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Automated detection of sleep apnea using sparse residual entropy features with various dictionaries extracted from heart rate and EDR signals

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ABSTRACT

Sleep is a prominent physiological activity in our daily life. Sleep apnea is the category of sleep disorder during which the breathing of the person diminishes causing the alternation in the upper airway resistance. The electrocardiogram derived respiration (EDR) and heart rate (RR-time-series) signals are normally used for the detection of sleep apnea as these two signals capture cardio-pulmonary activity information. Hence, the analysis of these two signals provides vital information about sleep apnea. In this paper, we propose the novel sparse residual entropy (SRE) features for the automated detection of sleep apnea using EDR and heart rate signals. The features required for the automated detection of sleep apnea are extracted in three steps: (i) atomic decomposition based residual estimation from both EDR and heart rate signals using orthogonal matching pursuit (OMP) with different dictionaries, (ii) estimation of probabilities from each sparse residual, and (iii) calculation of the entropy features. The proposed SRE features are fed to the combination of fuzzy K-means clustering and support vector machine (SVM) to pick the best performing classifier. The experimental results demonstrate that the proposed SRE features with radial basis function (RBF) kernel-based SVM classifier yielded higher performance with accuracy, sensitivity and specificity values of 78.07%, 78.01%, and 78.13%, respectively with Fourier dictionary and 10-fold cross-validation. For subject-specific or leave-one-out validation case, the SVM classifier has sensitivity and specificity of 85.43% and 92.60%, respectively using SRE features with Fourier dictionary (FD).

1. Introduction

Sleep is one of the vital physiological activities which provides rest and rejuvenates the body. A normal person needs an average sleep of seven to eight hours a day to stay active and healthy [1]. The sleep apnea is a type of sleep based disorder resulting in irregular breathing and in this condition, the patient suffers from the blockage of airflow and thereby reducing the breathing rate [2,3]. The partial blockage of airflow is termed as hypopnea, and sleep apnea may be classified as obstructive sleep apnea (OSA), central sleep apnea and complex sleep apnea syndrome [4]. During sleep apnea, there is interruption in the respiratory activity for more than ten seconds with complete blockage in the airways. If the blockage is higher than 50%, then this symptom is called as hypoapnea [5]. The daytime somnolence, snoring and headache are the symptoms of sleep apnea. During sleep, the relaxing muscles cannot completely resist the negative pressure, as a result, there is a reduction in the size of pharyngeal airways and this syndrome enhances the occurrence of the sleep apnea [6]. The OSA is further subgrouped into mild, moderate and severe OSA depending on the intensity of air passage blockage. The symptom of central sleep apnea is the periodic on-off in breathing activity whereas the blockage in the upper airways causes abnormal breathing during OSA [7]. The presence of apnea and hypopnea can be quantitatively understood using the apnea hypopnea index (AHI) which is defined as the average number of respiratory events per hour of sleep [8]. The AHI value between 5 and 15 events per hour indicates mild OSA whereas the AHI value less than 30 events per hour reveals moderate OSA. The AHI value of above 30 events per hour is considered as the severe OSA [9]. The common symptoms of sleep apnea are loud snoring, fatigue, mood swings, and insomnia. Detection of sleep apnea is important as it leads to diabetes, hypertension and cardiovascular diseases like heart attack [10–12]. In sleep apnea condition, the heart rate and blood sugar increase thereby

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creating stress on the heart and impairs the blood vessels [11]. Therefore, the continuous monitoring of the heart rate and respiratory activity is necessary for the accurate diagnosis of sleep apnea pathology.

From last two decades, various approaches have been proposed for the automated detection of sleep apnea using EDR and heart rate (RR-time series) signals [4,13–16]. Among them, Sadr and Chazal [17] used the principal component analysis (PCA) method to evaluate the features from EDR signal. They have considered extreme learning machine (ELM) and Gaussian discriminant analysis (GDA) classifiers with leave-one-out cross-validation for the detection of sleep apnea and achieved accuracy values of 76.4% and 78.4%, respectively. In another work, Janbakhshi and Shamsollahi [18] extracted EDR and heart rate signals from the ECG signal and evaluated various morphological features from these two signals, and reported an accuracy 90.9% with artificial neural network (ANN) classifier. Similarly, Pinho et al. [19] evaluated the features like mean and standard deviation from the EDR and heart rate signals. An ANN classifier with tansig and purelin activation functions at hidden and output layers resulted in an accuracy value of 82.12%. Chazal and Sadr [20] used cardiopulmonary coupling features in addition to the individual features from EDR and heart rate signals with linear discriminant analysis (LDA) classifier for the detection of sleep apnea. Ali and Hossein [21] used various classifiers for the identification of sleep apnea using statistical and spectral features extracted from heart rate signal, and resulting in the highest accuracy of 96.67%. Mitiche et al. [22] devised RR-interval based feature extraction method using Pearson correlation coefficient. They have detected sleep apnea from heart rate signal features using ELM classifier and obtained an accuracy of 80.30%. Timus and Bolat [23] used features from EDR and heart rate signals with wrapper based selection of features for the detection of sleep apnea. They have obtained maximum accuracy of 97% using K-nearest neighbor (KNN) classifier. In another study, Sandeep et al. [24] used the real-time data derived from the mathematical modeling of the cardiopulmonary system corresponding to heart rate obtained from ECG signal and peripheral oxygen saturation (SpO_2). The combination of both features obtained maximum accuracy of 81.56% based on likelihood ratio test classifier. In another study, Li et al. [25] developed an approach for the detection of sleep apnea using sparse auto-encoders and Hidden Markov model (HMM) with classifiers like SVM and neural network and reported the highest accuracy of 84.7%. Tripathy [26] extracted fuzzy entropy and energy features from the Fourier decomposition based intrinsic mode functions of both heart rate and EDR signals for the detection of sleep apnea. Recently, Banluesombatkul et al. [27] used the ECG signal itself and convolutional neural network (CNN) for the detection of sleep apnea and achieved an accuracy of 79.45%.

From literature, it is evident that the cardio-pulmonary features extracted using the analysis of both RR-time-series and EDR signal have shown higher performance in detecting sleep apnea. The objective of this research is to develop an automated algorithm for the detection of sleep apnea using new cardio-pulmonary features obtained from both heart rate and EDR signals. The sparse representation based feature extraction has been used for the detection of neonatal seizure from electroencephalogram (EEG) signal [28]. They have evaluated the features from sparse residual using the atomic decomposition of the EEG signal with different dictionaries. The atomic decomposition is based on the reconstruction of the signal using the atoms or components of the dictionary [28,29]. The sparse residual can be evaluated based on the difference between the original and estimated signals using atomic decomposition. The entropy measures the randomness of the signal [30], and we can expect that the entropy features evaluated from the sparse residuals of both heart rate and EDR signals can be used for the sleep apnea detection. In this study, we have developed a new entropy feature called as sparse residual entropy (SRE), which is evaluated using sparse representation and six different dictionaries such as Fourier, Wavelet, cosine, eigen and two Learned dictionaries as apnea specific learned dictionary, normal specific learned dictionary. The SRE features are evaluated using both EDR and heart rate signals (annotated and unannotated). The fuzzy K-means clustering is used to evaluate the class labels in unannotated EDR and heart rate signals [31]. The support vector machine (SVM) classifier is used for the applications like the sleep apnea detection and classification of sleep stages from various physiological signals [32–35]. We can expect that the combination of SRE features extracted from both EDR and heart rate signals, and SVM classifier can be used for the accurate detection of sleep apnea. The remaining parts of this manuscript are structured as follows. In Section 2, the proposed method for the detection of sleep apnea is described. The detailed mathematical expressions and the flow-chart for evaluating the SRE measure are discussed in Section 2. The results and the discussion sections are presented in Section 3 and Section 4, respectively, and finally, the conclusions of this manuscript are described in the last section.

2. Proposed method

This section provides a detailed description of the proposed method used for the detection of sleep apnea. We have formulated the detection process in four sub-stages: (a) electrocardiogram (ECG) signal collection from the public database, (b) filtering, segmentation, and extraction of heart rate and EDR signals from ECG, (c) sparse residual entropy features evaluation, and (d) detection of apnea episodes using SVM classifier. The entire apnea episode detection process is outlined in Fig. 1. The details about each block embedded in the block diagram are described in the following four subsections.

2.1. ECG database with sleep apnea pathology

In the present study, the apnea-ECG database from physionet is used to extract proposed SRE features [36,37]. There are 70 ECG recordings (35 recordings with each recording being minute by minute annotated as either normal or sleep apnea, and 35 unannotated ECG recordings) present in this database. In addition to the ECG recordings, this database also comprises of 8 respiratory signals. Each recording contains 10,00,000 ECG samples which were sampled with the sampling frequency of 100 Hz. In this work, few ECG recordings such as b04, c02, c04, c10 are excluded from the annotated data due to the presence of noise, and patterns other than P, QRS and T waves [38]. Therefore, 31 annotated ECG recordings are selected for the analysis and extraction of SRE features. Similarly, from the unannotated dataset, all 35 ECG recordings are chosen for the analysis.

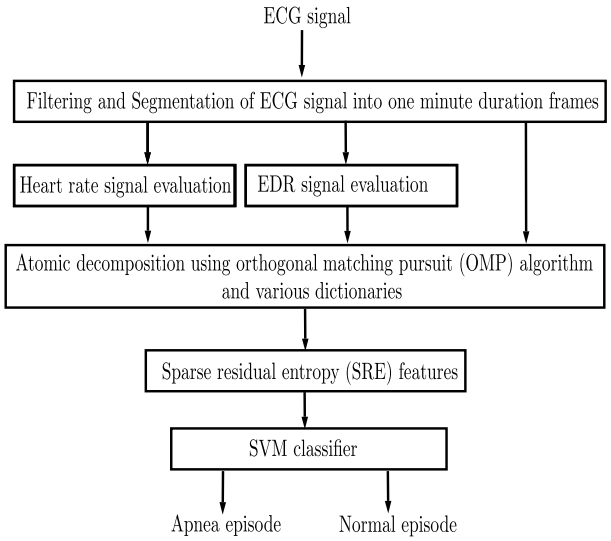

Fig. 1. Detection of sleep apnea using the proposed method.

2.2. Preprocessing and extraction of EDR and heart rate signals

In this work, both heart rate and EDR signals are extracted from each one minute segment of the ECG signal. For that, we have divided each ECG recording into minute frames or segments containing 6000 samples. Then, the bandpass filter with a frequency range from 0.5 Hz to 45 Hz has been used to filter out the noises from the ECG signal [39]. In total, 10186 annotated and unannotated ECG segments are extracted. For each ECG frame, the R-peaks are detected using Pan Tomkin's algorithm and the heart rate signal is obtained from these R peaks [40]. For EDR signal extraction, we have adopted the principal component analysis (PCA) based technique which is based on the formulation of ECG beat matrix (The matrix created by considering different ECG beats) and eigen-analysis of the ECG beat matrix [41]. The ECG beats are evaluated by considering 30 samples before and 50 samples after each detected R-peak using the standard Pan Tomkin's algorithm [40]. The extracted EDR and heart rate signals are used for the analysis and extraction of SRE features. The procedure for evaluation of SRE features is given below.

2.3. Proposed sparse residual entropy features

In this study, the SRE features are computed from heart rate, EDR and ECG signals. These features are extracted in four steps. The flowchart for the evaluation of SRE features is depicted in Fig. 2. In the initial step (step 1), the residual is assigned as the signal itself and dictionary is denoted as $D = [\Psi_i]$ [28]. The other parameters K and N are the number of iterations and the length of the signal respectively. The parameter l_k is the label set at k^{th} iteration and its initial value is assigned to 0 and also, the initial values of basis vectors ϕ_k is 0. The ith label value is computed based on the following equation as [42].

$$i = arg\ max_i [(res^k)^T . \Psi_i] \tag{1}$$

Then in the second step, the label set and the dictionary atoms are updated for $(k+1)^{\text{th}}$ iteration using the following equations:

$$l_{k+1} = l_k \cup i \tag{2}$$

and

$$\Phi_{k+1} = \left[\Phi_k,\ \psi_{l_{k+1}}\right] \tag{3}$$

After that in the third step, the sparse coefficient vector is evaluated by solving the optimization problem as

$$\alpha_{k+1} = arg\ min_\alpha \|res^k - \Phi_k \alpha_k\|^2 \tag{4}$$

Then solution for this optimization problem is given by

$$\alpha_{k+1} = (\Phi_k^T * \Phi_k)^{-1} \Phi_k^T res^k \tag{5}$$

Then, the new residual vector at $(k+1)^{\text{th}}$ iteration is computed as [28].

$$res^{k+1} = res^k - \Phi_{k+1}\alpha_{k+1} \tag{6}$$

The above steps are repeated upto K iterations and the residual for

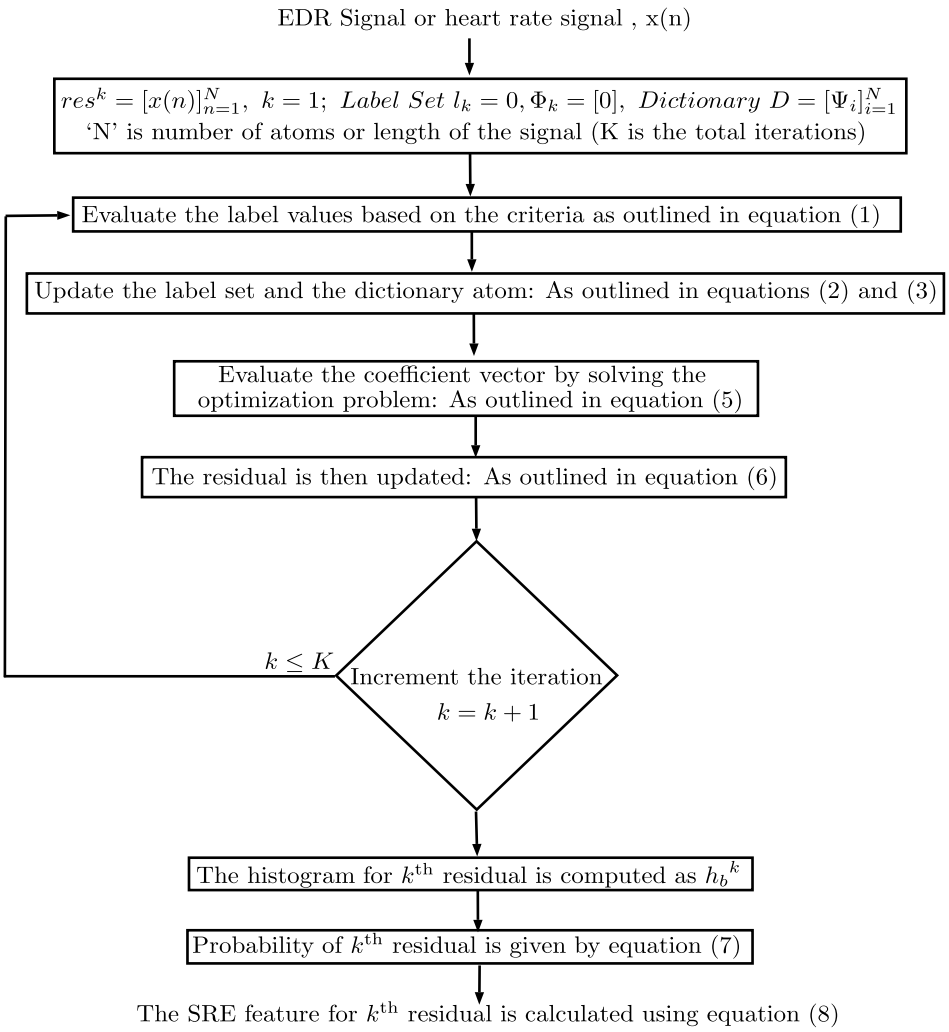

Fig. 2. Flowchart showing the algorithm to evaluate SRE features.

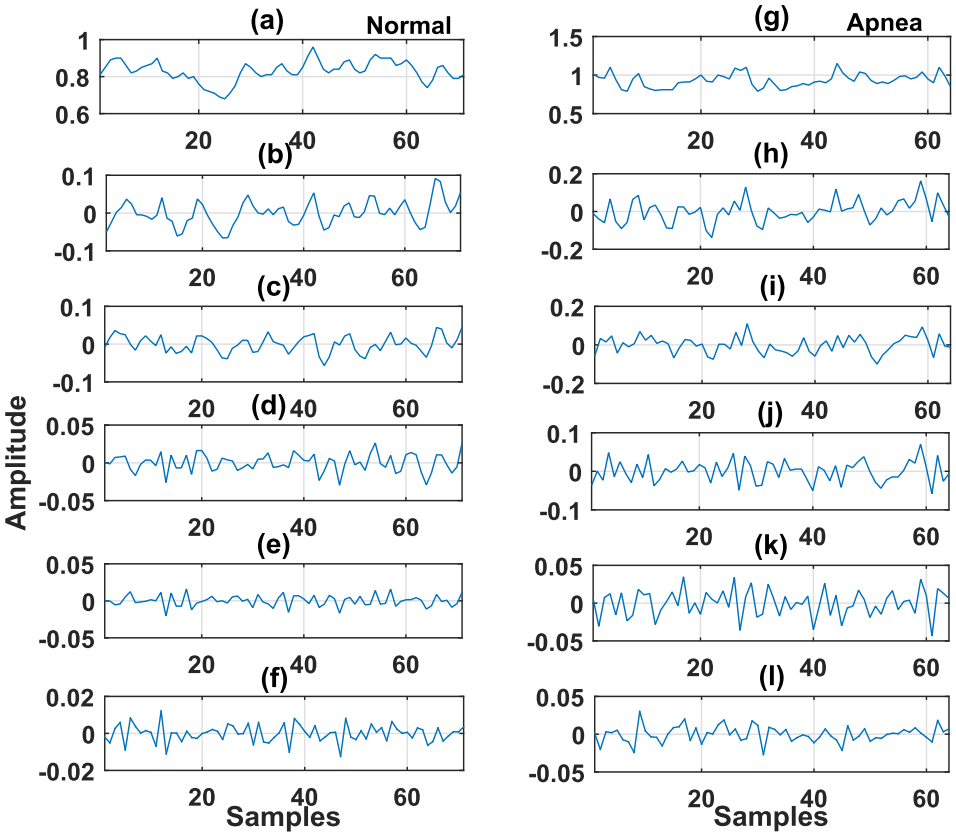

Fig. 3. (a) heart rate signal for normal class. (b) 5th residual vector of heart rate signal for normal class. (c) 10th residual vector of heart rate signal for normal class. (d) 20th residual vector of heart rate signal for normal class. (e) 30th residual vector of heart rate signal for normal class. (f) 40th residual vector of heart rate signal for normal class. (g) heart rate signal for apnea class. (h) 5th residual vector of heart rate signal for apnea class. (i) 10th residual vector of heart rate signal for apnea class. (j) 20th residual vector of heart rate signal for apnea class. (k) 30th residual vector of heart rate signal for apnea class. (l) 40th residual vector of heart rate signal for apnea class.

each iteration (kth iteration) is evaluated and it is denoted as res^k. The last step includes the extraction of entropy features from kth residual vector.

The heart rate signal data for normal and apnea classes are depicted in Fig. 3 (a) and Fig. 3 (g), respectively. Similarly, Fig. 4 (a) and 4 (g) show the EDR signals for normal and apnea classes. It can be seen from these figures that, there are cyclic variations in the morphology of heart rate and EDR signals for apnea and normal cases [43]. It is also observed that not only cyclic variations but also the amplitudes of EDR and heart rate signals show significant variations for normal and apnea classes. In literature, various non-linear approaches have been used in the time-domain and transform domain to quantify features from heart rate and EDR signals for the detection of sleep apnea [43–45]. In this study, the residual vectors are computed from both EDR and heart rate signals. The 5th, 10th, 20th, 30th and 40th residual vectors extracted from heart rate signal are depicted in Fig. 3(b)–(f) and Fig. 3(h)–(l), respectively for normal and apnea classes. Similarly, we have shown the 5th, 10th, 20th, 30th and 40th residual vectors of EDR signals for normal and apnea classes in Fig. 4(b)–(f) and Fig. 4(h)–(l), respectively. It is evident from these plots that the residual vectors capture the local information present in the EDR signal and heart rate signal and these vectors have different temporal and spatial characteristics for normal and apnea classes. The entropy is widely accepted feature to measure the chaoticness, complexity, and non-linearity of a time series [46]. In this work, the residual vectors are evaluated non-linearly using the atomic decomposition with a dictionary and hence, the entropy features extracted from these residuals can be used to capture the morphological variations in both EDR and heart rate signals for the detection of sleep apnea.

In this study, the Shannon entropy features are computed from each residual of both EDR and heart rate signals [47]. To evaluate the entropy, first the histogram for kth residual vector is calculated and it is denoted by h_m^k. Then, the probability of kth residual vector is computed as [48].

$$P_m^k = \frac{h_m^k}{\sum_{m=1}^{M} h_m^k} \tag{7}$$

where $m = 1,2, ...,M$ is denoted as the bin number for each residual vector and in this study, the total number of bins, M is fixed as 10. The entropy for kth residual vector which is also called as the sparse residual entropy(SRE) is then computed using the following equation as

$$E^k = -\sum_{m=1}^{M} P_m^k \log_2 P_m^k \tag{8}$$

In this work, we have considered six different dictionaries to extract the SRE features from both heart rate and EDR signals. These are Cosine dictionary (CD), Fourier dictionary (FD), Eigen dictionary (ED), Wavelet dictionary (WD), Normal-specific learned dictionary (NSLD) and Apnea-specific learned dictionary (ASLD), respectively. The CD is given by Ref. [29].

$$\mathbf{D} = \frac{1}{\sqrt{N}} cos\left(\frac{2\pi nk + 1}{2N}\right) \tag{9}$$

Similarly, the FD is written as [49].

$$\mathbf{D} = \frac{1}{\sqrt{N}} e^{\frac{-j2\pi nk}{N}} \tag{10}$$

where n and k are the samples and frequencies for the CD and FD, respectively and $\{n, k\} \in \{1,2...N\}$. The eigen dictionaries for EDR and heart rate signals are the matrices which contain the eigen vectors based on the diagonalization of the covariance matrices of EDR and heart rate signals. The covariance matrix is evaluated as $\mathbf{C} = \frac{1}{N}\mathbf{x}^T\mathbf{x}$, where $\mathbf{x} = [x(n)]_{n=1}^{N}$ is either EDR signal or heart rate signal. The diagonalization of covariance matrix is given as $\mathbf{C}\ \Lambda = \mathbf{D}\Lambda$, where $\mathbf{D}$ and Λ are termed as the eigen dictionary and the diagonal matrix containing the singular values of either heart rate signal or EDR signal. Moreover, in this work we have considered the Daubechies WD for the atomic decomposition and extraction of SRE features [50,51]. The

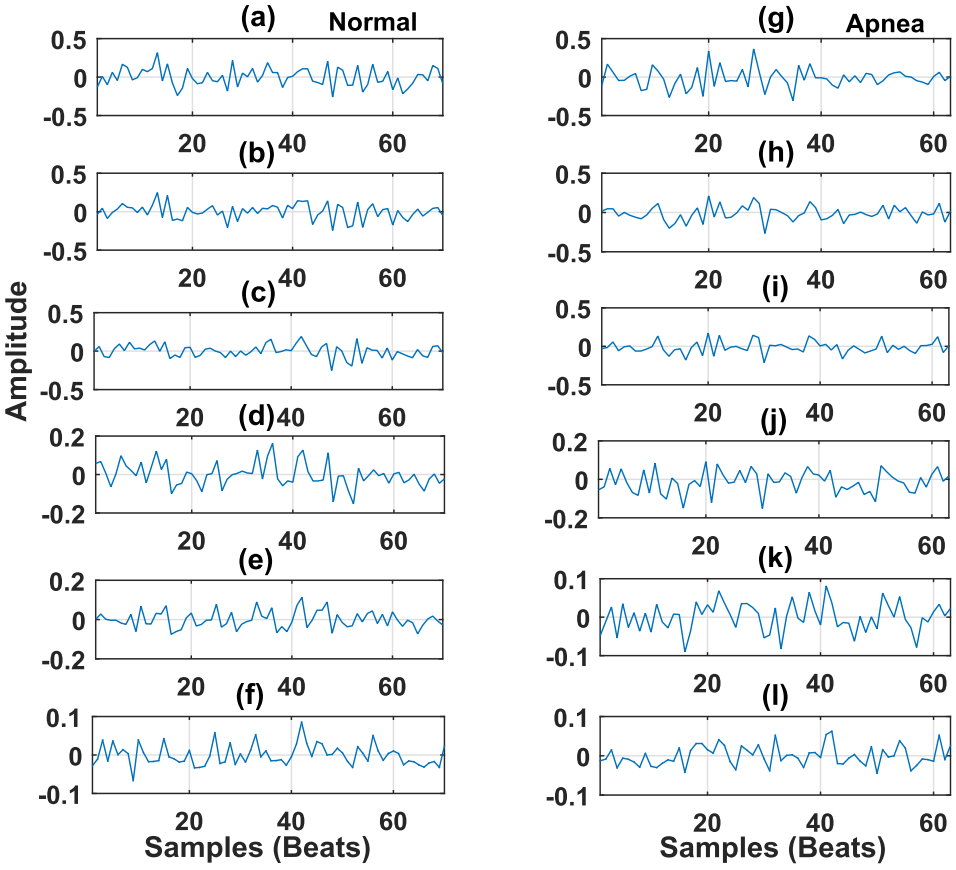

Fig. 4. (a) EDR signal for normal class. (b) 5th residual vector of EDR signal for normal class. (c) 10th residual vector of EDR signal for normal class. (d) 20th residual vector of EDR signal for normal class. (e) 30th residual vector of EDR signal for normal class. (f) 40th residual vector of EDR signal for normal class. (g) EDR signal for apnea class. (h) 5th residual vector of ECR signal for apnea class. (i) 10th residual vector of EDR signal for apnea class. (j) 20th residual vector of EDR signal for apnea class. (k) 30th residual vector of EDR signal for apnea class. (l) 40th residual vector of EDR signal for apnea class.

NSLD and ASLD are evaluated using dictionary learning approach, which is based on the K-SVD algorithm [52]. For evaluating the NSLD for heart rate signal case, we have formulated a matrix $\mathbf{Y}$ which contains the fixed length heart rate signals from normal class. The length of each heart rate signal in $\mathbf{Y}$ matrix is 50. The learned dictionary (NSLD) and the corresponding sparse representation matrix are evaluated by solving the optimization problem as [52].

$$\underset{\mathbf{D},\mathbf{W}}{\arg\min} \quad \|\mathbf{Y}-\mathbf{D}\mathbf{W}\|_F^2 \tag{11}$$

subjected to, $\mathbf{y}_i \leq S$ for all i and S is termed as the desired sparsity level. Here, the desired sparsity level for both EDR and heart rate signals is selected as 10. The matrix $\mathbf{Y} = [\mathbf{y}_i]_{i=1}^{T}$ consists of T number of heart rate signals. The ASLD is also evaluated using the solution for same equation (11), where the matrix $\mathbf{Y}$ contains the T number of fixed length EDR signals. In this study, for each dictionary case we have considered 50 iterations and, hence 50 SRE features are extracted from each heart rate signal and EDR signal. We have also combined 50 dimensional SRE based heart rate signal feature vector (SRE_{RR}) and 50 dimensional SRE based EDR signal feature vector (SRE_{EDR}) to formulate the SRE based cardio-pulmonary (CP) feature vector (SRE_{CP}). The performance of SRE_{RR}, SRE_{EDR} and SRE_{CP} feature vectors is evaluated using SVM classifier for the detection of sleep apnea.

2.4. Sleep apnea detection using SVM

In this work, we have considered SVM classifier with the kernel function as radial basis function (RBF) for the classification of sleep apnea and normal episodes using SRE_{RR}, SRE_{EDR} and SRE_{CP} feature vectors. As the database consists of ECG recordings from both annotated and unannotated cases, a semi-supervised learning scheme is considered for the classification. For annotated EDR signal and heart rate signal feature vectors, the class labels are mentioned in the database. However, for unannotated EDR signal and heart rate signal feature vectors, we have evaluated the class labels using K-means clustering with fuzzy membership function [53]. After evaluating the cluster centers for unannotated data, the distances between the annotated and unannotated cluster centers are calculated and based on the minimum distance, the class labels are assigned to the unannotated EDR signal and heart rate signal feature vectors. After assigning the class labels for the unannotated EDR signal and heart rate signal feature vectors, we have formulated the feature matrix which consists of rows as the number of instances (q) and columns as number of SRE features (r) and this matrix is denoted as $\mathbf{Y} \in R^{q\times r}$ and the ith instance of this matrix is given as $\mathbf{I}_i$. Both balanced and unbalanced datasets are used for the classification using SVM classifier. The balanced dataset (total 8134 instances) consists of 4067 normal and 4067 apnea instances, whereas the unbalanced dataset (total 10186 instances) comprises of 4067 apnea and 6119 normal instances. To select the training and the test episodes or instances of SVM from the feature matrix, we have considered hold-out cross-validation, 10-fold cross-validation and leave-one-out (subject-specific) cross-validation methods [20,54]. The hold-out cross-validation uses 70% of the EDR signal or heart rate signal instances as training and the rest of the instances are evaluated during testing. The SVM is a two-class classification algorithm where the class labels for test feature vectors are obtained using the weight vector ($\mathbf{w}$), bias value (b) and the kernel function, $\mathbf{K}(I_i, I_{test})$ [55]. The parameters $\mathbf{w}$ and b are evaluated during training. For training the feature matrix, the objective of SVM is to estimate optimal decision boundary by formulating the optimization problem as [55].

$$\min_{w,b,e} \frac{\mathbf{w}^T\mathbf{w}}{2} + \eta\sum_{i=1}^{q} e_i \tag{12}$$

such that $t_i(w^T\tilde{\phi}(I_i) + b) \geq 1 - e_i, e_i \geq 0$, where η is parameter of regularization which helps in assigning membership to the error $e_i = t_i - \hat{t}_i$, where t_i and $\hat{t}_i$ are actual and predicted class labels for i^{th}

training instance. The above optimization problem mentioned in equation (12) can be solved using Lagrangian which is abbreviated as the dual and is given by Ref. [55].

$$max_{\gamma} J(\gamma) = \sum_{i=1}^{q} \gamma_i - \frac{1}{2} \sum_{i=1}^{q} \sum_{i=1}^{q} \gamma_i \gamma_j y_i y_j \mathbf{K}(I_i, I_j) \tag{13}$$

where the RBF kernel is given as $\mathbf{K} = e^{\frac{\|I_{test} - I_i\|^2}{2\sigma^2}}$. Moreover, the class label for a test instance (I_{te}) is evaluated as [56].

$$t_{te} = sgn\left[\sum_{i=1}^{q} \gamma_i y_i \mathbf{K}(I_i, I_{te}) + b \right] \tag{14}$$

In this study, the performance of RBF kernel based SVM classifier for all test instances is evaluated using the measures such as accuracy, sensitivity and specificity and these are computed as [56,57].

$$Accuracy\ (Acc(\%)) = \frac{a_1 + a_2}{a_1 + f_1 + a_2 + f_2} * 100 \tag{15}$$

$$Sensitivity\ (Sen(\%)) = \frac{a_1}{a_1 + f_2} * 100 \tag{16}$$

$$Specificity\ (Spe(\%)) = \frac{a_2}{f_1 + a_2} * 100 \tag{17}$$

where a_1, a_2, f_1 and f_2 are the notations for the true positives, true negatives, false positives and false negatives classified using RBF kernel based SVM classifier [56].

3. Results

In this section, we have presented the statistical analysis results of the selected SRE features obtained from both EDR signal and heart rate signal of normal and apnea classes. The within-class variations of 10th, 20th, 30th, 90th and 100th SRE features from CP feature vector for CD, FD and WD are shown as boxplots in Fig. 5(a)–(e), Fig. 5(f)–(j), and Fig. 5(k)–(o), respectively. Similarly, the mean and standard deviation values of these selected features are shown in Table 1. From the boxplots, we have observed that, the SRE features have distinct median, lower quartile and upper quartile values for normal and apnea classes using different dictionaries. From Table 1, it can be seen that, the 40th and 50th SRE features obtained from EDR signal have lower mean values for apnea class. During obstructive sleep apnea, the upper respiratory airways are obstructed and the breathing patterns may cutoff periodically. The subjects with mild obstructive sleep apnea may experience 5 to 14 interruptions of breathing patterns per hour of sleep and these symptoms affect the morphology of respiratory (EDR) signal [58,59]. Hence, the lower mean values are observed for these SRE features in apnea class. It can also observed that, the selected SRE features from heart rate signal have higher mean values for apnea class using CD, FD and WD as compared to the normal class. The statistical significance of the proposed SRE features obtained from both EDR and heart rate signals is carried out using the Students t-test approach [60]. It can be noted from the Students t-test results that, all 50 SRE features have p-value <0.001 obtained from SRE_{EDR} feature vector using CD, FD, WD, and ED. However, for ASLD and NSLD cases, 49 SRE features have p-value <0.001 obtained from the SRE_{EDR} feature vector. Similarly, using CD, FD, WD, and ED, it has been found that, all 50 SRE features obtained from SRE_{RR} feature vector are statistically significant with p-values less than 0.001. Moreover, when ASLD and NSLD are considered, only 31 and 38 SRE features have p-value <0.001 from SRE_{RR} feature vector. The non-parametric statistical test called Mann-Whitney test is also used to evaluate the statistical significance of the proposed SRE features [61]. Out of 100, SRE features from EDR and heart rate signals, 79, 73, 74 and 99 features corresponding to CD, FD, WD and ED have p values less than 0.001 obtained using Mann-Whitney test. Henceforth, these SRE features are found as statistically significant for the detection of sleep apnea.

The accuracy, sensitivity, and specificity of SVM-RBF classifier with hold-out cross-validation for SRE features extracted using different dictionaries are tabulated in Table 2. In Ref. [62], authors have formulated both balanced and unbalanced feature matrices to evaluate the performance of convolutional neural network for the detection of heart failure using ECG signals. Motivated from this work, balanced and unbalanced datasets are considered for the detection of sleep apnea

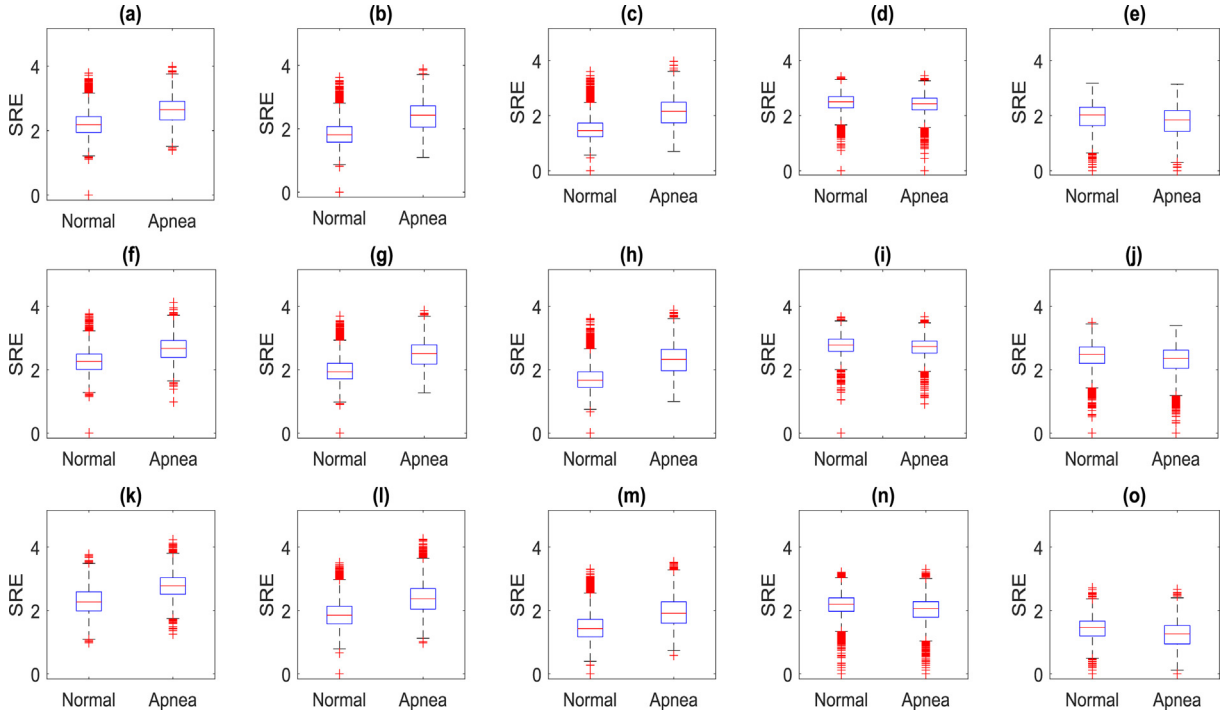

Fig. 5. (a)–(e) Boxplot of 10th, 20th, 30th, 90th and 100th SRE features from CP feature vector for CD. (f)–(j) Boxplot of 10th, 20th, 30th, 90th and 100th SRE features from CP feature vector for FD. (k)–(o) Boxplot of 10th, 20th, 30th, 90th and 100th SRE features from CP feature vector for WD.

Table 1
Results of mean (μ) and standard deviation (σ) values of selected SRE features for EDR, heart rate and ECG signals signals obtained using different dictionaries.

Signal	Dictionary	Feature number	Normal ($\mu \pm \sigma$)	Apnea ($\mu \pm \sigma$)	p-val (ttest)	p-val (MWtest)
heart rate signal + EDR Signal	CD	10 (RR)	2.1513 ± 0.3762	2.6144 ± 0.4146	$p < 0.001$	$p < 0.001$
		20 (RR)	1.8012 ± 0.4061	2.3860 ± 0.4854	$p < 0.001$	$p < 0.001$
		30 (RR)	1.4532 ± 0.4201	2.1152 ± 0.5497	$p < 0.001$	$p < 0.001$
		40 (EDR)	2.4304 ± 0.3980	2.3998 ± 0.3718	$p < 0.001$	$p < 0.001$
		50 (EDR)	1.8086 ± 0.7030	1.7250 ± 0.6704	$p < 0.001$	$p < 0.001$
	FD	10 (RR)	2.2246 ± 0.3627	2.6509 ± 0.3879	$p < 0.001$	$p < 0.001$
		20 (RR)	1.9350 ± 0.3872	2.4811 ± 0.4374	$p < 0.001$	$p < 0.001$
		30 (RR)	1.6745 ± 0.4009	2.2947 ± 0.4939	$p < 0.001$	$p < 0.001$
		40 (EDR)	2.7379 ± 0.3590	2.7068 ± 0.3197	$p < 0.001$	$p < 0.001$
		50 (EDR)	2.2933 ± 0.7012	2.2140 ± 0.6748	$p < 0.001$	$p < 0.001$
	WD	10 (RR)	2.2577 ± 0.4215	2.7746 ± 0.4081	$p < 0.001$	$p < 0.001$
		20 (RR)	1.8299 ± 0.4199	2.3783 ± 0.4873	$p < 0.001$	$p < 0.001$
		30 (RR)	1.4143 ± 0.4148	1.9470 ± 0.4966	$p < 0.001$	$p < 0.001$
		40 (EDR)	2.1605 ± 0.3971	2.0089 ± 0.4369	$p < 0.001$	$p < 0.001$
		50 (EDR)	1.4216 ± 0.3804	1.2135 ± 0.4536	$p < 0.001$	$p < 0.001$

using SVM classifier. The analysis of balanced dataset results shows that for EDR signal, SVM classifier with SRE features and WD has attained maximum accuracy of 74.78%. Similarly, for the NSLD case, SRE features combined with SVM classifier achieved a maximum sensitivity value of 79.47%. The balanced dataset uses an equal number of instances for different classes for the training of the classifier and due to this reason, the performance of the SVM classifier is high for this dataset as compared to the unbalanced dataset case. In terms of overall performance of SVM classifier, the SRE features from EDR signal extracted using WD yielded maximum accuracy, sensitivity, and specificity of 74.78%, 76.32%, and 73.25%, respectively. For RR time-series, the SVM classifier with SRE features computed using FD has obtained maximum accuracy and sensitivity values of 78.17% and 78.26%, respectively whereas for CD, a maximum specificity value of 79.32% is obtained. The overall performance of SVM classifier in terms of accuracy, sensitivity, and specificity values are 78.17%, 78.26%, and 78.08%, respectively using SRE features from the heart rate signal and FD. For the combination of SRE features obtained from both heart rate and EDR signals with FD, NSLD, and CD, yielded the maximum accuracy, maximum sensitivity, and maximum specificity values of 77.63%, 78.31%, and 78.92%, respectively. In terms of overall performance, the SVM classifier with SRE features from both EDR signal and heart rate signal and FD gave maximum accuracy, sensitivity, and specificity values of 77.63%, 77.29%, and 77.96%, respectively. For the ECG signal, SVM classifier with SRE features and ED has obtained maximum accuracy and sensitivity of 76.26% and 84.97% while SRE features and FD reported the maximum specificity of 73.48%. In terms of overall performance, the SRE features of ECG signal extracted using FD gave maximum accuracy, sensitivity, and specificity of 76.04%, 78.61%, and 73.48%, respectively. The variations in the accuracy with respect to the number of bins and iterations for the evaluation of SRE features are depicted in Fig. 6 (a), and Fig. 6 (b) respectively. The accuracy values are evaluated by considering the balanced dataset during training and unbalanced dataset or feature matrix during testing and hold-out cross-validation. It is observed that the accuracy increases with increase in the number of bins in the histogram. Similarly, when the number of iteration is increased from 50 to 60, there is a sudden reduction in the accuracy of SVM classifier. The accuracy is improved when the number of iteration is increased beyond 80. Fig. 6 (a), and Fig. 6 (b) donot reflect the optimal parameters of SVM classifier, rather these figures reveal the variation of performance with respect to the number of residuals and bins in the OMP stage of SRE feature extraction algorithm.

Table 2
Performance of SVM-RBF classifier using SRE features with different dictionaries for unbalanced and balanced datasets.

Signal	Dictionary	Balanced Dataset			Unbalanced Dataset		
		Acc (%)	Sen (%)	Spe (%)	Acc (%)	Sen (%)	Spe (%)
EDR	CD	72.99 ± 0.71	73.79 ± 1.22	72.19 ± 1.54	78.05 ± 0.49	68.38 ± 0.75	84.39 ± 0.43
	FD	73.87 ± 0.81	73.79 ± 1.08	73.94 ± 1.21	77.84 ± 0.49	70.91 ± 1.12	82.79 ± 0.67
	WD	74.78 ± 0.91	76.32 ± 0.76	73.25 ± 1.37	78.09 ± 0.65	72.57 ± 1.30	82.18 ± 0.59
	ED	67.72 ± 0.83	64.33 ± 1.83	71.10 ± 0.85	80.20 ± 0.41	49.19 ± 1.32	93.27 ± 0.59
	ASLD	70.87 ± 0.59	77.62 ± 0.99	64.13 ± 1.38	74.07 ± 0.72	75.71 ± 1.04	72.78 ± 1.05
	NSLD	71.58 ± 0.61	79.47 ± 0.99	63.69 ± 0.77	73.88 ± 0.64	78.68 ± 0.54	69.71 ± 1.06
RR	CD	77.42 ± 0.38	75.52 ± 1.17	79.32 ± 1.33	82.99 ± 0.73	67.84 ± 1.05	91.37 ± 0.65
	FD	78.17 ± 0.83	78.26 ± 1.42	78.08 ± 2.20	82.57 ± 0.46	69.97 ± 0.97	89.97 ± 0.58
	WD	75.64 ± 0.44	74.44 ± 1.19	76.84 ± 1.14	80.25 ± 0.52	69.21 ± 1.22	87.18 ± 1.34
	ED	64.43 ± 1.24	63.59 ± 3.47	65.27 ± 2.69	80.04 ± 0.39	35.74 ± 1.33	96.13 ± 0.40
	ASLD	67.65 ± 1.20	75.01 ± 1.36	60.29 ± 1.42	75.54 ± 0.76	62.27 ± 2.08	82.99 ± 0.63
	NSLD	68.53 ± 0.92	73.89 ± 0.85	63.17 ± 1.46	77.58 ± 0.35	55.79 ± 1.14	87.85 ± 0.65
RR + EDR	CD	77.31 ± 0.75	75.69 ± 1.26	78.92 ± 0.75	82.46 ± 0.50	69.21 ± 1.25	90.26 ± 0.36
	FD	77.63 ± 0.57	77.29 ± 1.07	77.96 ± 0.88	82.08 ± 0.59	71.43 ± 0.95	88.74 ± 0.58
	WD	75.81 ± 0.59	75.14 ± 1.08	76.48 ± 0.79	79.36 ± 0.49	69.51 ± 0.78	85.92 ± 0.67
	ED	68.36 ± 0.85	65.69 ± 1.56	71.02 ± 1.84	79.68 ± 0.60	41.69 ± 1.29	94.80 ± 0.46
	NSLD	71.04 ± 0.73	78.31 ± 1.65	63.76 ± 1.46	73.32 ± 0.45	75.06 ± 1.17	71.89 ± 0.75
ECG	CD	76.21 ± 0.94	80.58 ± 1.31	71.83 ± 1.27	77.57 ± 0.41	79.67 ± 0.76	75.61 ± 0.78
	FD	76.04 ± 0.63	78.61 ± 1.14	73.48 ± 0.94	77.66 ± 0.59	76.52 ± 1.18	78.63 ± 1.26
	WD	75.77 ± 0.81	81.50 ± 1.22	70.02 ± 1.69	76.37 ± 0.59	81.44 ± 0.46	71.59 ± 1.13
	ED	76.26 ± 0.41	84.97 ± 1.15	67.55 ± 1.58	76.83 ± 0.58	87.15 ± 1.17	65.79 ± 1.29
	ASLD	70.62 ± 0.59	73.72 ± 1.44	67.52 ± 1.52	80.13 ± 0.56	56.09 ± 1.48	90.78 ± 0.48
	NSLD	69.50 ± 0.89	73.50 ± 1.06	65.49 ± 1.77	79.62 ± 0.38	54.70 ± 1.52	90.70 ± 0.29

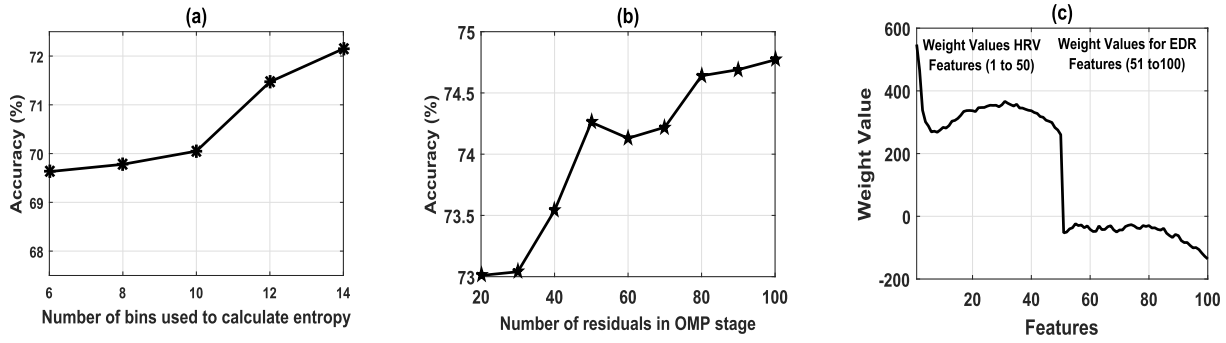

Fig. 6. (a) Variation of accuracy versus number of bins during Shannon entropy. (b) Variation of accuracy versus number of residuals in OMP stage of SRE features, and (c) Variation of weight values versus SRE features from EDR and heart rate (HRV) signals.

The computation time for the extraction of SRE features will increase, if more residuals are selected in OMP stage. Similarly, if the number of bins increases, the computational time for the evaluation of Shannon entropy will also increase. The optimal parameters (η, and σ) for SVM classifier are evaluated during the training phase using the grid-search approach [57]. The optimal parameters of SVM classifier for balanced training are evaluated as $\eta = 0.5$ and $\sigma = 5.62$. The weight value of each feature is estimated after the training of SVM classifier using the aforementioned optimal parameters. The variation of weight values with respect to the SRE features for the annotated dataset is depicted in Fig. 6 (c). It is evident that, the weight value decreases with an increase in the number of features for EDR and heart rate signals. Hence, in this study, we have selected the number of bins and residuals as 10 and 50 for the evaluation of SRE features.

For ten-fold cross-validation; the accuracy, sensitivity, and specificity of SVM-RBF classifier with SRE features with different dictionaries are mentioned in Table 3. The ten-fold analysis indicates that maximum specificity of 79.61% is achieved by SVM classifier with SRE features using both RR time series and EDR signal with CD whereas the maximum sensitivity of 81.24% is achieved by ECG signal using WD. The overall best performance is obtained using the features from the RR time series and EDR signal using FD with accuracy, sensitivity, and specificity of 78.07%, 78.01%, and 78.13%, respectively. This is because the sinusoidal basis correctly measures the correlation in RR time series and EDR signal whereas other basis fails to measure the correlation. The ECG contains minute information about the physiological changes and different spectral characteristics happening during apnea. The EDR signal contains the respiratory information which decreases during apnea resulting in the reduction of SRE features. The performance due to ECG signal alone is lesser than the performance due to the combination of heart rate signal and EDR signal for hold-out and ten-fold cross-validations. From the above observation, it can be inferred that, the SRE features from RR signal extracted using FD gave the best performance followed by a combination of RR time series, and EDR signal, ECG signal, and EDR signal.

The performance of SVM classifier is also evaluated separately by considering the SRE features from annotated and unannotated EDR and heart rate signals with hold-out cross-validation, balanced training along-with unbalanced testing, and subject-specific or leave-one-out cross-validation approaches for FD, and it is shown in Table 4. It is observed that the average accuracy, average sensitivity, and average specificity values are high for the feature vectors of unannotated EDR and heart rate signals for all types of validation cases. The balanced training along-with unbalanced testing based cross-validation is performed by considering total number instances as same for normal and apnea classes during training, and in the testing part, the total number of instances are different for each class. The unannotated EDR and heart rate signals are labeled based on the fuzzy k-means clustering technique and the distance between the cluster centers of the estimated class labels of unannotated and annotated EDR and heart rate signals.

4. Discussion

The goal of this research work is to detect sleep apnea using novel SRE features from both heart rate and EDR signals. Due to the interruption in the breathing during sleep apnea, the lungs and the cardiac outputs vary and these variations affect the characteristics of both EDR and heart rate signals [58,59,67]. It is reported in the literature that, during severe apnea, the HRV parameters have higher values as compared to the normal case [68]. In this study, we have found that for apnea class, all SRE features obtained from heart rate signal with dictionaries as FD, CD, and WD have higher mean values. The heart rate signal show cyclic variations in amplitudes and frequencies during sleep apnea [13,67] and the residuals evaluated from the heart rate signal

Table 3
Performance of SVM-RBF classifier with ten fold cross validation using SRE features of balanced dataset with different dictionaries.

Signal	RR + EDR									ECG		
Dictionary	CD			FD			WD			WD		
Folds	Acc (%)	Sen (%)	Spe (%)	Acc (%)	Sen (%)	Spe (%)	Acc (%)	Sen (%)	Spe (%)	Acc (%)	Sen (%)	Spe (%)
1	81.59	79.63	83.55	78.80	78.83	78.77	74.66	74.69	74.63	76.86	82.14	71.56
2	78.97	78.57	79.37	79.21	79.08	79.34	76.04	74.45	77.64	74.98	80.60	69.36
3	77.78	74.87	80.69	78.44	80.87	76.02	76.54	76.90	76.17	73.57	79.47	67.67
4	76.56	74.80	78.31	77.42	76.02	78.83	76.90	80.59	73.22	75.07	81.54	68.61
5	77.09	73.21	80.95	78.19	76.53	79.85	76.90	74.69	79.12	77.23	82.30	72.18
6	77.48	73.47	81.48	78.19	80.10	76.28	74.66	75.86	73.46	73.94	80.23	67.67
7	74.04	72.15	75.93	76.40	73.47	79.34	75.28	77.59	72.97	76.29	82.14	70.43
8	76.29	74.60	77.98	76.79	75.26	78.32	78.11	77.34	78.87	75.63	82.14	69.11
9	78.68	78.31	79.05	77.55	78.06	77.04	75.28	75.43	75.12	74.60	80.64	68.55
10	76.95	75.13	78.78	79.69	81.84	77.55	78.35	77.89	78.82	77.23	81.20	73.26
Average	77.54	75.47	79.61	78.07	78.01	78.13	76.27	76.54	76.00	75.54	81.24	69.84

Table 4
Performance of SRE features for the combination of EDR and RR signals with FD for annotated and unannotated cases using various cross-validation techniques.

Cross-validation schemes	Accuracy (%)	Sensitivity (%)	Specificity (%)
Hold-out on annotated data	71.19 ± 0.99	60.05 ± 1.56	79.27 ± 1.69
Hold-out on unannotated data	98.96 ± 0.32	98.18 ± 0.56	99.39 ± 0.37
Balanced training on annotated data	69.19 ± 0.95	70.26 ± 3.13	69.14 ± 0.96
Balanced training on unannotated data	98.40 ± 0.27	99.27 ± 1.18	98.38 ± 0.27
Subject-specific validation on annotated data	68.56 ± 14.56	62.31 ± 15.70	78.89 ± 16.82
Subject-specific validation on unannotated data	96.31 ± 1.81	93.51 ± 5.70	93.59 ± 6.41

based on the atomic decomposition capture these variations. Therefore, this may be the reason for higher mean values of SRE features for apnea class. Our results show that, these features correctly correlate with the physiological changes in the heart rate signal during sleep apnea and normal conditions. Moreover, it has also been found that, all SRE features from EDR signal have lower mean values for apnea class using the same dictionaries. There is reduction in the respiratory activity during severe apnea and thereby, these physiological changes vary the morphology of the EDR signal. The non-parametric test results also reveal that the SRE features computed from both EDR and heart rate signals are significant to capture cardio-pulmonary information for the detection of sleep apnea. In this study, the robustness of the proposed approach is verified by comparing with existing approaches for the detection of sleep apnea using both heart rate and EDR signals. The results of comparison is shown in Table 5. The approach reported by Thomas et al. [63] have extracted Fourier based cardio-pulmonary (CP) features from 8.5 min duration ECG signal for the detection of sleep apnea, and reported sensitivity and specificity values of 66.80% and 72.90%, respectively. Similarly, in another study, Liu et al. [64] have used Hilbert Huang transform (HHT) to extract CP features from 1 min ECG episodes from apnea-ECG database. Their method reported sensitivity and specificity of 73.10% and 71.20%, respectively using threshold classifier for the detection of sleep apnea. It is clear from the comparison table that, the performance of the proposed method is higher than the Fourier and HHT based CP features for the sleep apnea detection. Moreover, De Chazal *et al*. [20] combined the features from EDR and heart rate signals to formulate cardiopulmonary coupling features. They used logistic regression classifier for the detection of sleep apnea and achieved sensitivity and specificity of 81.90% and 91.50%, respectively with leave-one-out cross-validation. Similarly, in Ref. [26], the author has calculated fuzzy entropy and energy features from subband signals of both heart rate and EDR signals. However, in that work, the author has used annotated ECG signals for the feature extraction and detection of sleep apnea. They reported a sensitivity and a specificity value of 78.02%, and 74.64%, respectively for 10-fold cross-validation case. However, the author has not evaluated the performance of his algorithm with subject-specific or leave-one-out cross-validation startegy. The proposed SRE features coupled with SVM classifier has obtained higher specificity and sensitivity value as compared to the intrinsic band function based features extracted from both EDR and heart rate signals. Khandoker et al. [33] have extracted wavelet-based features from EDR and heart rate signals. They have considered leave-one-out cross-validation approach, and SVM classifier for the detection of sleep apnea. The sensitivity and specificity values of 94.40% and 98.80% have been reported. As compared to the proposed approach, the method reported by Khandoker et al. [33] have higher performance for the detection of sleep apnea. However, they have used different ECG database for the automated detection of sleep apnea. In an another study, Varon et al. have used statistical features from EDR and heart rate signals for sleep apnea detection with least square SVM (LS-SVM) classier. They have reported a sensitivity and a specificity values of

Table 5
Comparison of developed method with existing sleep apnea detection systems using both EDR and heart rate signals.

Authors	Methods used	Classifier used	Sensitivity (%)	Specificity (%)	Cross-Validation Scheme	Database Used (Subjects)
Thomas et al. [63]	Fourier transform based CP features	Threshold	81	68	Hold-out	Own database
Thomas et al. [63,64]	Fourier transform based CP features	Threshold	66.80	72.90	Hold-out	Apnea-ECG database
Liu et al. [64]	HHT based CP features	Threshold	73.10	71.20	Hold-out	Apnea ECG database
Khandoker et al. [33]	Wavelet based features from EDR and HRV signals	SVM	94.40	98.80	Leave-One-Out	SRU-Database [33]
Varon et al. [65]	Statistical features from EDR and HRV signals	LS-SVM	88.84	83.29	Leave-One-Out	Apnea-ECG database
De Chazal et al. [20]	Cross-spectral analysis of EDR and heart rate signals	Logistic regression	81.90	91.50	Leave-one-out	Apnea-ECG database
Sadr and De Chazal [66]	Features from EDR signals	ELM	76.30	87.32	Leave-One-out	Apnea-ECG database
Tripathy [26]	Intrinsic band function based analysis and feature extraction	KELM	78.02	74.64	10-fold	Apnea-ECG database
Proposed Work	SRE features with different dictonaries	SVM	78.01	78.13	10-fold	Apnea-ECG database
Proposed Work	SRE features with different dictonaries	SVM	85.43	92.60	Leave-one-out (Subject-Specific)	Apnea-ECG database

88.84%, and 83.29%, respectively. However, in their work, they have evaluated the performance using LS-SVM classifier with features from annotated ECG signals. In our study, we have used both annotated and unannotated ECG signals, and subject-specific cross-validation to achieve the average sensitivity and specificity of 85.43%, and 92.60%, respectively. The salient features of this paper are given below.

(i) Novel SRE features based on atomic decomposition and residual estimation are proposed.
(ii) The atomic decomposition based residual information captures the contribution of each atom from the dictionary developed using EDR and heart rate signals.
(iii) Various dictionaries such as FD, WD, CD, ED along-with two learned dictionaries as NSLD and ASLD are used for the calculation of SRE features.
(iv) The method is based on a semi-supervised learning framework as it used both annotated and unannotated physiological signals.
(v) The SVM classifier obtained higher sensitivity and specificity values using Fourier dictionary based SRE features as compared to dictionary developed using other features.

The proposed method has obtained less performance as compared to the work by De Chazal et al. [20] developed using cross-spectral CP features. In Ref. [20], authors extracted the cross-spectral CP features from 35 annotated ECG signals for the sleep apnea detection. However, in the present work, we have considered both annotated and unannotated ECG signals for the detection of sleep apnea. The non-linear entropy measures such as dispersion entropy, bubble entropy, and state space correlation entropy features can be extracted from both EDR and heart rate for the detection of sleep apnea [48,69,70]. The proposed SRE features can also be used for the classification of other cardiac and neural diseases using ECG and electroencephalogram (EEG) signals. Also, the SRE features can be evaluated from other physiological signals by considering the Gabor dictionary and time-frequency dictionaries for the identification of sleep apnea episodes and other sleep related disorders. Different deep neural networks as reported in Refs. [71–75] can be used to detect sleep apnea from the residual vectors of both heart rate and EDR signals.

5. Conclusions

In this paper, the novel SRE features have been presented for sleep apnea detection using EDR and heart rate signals. These features are extracted by considering the atomic decomposition of both EDR and heart rate signals with various dictionaries as FD, CD, WD, ED, ASLD, and NSLD, respectively. The important observations from this work are (i) SRE features computed from the EDR signal have lower mean values, whereas the higher mean values are observed for the features from heart rate signal for apnea classes. The SRE features from both EDR and heart rate signals coupled with SVM classifier have higher accuracy, sensitivity and specificity values by considering FD. The performance of the proposed approach can be improved by extracting more robust features using other entropy metrics from the residual vectors. The convolutional neural network, stacked autoencoder and other deep learning approaches can also be applied on the original signal to detect the sleep apnea. The hypopnea happens due to partial obstructions of the airways, and it is also a challenging task to detect these abnormal patterns in both EDR and heart rate signals. In the future, new cardiopulmonary features can be extracted using both EDR and heart rate signals for the detection of hypopnea.

Conflicts of interest

This is an academic research work and all the authors declare that there is no conflict of interest for this paper.

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