Support Vector Regression Model for Assessing Respiratory Effort during Central Apnea Events Using ECG Signals

AH Khandoker, M Palaniswami

The University of Melbourne, Parkville, Australia

Abstract

The aim of the present study is to investigate whether wavelet based features of ECG signals during central sleep apnea (CSA) can act as surrogate of respiratory effort measured by respiratory inductance plethysmography (RIP). Therefore, RIP and ECG signals during 125 pre-scored CSA events and 10 seconds preceding the events were collected from 7 patients. Wavelet decompositions of ECG signals upto 10 levels were used as input to the support vector regression (SVR) model to recognize the drop in RIP signal amplitudes during CSA. Using 25-fold cross validation, an optimal showed that it correctly recognized 115 CSA events (92% detection accuracy) using a subset of selected combination of wavelet decomposition levels (level 9 and 10; 0.12-0.24 Hz) of ECG. Results suggest superior performance of SVR using ECG as the surrogate in recognizing the fall of respiratory effort during CSA.

1. Introduction

Observation during central sleep apnea (CSA) reveals an absence of respiratory movements, which differentiate these apneas from obstructive sleep apnea (OSA). These observations can be confirmed by sleep studies in which abdominal and chest wall movement recordings are combined with airflow and oximetry. CSA is recognized when respiratory effort falls below 15% of pre-event peak to peak amplitude of the respiratory effort. The arousals are less frequent than in OSA because of the absence of any increased inspiratory effort as an arousal stimuli. During CSA the Pco_2 gradually rises and when it reaches the apnoeic threshold, a period of hyperventilation then begins to lower the Pco_2 again [1].

At present, the clinical technique for respiratory monitoring during sleep is the use of two inductance plethysmography measurements (rib-cage and abdominal), which can be used with reasonable agreement with those of the standard reference methods of measurement for respiratory effort-related arousals (RERA), central hypopnea–apnea, and Cheyne–Stokes respiration (CSR) associated with central sleep apnea CSR-CSA [2].

In this study, we use discrete wavelet transform of ECG signals to extract the respiratory related components and combine them using support vector regression .The aim of this study is to determine whether surrogate respiratory signal extracted from ECG signal surrounding CSA can correlate with respiratory signal measured by respiratory inductance plethysmography (RIP).

2. Methods

2.1. Subjects and sleep studies

In total, 7 sleep studies were used to develop and validate our classification algorithms. Sleep studies were collected from the database of Institute of breathing and sleep, Austin Hospital, Melbourne, Australia. Brief descriptions of the databases are as follows. The research protocol was approved by Austin Ethics in Human Research Committee (H2008/03252). The polysomnograms (PSG) of 7 sleep apnea patients [(mean ±SD) age 51±5 yrs, body mass index (BMI) 30±4 kg/m2] were analysed by Pro-Fusion software version 3 (Compumedics Pty Melbourne, Australia). PSG study included electroencephalogram (channel C3-A2 and C4-A1), left and right electrooculogram, leg movements, body positions, thoracic and abdominal wall expansion (by respiratory inductive plethysmography), oronasal airflow (by Nasal pressure), arterial oxygen saturation SaO2 (by pulse oximetry) and ECG (sampling frequency=250 Hz with a resolution of 16bits/sample). All subjects were free of any cardiac history. Diagnosis was based on clinical symptoms and polysomnographic (PSG) outcomes. Respiratory events were scored using criteria proposed by the AASM[3]. 125 pre-scored CSA events were selected from 7 patients respectively for the analysis. CSA was scored as the absence of oronasal airflow for >10 s in using the criteria that a reduction of more than 85% from peak to peak (mean positive to mean negative) amplitude of respiratory inductive plethysmography signals; the reduction must be in both

the thoracic and abdominal movement channels (which were recorded on separate channels for this study is associated with either an oxygen desaturation of >3% or an arousal. The range of apnea-hypopnea index (AHI) of patients was 12.5~85.45.

ECG clips: Total 125 simultaneous ECG and RIP signal clips (10-second preceding and 10- second following the onset of CSA events) from 125 pre-scored CSA events with/without arousals were extracted for analysis in this study.

2.2. ECG derived respiratory (EDR) signals from wavelet decomposed ECG signals

Wavelet-EDR: A discrete wavelet transform of 20-second ECG clip during central apnea breathing episodes was used to decompose into a set of approximate and detailed coefficients of level up to 10. Reconstructed detailed coefficients up to level 10 were computed. A symlet wavelet with order 8 was chosen as the mother wavelet for decomposition. Reconstructed decomposition level 8, 9 and 10 (i.e., 0.12-0.5 Hz) was chosen as the wavelet-EDR feature. Wavelet decomposition of ECG signals (during central apnea breathing episodes) of a sleep apneoa patient (AHI=48.5) are illustrated in Figure 1.

2.3. Support vector regression

In this study, support vector regression (SVR) model was considered to automatically recognize CSA from ECG features. In order to match the number of samples in RIP as the target signal (total 640 samples in 20 seconds with sampling frequency 32 Hz), wavelet-EDR signals were resampled using cubic spline interpolation (MATLAB) to make 640 samples. The basis of SVR theory is to nonlinearly map the input data into some (possibly infinite dimensional) feature space where the problem may be treated as a linear one. In particular, when tackling regression problems using SVR, the output is a linear function of position in feature space. However, the complexities of this feature space (and the non-linear map associated with it) are "hidden" using a kernel function. It is this ability to hide complexity (resulting in a simple linearly constrained N-dimensional quadratic programming problem with no non-global minima), along with the ability to use complex models while avoiding overfitting, that has made SVR methods so popular over recent years. The major difference between Support Vector Machines (SVMs) and many other Neural Network (NN) approaches is that instead of tackling problems using the traditional empirical risk minimisation (ERM) method, SVMs use the concept of regularised ERM. This has enabled people to use SVMs with potentially huge capacities on smaller datasets without running into the usual difficulties of overfitting and poor generalisation performance. The theory of SVR can be found in [4].

Radial basis function (RBF) defined as $\mathbf{K}(\mathbf{x_i}, \mathbf{x_j}) = \exp\left(\frac{-\|\mathbf{x_i} - \mathbf{x_j}\|^2}{2\sigma^2}\right)$ was used in this study as the kernel function where σ denotes the width of the RBF. In this study, σ=0.7 is used for all experiments.

2.4. Training and testing the linear SVR

A twenty five-fold cross validation scheme was adopted to evaluate the generalization ability of the SVR as a classifier for CSA. In this scheme, 125 events data set was uniformly divided into 25 subsets with 5 events were used for testing and the remaining 120 records were used to train SVR parameters. This was repeated for other subsets so that all subsets were used as the cross validation test sample. Only RBF kernel was tested in this study. Maximum mean cross validation accuracy was found to be 92% with $C=2^6$; $\varepsilon=2^{-2}$ using RBF kernel where C is the coefficient for trade-off between empirical and structural risk and ε is the width of ε-insensitive region. The best feature subset was the combination of the wavelet decomposition level (level 9 and 10; 0.12-0.24 Hz) of ECG signals. Parameter optimization was performed using cross-validation set with each experiment being repeated 25 times.

A grid search proposed Bao [5] was used in this study for parameters setting of C and ε. To reduce the computational burden, a finer grid search on that region was conducted only after identifying a better region on the grid. We first used a coarse grid search and found the best (C, ε) as (2^8, 2^{-2}) with ten-fold cross-validation accuracy 88.5% on 50 OSA and 50 CSA events. After the best (C, ε) was found, the model was trained with whole training set (125 events) again to generate the final classifier. The parameter set of C and ε which generated the maximum CSA recognition accuracy (92%) was considered as the best parameter set. All SVM architectures were trained and tested on the MATLAB SVM toolbox [6].

3. Results

Figure 2 shows RIP (thoracic movement) signal and SVR based surrogate respiratory signal of (10-second preceding and 10- second following the onset of CSA

events) from a pre-scored CSA event. Figure 3 shows the correlations of percentage (%) drop in thoracic and surrogate respiratory signals from 10 second preceding the events for 125 CSA events. Significant correlation ($r=0.51$; $p<0.01$) was found between reductions in thoracic and that in surrogate respiratory signals. Using surrogate respiratory signals 115 CSA events are correctly recognized. 85% drop from the preceding thoracic movement was considered as the threshold.

The Bland-Altman plot is the preferred method for assessing whether an established and a new measurement technique agree. It shows the paired difference between two observations on each subject against the mean of these two observations. Figure 4 shows Bland-Altman-plots for CSA events. Percentage (%) drop in thoracic signals during CSA events was overestimated by less than 2% (mean bias= +1.31%; +2 SD: + 7.91%, -2 SD: -5.28%).

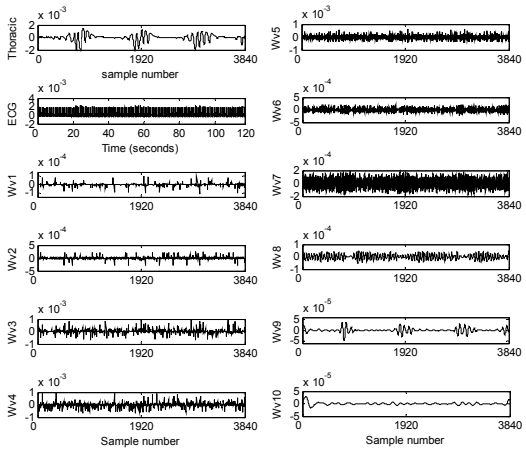

Figure 1. Two-minute recording of thoracic movement signal (volts), ECG signals and its reconstructed wavelet detailed decomposition up to level 10 of a sleep apneoa patient (AHI=48.5) during four central apnea breathing episodes. Wavelet decomposed ECG signals were resampled using cubic spline interpolation to make 3840 samples.

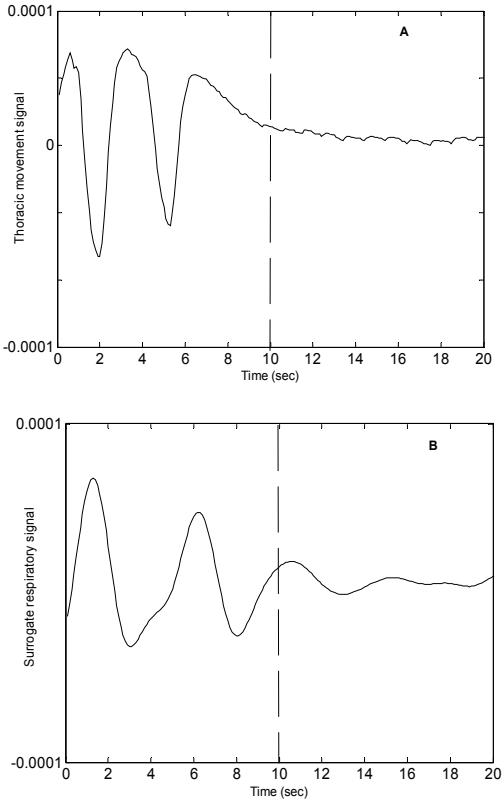

Figure 2. An example of thoracic signal (panel A) and SVR based surrogate respiratory signal (panel B) 10 second preceding and 10 second after the start of a CSA event. The dashed line represents the start of the pre-scored CSA event.

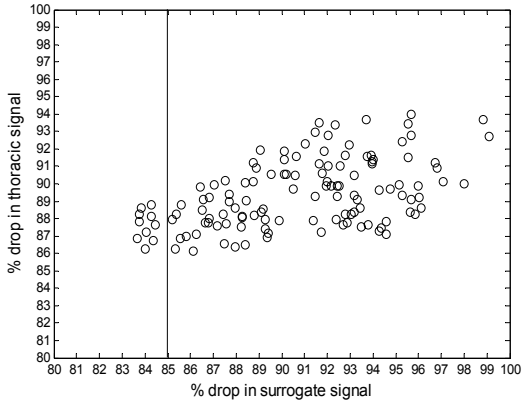

Figure 3. Percentage (%) drop in thoracic and surrogate respiratory signals from 10 second preceding the events. Total 125 CSA events are shown. Using surrogate respiratory signals 115 CSA events are correctly

recognized. 85% drop from the preceding thoracic movement was considered as the threshold.

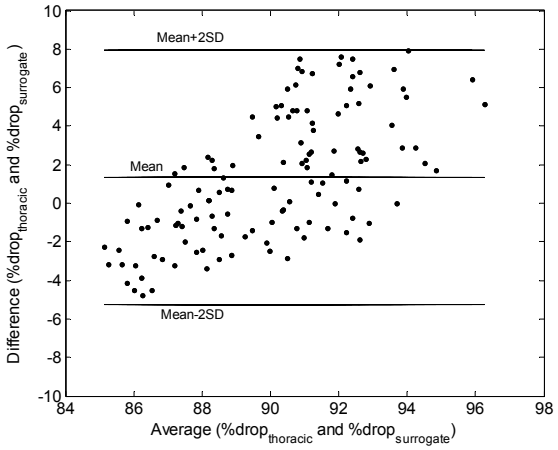

Figure 4. Bland-Altman plot of the relationship of the difference between % drop in thoracic signal and % drop in surrogate respiratory signals for 125 CSA events versus their average value. Mean bias (—), +2SD and -2SD lines are shown. SD= standard deviation.

4. Discussion and conclusions

The study results indicate a correlation between changes in amplitudes of surrogate respiratory signal obtained from ECG and the amplitudes of breathing movement during CSA. Results also showed that SVR with an optimal parameter set correctly recognized 115/125 CSA events (92% recognition). An important aspect of our work is that postural position appears to have only a small effect on the wavelet-EDR estimates because wavelet decomposition excludes the body position influence on ECG.

Model parameters such as C and ε are selected by users based on a priori knowledge and/or user expertise [7]. Obviously, this approach is not appropriate for non-expert users. It is well known that SVR generalization performance (estimation accuracy) depends on a good setting of meta-parameters parameters C, ε and the kernel parameters. The problem of optimal parameter selection is further complicated by the fact that SVR model complexity (and hence its generalization performance) depends on all three parameters. Existing software implementations of SVR usually treat SVR meta-parameters as user-defined inputs. In this paper we focused on the choice of C and ε, rather than on selecting the kernel function. Parameter C determines the trade off between the model complexity (flatness) and the degree to which deviations larger than ε are tolerated in optimization formulation. For example, if C is too large (infinity), then the objective is to minimize the empirical risk only, without regard to model complexity part in the optimization formulation. Parameter ε controls the width of the ε -insensitive zone, used to fit the training data. The value of ε can affect the number of support vectors used to construct the regression function. The bigger ε, the fewer support vectors are selected. On the other hand, bigger ε -values result in more 'flat' estimates. Hence, both C and ε-values affect model complexity (but in a different way).

In addition to CSA recognition, other potential application of our model may be to assess the severity of airway obstruction in patients with obstructive airway disease including asthma, bronchiolitis, and chronic obstructive pulmonary disease (COPD).

Acknowledgements

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Address for correspondence

Dr Ahsan Khandoker
Dept. of Electrical & Electronic Engg.
The University of Melbourne, Parkville, VIC -3010, Australia.
E-mail:ahsank@unimelb.edu.au