A COMPARATIVE STUDY OF FOUR NOVEL SLEEP APNOEA EPISODE PREDICTION SYSTEMS

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ABSTRACT

The prediction of sleep apnoea and hypopnoea episodes could allow treatment to be applied before the event becomes detrimental to the patients sleep, and for a more specific form of treatment. It is proposed that features extracted from breaths preceding an apnoea and hypopnoea could be used in neural networks for the prediction of these events. Four different predictive systems were created, processing the nasal airflow signal using epoching, the inspiratory peak and expiratory trough values, principal component analysis (PCA) and empirical mode decomposition (EMD). The neural networks were validated with naïve data from six overnight polysomnographic records, resulting in 83.50% sensitivity and 90.50% specificity. Reliable prediction of apnoea and hypopnoea is possible using the epoched flow and EMD of breaths preceding the event.

1. INTRODUCTION

Obstructive sleep apnoea (OSA) is the repeated pause in breathing during sleep due to the obstruction and collapse of the upper airway. OSA is the most common medical disorder causing excessive daytime sleepiness affecting 4% of men and 2% of women [1]. Excessive daytime sleepiness results from the transient arousals that occur in response to the increased inspiratory effort to maintain adequate ventilation [2]. There is growing association between OSA, obesity, hypertension and other cardiovascular diseases [3], as well as the long-term development of metabolic disorders, such as diabetes mellitus[4].

The 'gold standard' test for the diagnosis of OSA is polysomnography (PSG), a multi-signal technique for the monitoring of sleep and its stages, and the monitoring of respiration. PSG records many biosignals, including, but not limited to: electroencephalogram (EEG), electrooculogram (EOG), electromyogram (EMG) of the chin and legs, electrocardiogram (ECG), respiratory function (i.e. airflow, chest wall movement and pulse oximetry), body position and snoring using a microphone.

The most commonly prescribed treatment for OSA is continuous positive airway pressure, or CPAP. It is the general view that PAP works like a pneumatic splint for the upper airway, preventing its collapse against negative inspiratory pressure and stabilising the upper airway [5]. CPAP treatment continually applies air to the nose and/or mouth, preventing the apnoea from occurring, therefore having high sensitivity but low specificity. CPAP is not well tolerated due to nasal and oral dryness and mask discomfort [6]. This leads to patients failing to comply, which can have severe consequences, because OSA will only improve while treatment is used, and it will return to its original severity when treatment stops.

The focus of research into OSA has been on reducing the number of channels required for diagnosis, with researchers concentrating on cardiorespiratory parameters (mainly heart rate variability and pulse oximetry). These signals are able to detect apnoeas, but in the case of pulse oximetry, hypopnoeas are not always detected. The response to the apnoea event, measured in the cardiorespiratory signals, occurs after the start of the event. The delay in response is dependent on the haemodynamic status of the patient [7] and a lag of many seconds may be present [8].

There is a need for a device that can predict the likelihood of an apnoea event in the time preceding its generation and before it has a detrimental effect. There are few devices that have the ability to predict the onset of apnoea for patients who have already been diagnosed. A positive airway pressure device [9] recognizes the snoring pattern as being a parameter for the detection of imminent onset of apnoeas.

The airflow signal has been used in the development of a single channel monitor for the screening of sleep-disordered breathing [10]. The algorithm developed uses power spectral analysis to analyse the variation in amplitude of the airflow signal, and gave diagnostic sensitivity of 96% and 76% specificity. Aittokallio *et al* [11] used flow shape analysis in the reduction of redundant information to decrease the amount of time to score overnight sleep recordings. The ultimate aim of the work was to develop a simple method for the rapid monitoring of sleep disordered breathing.

Inspiratory flow shape analysis has also been used in con-

tinuous positive airway pressure devices [9, 12, 13]. These methods look at the roundness of the inspiratory airflow signal and adjust the CPAP pressure applied until the flow contour is more rounded, which coincides with adequate airway patency. Montserrat *et al* [13] suggests that the characteristics of the inspiratory flow contour are a good marker of the level of upper airway stability and it should be used in finding the optimal level of CPAP pressure.

This paper presents a comparative study assessing whether the nasal airflow signal as recorded during PSG could be used in the prediction of sleep apnoea episodes. It is believed that the airflow signal is the primary signal that can record the instant that an apnoea occurs. Prediction was performed using four different neural networks, with four different inputs: (i) epoched flow signal, (ii) inspiratory peak and expiratory trough values, (iii) weights calculated from principal component analysis and (iv) intrinsic mode functions; each of which will be outlined in the methodology section.

2. METHODOLOGY

2.1 Subject Data

Full polysomnographic data was obtained for 39 patients (24 male) with a mean ± standard deviation age of 39.31 ± 13.18. Data from six patients (3 male) was reserved as unseen data for validation of the created neural networks, with age of 41.83 ± 10.74. Further patient characteristics can be see in table I.

	Original Patients	*Unseen Patients*
Subjects	39	6
Males (%)	61.54	50
Age (years)	39.31 ± 13.18	41.83 ± 10.74
BMI (kg/m^2)	27.89 ± 7.65	30.76 ± 3.91
AHI (no./hr)	21.35 ± 31.48	20.23 ± 33.74

Table 1 - Patient Characteristics. Data is shown in mean ± standard deviation. BMI - body mass index, AHI - apnoea/hypopnoea index.

The PSG data was obtained from the Edinburgh Sleep Centre using Alice 5, (*Respironics)* recording 18 channels of data. The channels recorded were left and right EOG, four channels of EEG (C3A2, C4A1, O1A2, O2A1), chin EMG recorded from electrodes placed under the chin, air-flow with a nasal cannula, thoracic and abdominal motion, microphone or vibration sensor placed on the side of the neck for snoring, two channels of ECG, finger pulse oximetry, body position, and left and right leg movement. The PSG data was manually scored by trained clinical staff, identifying obstructive, central (cessation in breathing due to neurological condition) and mixed apnoeas (starts as a central event and progresses to obstructive), hypopnoeas (reduction in airflow) and other events that were not used in this work.

2.2 Predictive System

The predictive system is illustrated in figure 1. The system is composed of two main stages: signal conditioning and prediction using neural networks. The nasal airflow signal is first epoched and the peak and trough values from the breath are extracted. The epoched flow signal is then conditioned using principal component analysis (PCA), and empirical mode decomposition (EMD) [14]. These signals are then used to create four neural networks that are used to classify the apnoea and hypopnoea (class I) and normal episodes (class II).

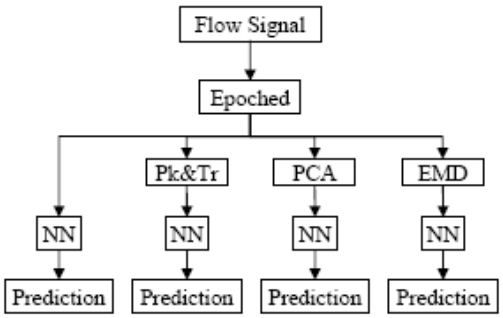

Figure 1. Flow diagram of the predictive system. Pk&Tr - Inspiratory peak and expiratory trough, PCA - Principal component analysis, EMD - Empirical mode decomposition, NN - Neural network.

2.3 Airflow Signal Extraction

The airflow signals were extracted from the PSG data and periods of obstructive, central and mixed apnoeas, hypopnoeas and periods of normal breathing were identified within the data.

The original airflow signal was epoched for a sequence of flow data before an apnoea and hypopnoeas. The inspiratory peak values and expiratory troughs were also identified within each flow signal. The epoched flow signals and the peak and trough values were used as inputs to the neural network.

2.4 Principal Component Analysis

Principal component analysis (PCA) [15] was used in the reduction of the data set. The weights were determined from the epoched flow signal, and were then used as an input to the neural network.

A training set, Γ, was created from two thirds of the apnoeas, hypopnoeas and normals. The mean flow signal was then calculated,

$$\Psi = \frac{1}{M}\sum_{n=1}^{m}\Gamma_n \tag{1}$$

The difference between each flow signal and the mean was calculated

$$\Phi_i = \Gamma_i - \Psi \tag{2}$$

The covariance matrix was then determined

$$C = \frac{1}{M}\sum_{n=1}^{M} \Phi_n \Phi_n^T \quad (3)$$

where $\Phi_n = [\Phi_1 \Phi_2 ... \Phi_M]$. The eigenvalues and eigenvectors were then calculated from the covariance matrix, and the eigenvalues were sorted into descending order and the top 20% were chosen. The flow signals, from the training and testing set, were then transformed into eigenflow components, the weights, using

$$w_k = u_k^T (\Gamma - \Psi) \quad (4)$$

where w_k is the eigenflow, u_k^T is the eigenvector, Γ the flow signal, and Ψ the mean flow image. The eigenflow were then used as an input to the neural network.

2.5 Empirical Mode Decomposition

Empirical mode decomposition (EMD) is a nonlinear technique used to represent non-stationary signals [14]. Nasal airflow signals are non-stationary due to the variation in respiration [16]. EMD decomposes a signal by generating intrinsic modes functions (IMF), which will extract the energies associated with the intrinsic time scales.

The epoched flow signals, Γ_n, are analysed and the maxima and minima are located. The maxima are connected by a cubic spline line to create the upper envelope and this is repeated for the minima, creating the lower envelope, the mean of the envelopes is calculated, m_n. The detail, or the intrinsic mode, is extracted using

$$IMF_n = \Gamma_n - m_n \quad (5)$$

and this should be the first IMF. The IMF must satisfy two conditions: the first condition is that in the whole data the IMF must have an equal number of extrema and number of crossings or they can differ by at most one and the second condition is that the mean value calculated from the envelopes is zero. If these conditions are not satisfied then a sifting process is carried out, to eliminate riding waves and to make the wave profile more symmetric,

$$h_{n+1} = h_n - m_{n+1} \quad (6)$$

where h_1 is the difference between the original image and the mean. In reality, due to the nature of most signals, a sifting process has to be carried out. Sifting is repeated until the conditions are satisfied.

The first IMF should contain the finest scale or the shortest period component of the signal. It is then separated from the rest of the data, and the residual is treated as the new data and the sifting process is then repeated,

$$r_1 = \Gamma_n - IMF_1 \quad (7)$$

The process can be repeated on all the subsequent residuals until the signal becomes so small that no more IMFs can be extracted. The sum of the IMFs and the residuals allows the original data to be re-created. The first IMF is related to the highest frequency and the last to the lowest frequency.

The intrinsic mode function was then used in the neural network for the prediction of sleep apnoea episodes

2.6 Prediction of Events Using Neural Networks

The prediction of the airflow signal as apnoea/hypopnoea (class I) or normal (class II) was performed using two stage multi-layer perceptron neural networks. Four different networks were created for the four different inputs: epoched flow signal, inspiratory peak and expiratory trough values, eigenflow from PCA and the IMF from empirical mode decomposition.

The neural networks were created using episodes extracted from 39 sets of patient data. The apnoeas and hypopnoeas, and normal periods were separated into training and testing sets, with two thirds of the data in the training set and a third in the testing set. The training set comprised 1200 apnoeas, 1200 hypopnoeas and 2400 normals, and the testing set was 600 apnoeas, 600 hypopnoeas and 1200 normal periods.

Validation of the prediction networks was carried out using naïve data from 6 patients; this data had not been used in the adaptation of the neural network. This data set was composed of 300 apnoeas, 300 hypopnoeas and 600 normal periods.

3. RESULTS

Four different, two stage neural networks, were created using the epoched airflow signal, the inspiratory peak and expiratory trough values, the eigenflow components from PCA and the intrinsic mode function from the EMD of the breath before an apnoea and hypopnoea. The reliability of the neural networks was measured using sensitivity and specificity. Sensitivity is the percentage of flow signals that are correctly classified as class I (apnoea and hypopnoea). The specificity is the percentage of events that are correctly classified as class II (normal).

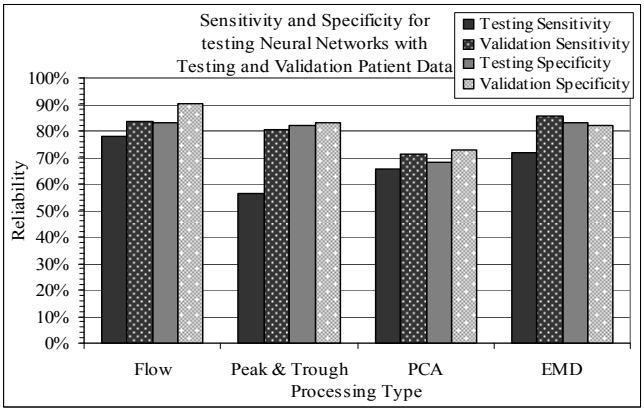

Figure 3 - Results for testing with original patient set and validation data. Solid black column is the sensitivity from the original testing data, black with white spots is the sensitivity from the validation data, Solid grey is the specificity for the original testing data, and the grey with white spots is the specificity from the validation data.

The results for the prediction of sleep apnoea and hypopnoea are shown in figure 3. The figure shows the sensitivities and specificities for testing with the original set of patient data and the validation testing set.

The greatest overall reliability, for testing with the original patient data, was recorded using the epoched flow signal as the input to the neural network, with 77.75% sensitivity and 83.33% specificity, although the EMD and peak and trough have very similar value for the specificity, 83.08% and 82.08%, respectively, but lower sensitivity. The network created using the eigenflow components from the PCA performed the poorest, with 65.67% sensitivity and 68.25% specificity.

The neural networks' performance was also high when tested with validation data. An average improvement in sensitivity of 12% was recorded for the four methods, although specificity was only improved an average of 3%. The pre-processing method that gave the greatest reliability was the epoched flow signal with 83.51% sensitivity and 90.50% specificity. Empirical mode decomposition showed greater sensitivity but the specificity was slightly lower, 85.67% and 82.17% respectively.

4. DISCUSSION

The results of this study show that it is possible to predict when apnoea and hypopnoea episodes are going to occur using only the nasal airflow signal with high sensitivity and specificity.

The method proposed in this paper was to predict when apnoea and hypopnoea episodes are going to occur, using the nasal airflow signals. The airflow signals are simple to record and can show the instant an episode occurs. It has been shown that this method can predict imminent events with 83.50% sensitivity and 90.50% specificity.

Future research will focus on the development of a real-time prediction system, as this method is currently carried out off-line. This work will also be incorporated into a device for the treatment of imminent apnoea, before the episode becomes detrimental to the patients sleep.

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