signal, and these features are mainly based on statistical, amplitude, temporal and spectral information of the signal. These features can uniquely relate the SCG morphology with the respiration
rate. The extraction process of all these features are illustrated in Fig. 2. A detailed description of feature extraction steps is provided below.

1) **Orthogonal Subspace Projection:** The proposed method is mainly based on the extraction of SCG cycles, which relies on accurate detection of prominent AO peaks in the SCG. The estimation of AO peaks is performed using an orthogonal subspace projection (OSP) scheme [17]. With the projection of an SCG signal onto ECG subspace, the details of SCG signal which are linearly related to the details of an ECG signal can be estimated. The ECG subspace is created by the original ECG signal and its delayed versions [17]. The linear relationship of an SCG signal $s$ and the corresponding ECG subspace $U$ can be expressed as [17]:

$$ Ux = s $$

(1)

The best estimate of $s$ on subspace $U$ is found by using a subspace projection as [17]:

$$ \hat{s} = U(U^T U)^{-1}U^T s $$

(2)

Finally, a first order Gaussian differentiator (FOGD) based logic is applied to the projected sequence $\hat{s}$, which ultimately indicates the locations of AO peaks in the SCG signal. The entire AO peak detection process is shown in Fig. 3.

2) **Heart Cycle Extraction:** In our proposed method, the estimated AO instants are used to extract heart cycles (HC) in the SCG signal. Changes of breathing levels indirectly alter oxygen content present in the blood, and so, the heart pumping rates change accordingly. Thus, heart rate (HR) variations can indicate respiratory effort levels. In order to extract the heart cycles, the intervals between consecutive AO instants are estimated and two different features, namely heart rate ($f_{HR}$) and heart rate difference ($f_{DHR}$) are estimated as follows:

$$ HC_i = AO_{i+1} - AO_i $$

(3)

$$ f_{i}^{HR} = 60/HC_i $$

(4)

$$ f_{i}^{DHR} = |f_{i-1}^{HR} - f_{i}^{HR}| $$

(5)

where, $|·|$ is absolute value operator; $i = 1, 2, ..., (P - 1)$, and $P$ denotes total number of AO peaks present in the SCG segment. $f_{HR}^{TT}$ makes $f_{HR}$ to be a circular sequence, and the
delay parameter D is judiciously chosen as 3 for identifying long breathing patterns.

3) Beat Interpolation: After utilizing temporal information of an SCG signal for indicating heart beats, all the beat-durations are normalized to a fixed length. The resulting interpolated SCG beats are used to estimate the following features: beat energy \( f^\text{BEnt} \), beat entropy \( f^\text{BEnt} \), beat energy difference \( f^\text{DBEnt} \), and beat entropy difference \( f^\text{DBEnt} \).

The beat energy is expressed as:

\[
f^\text{BEnt}(i) = \frac{1}{L} \sum_{l=0}^{L-1} |\vec{s}_i[l]|^2 \tag{6}
\]

where, \( \vec{s}_i[l] \) \( i \in [1, P - 1] \) denotes \( i \)th interpolated SCG beat. For the computation of \( f^\text{DBEnt} \) feature, the amplitude level of beat \( s_i[l] \) is normalized, say \( \tilde{s}_i[l] \), such that \( \tilde{s}_i[l] \in [0, 1] \) and \( \sum \tilde{s}_i[l] = 1 \). It expresses the distribution of relative components in a beat as:

\[
\tilde{s}_i[l] ← \frac{s_i[l] - M_s}{\sum_{l=0}^{L-1} (s_i[l] - M_s)} \tag{7}
\]

where, \( M_s = \min_{l=0:L-1} (s_i[l]) \). Hence, the beat entropy can be expressed as:

\[
f^\text{BEnt}(i) = -\sum_l \tilde{s}_i[l] \log(\tilde{s}_i[l]) \tag{8}
\]

The difference features corresponding to beat energy and beat entropy are computed as:

\[
f^\text{DBEnt}(i) = |f^\text{BEnt}(i) - f^\text{BEnt}(i - D)| \tag{9}
\]

\[
f^\text{DBEnt}(i) = |f^\text{BEnt}(i) - f^\text{BEnt}(i - D)| \tag{10}
\]

where, \( f^\text{BEnt} \) and \( f^\text{BEnt} \) denote circular versions of \( f^\text{BEnt} \) and \( f^\text{BEnt} \) sequences, respectively.

4) Mean Removal and Amplitude Normalization: After the estimation of beat energy and entropy features, DC-offset is subtracted from \( s_i[l] \), and the amplitude is normalized by its maximum value. This normalized beat, also denoted by \( \bar{s}_2[l] \), is shown in Fig.\( \text{a} \). Under this, three morphological features, namely kurtosis \( K(s_i) \), IM or IC amplitude \( f^\text{IA} \) and autocorrelation feature \( f^\text{ACF} \) are extracted from the SCG beat \( \bar{s}_2[l] \), which are described as follows:

- **Kurtosis (K):** It estimates the peakedness of the distribution for SCG beat \( \bar{s}_2[l] \). It is defined as [6]:

\[
f^K_i = \frac{1}{L} \sum_{l=0}^{L-1} (\bar{s}_2[l] - M_{\bar{s}_2})^4 \tag{11}
\]

where, \( M_{\bar{s}_2} = \frac{1}{L} \sum_{l=0}^{L-1} \bar{s}_2[l] \). As compared to other breathing patterns, larger Kurtosis values correspond to breathlessness conditions [9].

- **Autocorrelation feature (ACF):** The ACF feature is extracted from each of the beats as follows [6]:

\[
f^\text{ACF}_i = \sum_{l=-\infty}^{\infty} \{\bar{s}_2[l] s_2[l + P]\} \tag{12}
\]

where, the parameter \( P \) denotes a fixed lag. The ACF feature can detect interbeat variabilities and body vibrations resulted from varying respiration rates.

- **IM/IC amplitude (IA):** The IA is extracted by computing the maximum negative signal-strength of each beat \( \bar{s}_2 \) [9]. It indicates the amplitude of either IM or IC fiducial point. This feature is used to measure the amplitude sharpness of an SCG cycle induced by varying breathing patterns. It can be expressed as:

\[
f^\text{IA}_i = \min_{l=0:L-1} (\tilde{s}_2[l]) \tag{13}
\]

5) Diastole Profile Localization: In order to extract the diastolic features, the SCG diastole is segmented as follows. Initially, the beat \( \bar{s}_2 \) is divided at its middle (say \( M_1 \) point). The SCG systole can be localized in a segment between \( M_2 \) and \( M_3 \) points, where \( M_2 \) and \( M_3 \) are the mid-points of segments between start-point and \( M_1 \), and between \( M_1 \) and end-point, i.e.,

\[
M_1 = \frac{(L - 1)}{2}; \quad M_2 = \frac{(L - 1)}{4}; \quad M_3 = \frac{3(L - 1)}{2}
\]

The segmentation of diastolic region is also shown in Fig.\( \text{b} \) along with diastole profiles segmented from two subjects. To capture morphological variabilities especially in diastole profiles, two features, diastole Energy \( f^\text{DEnt} \) and diastole entropy \( f^\text{DEnt} \) are extracted. The expression of \( f^\text{DEnt} \) is given as follows:

\[
f^\text{DEnt}(i) = \sum_{l=M_2}^{L} (\bar{s}_2[l])^2 \tag{14}
\]

Usually, the SCG-diastole produces relatively smallest energy in breathlessness condition as compared to other breathing conditions. Thus, \( f^\text{DEnt} \) can be a dominant feature to detect breathing events. Subsequently, diastole entropy \( f^\text{DEnt} \) feature is extracted on \( d_1[n] \) \( d_1[n] ∈ [0, 1] \), which has a zero minima and it is normalized by its elemental-sum value as:

\[
d_1[n] = \frac{\bar{s}_2[M_2, M_2 + 1, M_2 + 2, ..., M_3]}{\sum_{n=M_2}^{M_3} (d[n] - M_d)} \tag{15}
\]

\[
d_1[n] = \frac{\bar{s}_2[M_2, M_2 + 1, M_2 + 2, ..., M_3]}{\sum_{n=M_2}^{M_3} (d[n] - M_d)} \tag{16}
\]
where, \( M_d = \min_{n=0:M_1-M_2} (d[n]) \) and the expression for \( f_{\text{DEnt}} \) is given as:

\[
 f_{\text{DEnt}}^1 = -\sum_n d_1^n \log(d_1^n) 
\]

(17)

6) Spectral Analysis: Four spectral features namely, maximum spectral amplitude \( f_{\text{MSA}} \), frequency at MSA \( f_{\text{FMSA}} \), beat spectral centroid \( f_{\text{BSC}} \), and beat spectral entropy \( f_{\text{BSEnt}} \) are extracted from magnitude-spectrum of each of the interpolated beats \( \{\hat{S}_i^f[l]\} \). Suppose, \( S_1[l] \) and \( \hat{S}_1^f[f] \) are Fourier transformation pairs, and \( |\hat{S}_1^f[f]| \) denotes the magnitude spectrum. Then, \( f_{\text{MSA}} \) and \( f_{\text{FMSA}} \) features are expressed as:

\[
 f_{\text{MSA}}^i = \max_{f=0,1,..,F/s} (|\hat{S}_1^f[f]|) 
\]

(18)

\[
 f_{\text{FMSA}}^i = \arg \max_{f=0,1,..,F/s} (|\hat{S}_1^f[f]|) 
\]

(19)

where, \( F/s \) denotes sampling frequency of the signal. The MSA and FMSA features characterize the beat by its dominating spectral component, which changes with varying respiratory rates. Similarly, the beat spectral centroid (BSC) and the beat spectral entropy (BSEnt) measure the center-of-gravity of the beat-spectrum and spectral randomness, respectively. Their expressions are given as follows:

\[
 f_{\text{BSC}}^i = \frac{\sum f|\hat{S}_1^f[f]|}{\sum f|\hat{S}_1^f[f]|} 
\]

(20)

\[
 f_{\text{BSEnt}}^i = -\sum f|\hat{S}_1^f[f]| \log(|\hat{S}_1^f[f]|) 
\]

(21)

where, \( S_1^f[f] \) corresponds to normalized \( \hat{S}_1^f[f] \) i.e., \( S_1^f[f] = \hat{S}_1^f[f]/(\sum \hat{S}_1^f[f]) \).

Finally, all the extracted features are concatenated together to create a feature vector \( (\mathbb{R}^{15}) \) corresponding to each of the SCG-beats.

C. Stacked Autoencoder-based DNN Model for Identification of Breathing Conditions

Autoencoder is a neural network with an input layer, a hidden layer, and an output layer as shown in Fig. 6(a) and (b). The autoencoder is trained to reconstruct input data using encoding and decoding processes [18]. Let \( x \) and \( b \) be the input vector and bias, respectively, then the hidden space is expressed as \( z = \phi(Ax + b) \), where ‘\( \phi \)’ is mapping or code vector, ‘\( A \)’ denotes the encoding weight matrix, and the linear or nonlinear nature of mapping can be set by activation function \( \phi(\cdot) \). Similarly, the decoder maps the hidden space data to the input vector as, \( \hat{x} = \phi'(A'z + b') \). In general, \( \phi'(\cdot) \) is considered linear, since input data belongs to the space of real numbers [19]. The learning of connection weights corresponding to encoding \( (A) \) and decoding \( (A') \) is achieved by minimizing the cost function given in [20].

\[
 J = \frac{1}{2R} \sum_{r=1}^R \sum_{k=1}^K (\alpha_{rn} - \tilde{x}_{kn})^2 + \frac{\lambda}{2} \sum_{k=1}^K (A)^2 + \sum_{k=1}^K (A')^2 + \beta \sum_{j=1}^N \text{KL}(\rho \| \tilde{\rho}_j) \]  

(22)

where, \( \sum \) denotes total number of observations in the dataset, weight regularization, and sparsity regularization parameters, respectively. KL, which represents Kullback-Leibler divergence, acts as a sparsity penalty component [20]. The indices \( \rho \) and \( \tilde{\rho} \) correspond to desired and average activation values, respectively.

For classification, the sparse autoencoders are stacked together and a deep neural network architecture is created. This is called as stacked autoencoder (SAE), where the weights are usually learned in a greedy manner [19]. Fig. 6 shows the proposed SAE network configuration for identification of respiratory rates. It is an ensemble of two sparse autoencoders with a soft-max classifier. As shown in Fig. 6, during the first learning phase, hidden space \( g \) is trained on input feature vector \( f \) to obtain the parameters \( U, U', b_1 \) and \( b_1' \). While, the next hidden layer \( h \) is trained on the \( g \) space to get the parameters \( V, V', b_2 \) and \( b_2' \). Subsequently, the output of the last hidden layer is fed into a soft-max classifier. Finally, all the SAE layers are used as a single unified model, and this model is fine-tuned for performance improvement as shown in Fig. 6(c).
III. EXPERIMENTAL RESULTS AND DISCUSSION

Initially, OSP-based AO peak detection algorithm is employed to estimate AO peaks of an SCG signal. The detected AO peaks are used to identify SCG cycles. Subsequently, fifteen significant features are extracted on each of the SCG cycles. The final feature set is represented as: \( f_{final} = \{ f_{HR}, f_{DHR}, f_{BE}, f_{BE}, f_{DBE}, f_{DDBE}, f_{K}, f_{A}, f_{ACF}, f_{DE}, f_{DE}, f_{MSA}, f_{FMSA}, f_{BSE}, f_{BSC} \} \).

A DNN architecture using SAE is proposed for classification, which can handle the feature engineering on its own. The parameters used in the proposed SAE are as follows: number of neurons in hidden layers equal to 12 and 10, respectively. The efficiency of the proposed DNN approach is established based on standard quantitative statistical assessments. The performance measures used are recognition accuracy (ACC), precision (Pr), true positive rate (TPR), true negative rate (TNR) and F1-score. The performance comparison of our method with other conventional classifiers namely, SVM (with different kernels namely RBF, linear and polynomial), kNN (with different number of neighbours), naive Bayes, linear discriminant analysis (LDA), and quadratic discriminant analysis (QDA) based classifiers. We deployed a statistical based feature analysis technique called multi-variate feature analysis (MANOVA) [21] technique to select dominant features for comparison of different classifiers. The features only having less than 5% level of significance are considered for this study. All the fifteen features are accepted as all of them show more than 5% level of significance. The performance comparison of our method with different classifiers is shown in Table III. The results clearly show that the proposed method outperforms other conventional methods. Also, ROC curves for all these classifiers are shown in Fig. 8.

A. Performance Comparison

The proposed technique is compared with other conventional classifiers namely, SVM (with different kernels namely RBF, linear and polynomial), kNN (with different number of neighbours), naive Bayes, linear discriminant analysis (LDA), and quadratic discriminant analysis (QDA) based classifiers. The performance measures used for the comparison are recognition accuracy (ACC), precision (Pr), true positive rate (TPR), true negative rate (TNR) and F1-score. The performance comparison of our method with other conventional classifiers namely, SVM (with different kernels namely RBF, linear and polynomial), kNN (with different number of neighbours), naive Bayes, linear discriminant analysis (LDA), and quadratic discriminant analysis (QDA) based classifiers.

IV. CONCLUSION

In this work, an SCG based breathing-state detector is developed for m-healthcare applications. The breathing-state detector which forms an essential component of the consumer electronics industry can thus be developed by the proposed method.
framework. In view of this, a mobile app is developed. The proposed method can accurately identify the degree-of-breathing, such as breathlessness, normal breathing, and long and labored breathing conditions. The concurrent ECG signal is also used to extract the SCG cycles using OSP-based scheme, and each of the cycles is used for feature extraction. A set of features is extracted from the SCG signal, which conveys the information of hemodynamic changes and physiological movement of lung and heart muscles due to varying breathing-rates. For classification of different breathing patterns, a SAE-based DNN architecture is proposed. The performance of our method is evaluated on 1147 SCG cycles in different breathing scenarios. The quantitative-assessment results clearly show that the proposed method can be deployed for consumer-grade applications. One major finding of this research work is that the SCG signal can be used not only for cardiac health measurement, but also for the assessment of respiration-rates and lung fitness.

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