PILOT STUDY OF SLEEP APNEA DETECTION WITH WAVELET TRANSFORM

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Abstract

The sleep apnea syndrom is defined as repeated pauses in breathing during sleep period which leads to interrupts in sleep and decreases in oxyhemoglobin saturation. It is well understood that quantity and quality of sleep could significantly affect work productivity. In this study multimodal analysis of breathing is done with two different sensors. The first sensor measures nasal air flow and the second sensor measure abdomen effort during breathing. As it is needed to manually go through records of whole night sleep to confirm some of an automatic classification of events that can disturb sleep, it is very important to have accurate classifier. This papers aim is to present results of pilot study of competitive neural network (CNN) classifier based on Wavelet transform, with which is possible to evaluate sleep apnea from multimodal breathing data with accuracy of 94.2 % with comparison to classification of Sleep apnea by doctor. Evaluation of the whole output of CNN is complicated as the neural network was trained without target data. It can detect all apnea events from length of 5 seconds, including those that are missing in the classification by a doctor.

1 Introduction

The Sleep Apnea Syndrom (SAS) is characterized by repeated pauses in breathing during sleep, which lead to the fragmentation of sleep and decreases in oxyhemoglobin saturation [6, 27]. The patients complains some of the following symptoms: unintentional sleep episodes during wakefulness, daytime sleepiness, unrefreshing sleep, fatigue, insomnia, gasping and choking and loud snoring [10, 3, 26, 16].

It is well understood that quantity and quality of sleep could significantly affect work productivity [18]. In severe sleep apnea extreme sleepiness can occur during activities that require more active attention, like during eating, walking or driving and it can be life-threatening and has been associated with cardiovascular morbidity and mortality.

The Polysomnography (PSG) is the current golden standard for the evaluation of sleep-disordered breathing, which is usually performed during night [20, 21, 1, 16]. It provides detailed data on respiratory effort, airflow, oxygenation, sleep state, and other variables, but it is costly and requires subjects to sleep overnight in a laboratory. It records many physiological parameters as electroencephalogram (EEG), electrocardiogram (ECG), electrooculography (EOG), electromyography (EMG), air flow and oxygen saturation simultaneously during sleep [4].

In this study multimodal analysis of breathing is done with two different sensors from PSG. The first sensor measures nasal air flow using a thermistor [9, 11]. The thermistor is special type of resistor whose resistance is dependent on temperature. The second sensor measure abdomen effort during breathing, which is realized as elastic belt with piezo-electric sensor, that directly generates a voltage when compressed or stretched, fastened around body [8].

As it is necessary to go through records of whole night sleep to confirm automatic classification of events that can disturb sleep, it is very important to have accurate classifier. This paper aim is to present such classifier based on wavelet transform and unsupervised training of simple competitive neural network that would accurately classify all drops in breathing from nasal airflow signal and abdomen effort signal.

2 Mathematical Background

2.1 Discrete Wavelet Transform

A wavelet transform is an alternative for a short-time Fourier transform. Both transforms return information about a frequency part of a signal, however the short-time Fourier transform can provide an exact frequency analysis but not that detailed time analysis. Benefit of the wavelet transform is that it can give us good time distinction with lower frequency detail, or with lower time distinction higher frequency detail. It provides as result a set of frequency-time representation of signal in different scales of resolution.

Discreet wavelet transform uses a set of two functions. The wavelet function defines a high-pass filter, and the scale function works as a low-pass filter. The result of input signal convolution with these two function form approximate and detail coefficients (Figure 2).

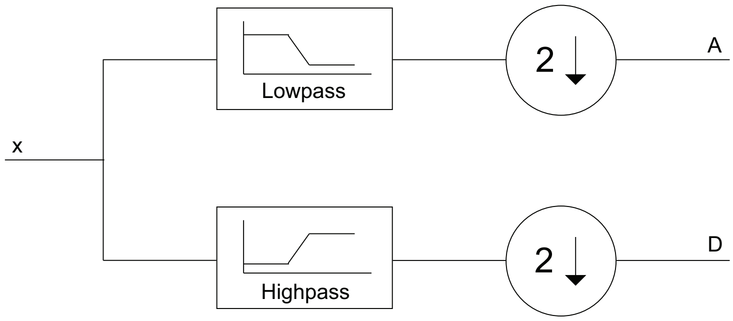

Figure 1: Discreet wavelet transform for first level decomposition of a signal x to approximate and detail coefficients.

A Haar wavelet transform is one of the basic types of discrete wavelet transforms. The approximation and the detailed coefficients are enumerated from two succeeding signal values in each step of the transform [25, 12, 25, 14]. The Haar matrix is defined as:

$$\mathbf{T} = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix} \tag{1}$$

The forward transform of a signal $\{x(n)\}_{n=0}^{N-1}$ for its subsequent values $\{x(n), x(n+1)\}$ for $n = 0, 2, \ldots, N-2$ is then:

$$\mathbf{y} = \begin{bmatrix} y_0(n) \\ y_1(n+1) \end{bmatrix} = \mathbf{T} \times \mathbf{x} = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix} \begin{bmatrix} x(n) \\ x(n+1) \end{bmatrix} \tag{2}$$

$$\mathbf{y} = \frac{1}{\sqrt{2}} \begin{bmatrix} x(n) + x(n+1) \\ x(n) - x(n+1) \end{bmatrix}$$

The resulting sequence $\{y_0(0), y_0(2), \ldots, y_0(N-2)\}$ is the lowpass part of input signal decomposition with its length halved. The complementary highpass part of decomposition is composed in the same way as $\{y_1(1), y_1(3), \ldots, y_1(N-1)\}$.

The backward transform from two input signals of lowpass part and highpass part of decomposition is:

$$\mathbf{x} = \begin{bmatrix} x(n) \\ x(n+1) \end{bmatrix} = \mathbf{T} \times \mathbf{x} = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & 1 \\ -1 & 1 \end{bmatrix} \begin{bmatrix} y_0(n_c) \\ y_1(n_c+1) \end{bmatrix} \tag{3}$$

$$\mathbf{x} = \frac{1}{\sqrt{2}} \begin{bmatrix} y_0(n_c) - y_1(n_c+1) \\ y_0(n_c) + y_1(n_c+1) \end{bmatrix}$$

where $\{x(n), x(n+1)\}$ $n = 0, 2, \ldots, N-2\}$ is an output for two input signals $y_0(n_c)$ $y_1(n_c)$ where $n_c = \frac{n}{2}, n = 0, 2, \ldots, N-2$.

2.2 Principal Component Analysis

Principal Component Analysis (PCA) is a statistical procedure that uses an orthogonal transform to convert a set of observations of possibly correlated signals into a set of values of uncorrelated signals called principal components. The number of principal components is always less than or equal to number of original signals. The transform is defined in such a way that the largest possible variance is in the first principal component, and each succeeding component has the highest variance possible under the constraint that it is orthogonal to the preceding components. The resulting vectors form an uncorrelated orthogonal basis set [22]. PCA has several advantages such as lack of redundancy, reduced complexity or reduction of noise [13].

PCA is mostly used as a tool in exploratory data analysis and for making predictive models. PCA can be done by eigenvalue decomposition of a data covariance (or correlation) matrix or singular value decomposition of a data matrix, usually after whitening.

3 Analysis of Respiratory Signal

The average breathing rate of an adult at rest is 16–20 breaths per minute, which means that one period of breathing is 3–3.75 seconds. For a person older than 65 years is breathing rate at rest 12–28 breaths per minute with one period of breathing 5–2.15 seconds. All possibilities have to be taken into account, so the shortest window for analysis of breathing signal is 5 seconds [5, 24].

Sleep apnea is characterized as pause of breathing during sleep and each pause can last from few seconds up to minutes resulting in lack of oxygen in body. There exists three types of sleep apnea, Obstructive sleep apnea accounts for 84%, Central sleep apnea for 0.4%, and 15% of cases are mixed [19].

The sleep apnea is divided into three categories [16]:

- **Obstructive sleep apnea** that is the most common category of sleep-disordered breathing. The muscle tone of the body ordinarily relaxes during sleep, and at the level of the throat the human airway is composed of collapsible walls of soft tissue which can obstruct breathing.
- **Central sleep apnea** that happens when the brain has imbalance in respiratory control. The neurological feedback mechanism does not react fast enough to higher levels of carbon dioxide in blood and body does not maintain even respiratory rate. The sleeper then cycle between apnea and hyperpnea. There is no effort to breath during apnea, and breathing may be faster after the episode for period of time.
- **Mixed sleep apnea** that is characterized as a combination of obstructive and central sleep apnea, and its occurrence ranges from 0.56% to 18%.

This paper focuses on processing and analysis of two signals connected to breathing: breathing effort and flow signal. The first signal represents abdomen effort during breathing and the second one represents a measurement of air flow from nose. These two measurements

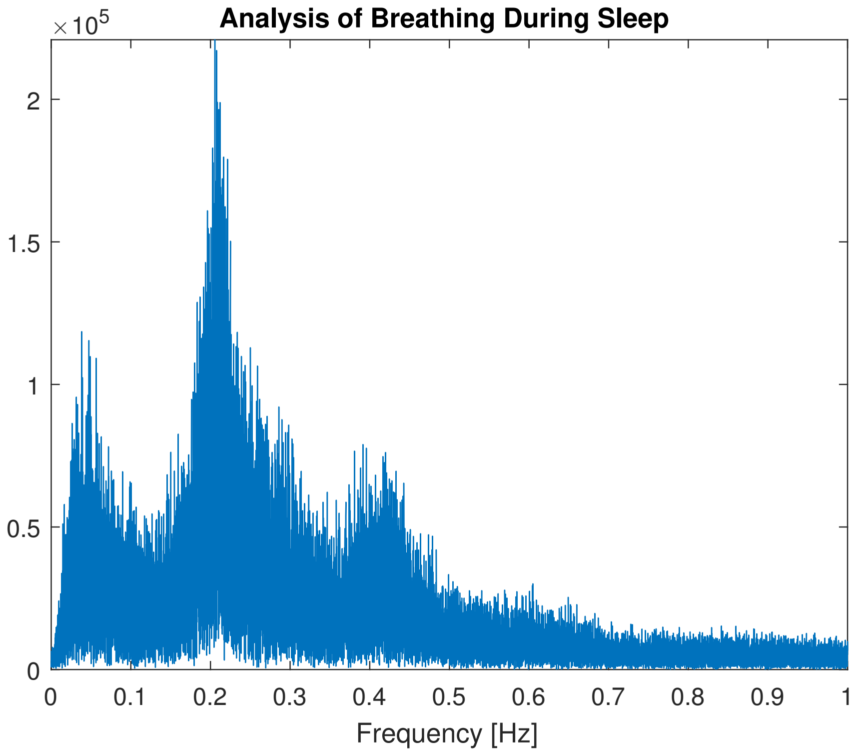

Figure 2: Frequency analysis of the full night record, showing presence of apnea (peak around 0.05 Hz), normal breathing (around 0.2 Hz) and hyperpnea (around 0.4 Hz). Hyperpnea is caused by Central Apnea.

are very close but the first signal stands for the effort of breathing and the second one points to the situation with the actual air intake (Figure 4) important for detection of sleep apnea.

There is a high correlation between the breathing effort signal and the flow signal, which means that there is a lot of useful information in these data with respect to that there should be 100% correlation for healthy patients.

The idea behind detecting sleep apnea is reduction of energy during occurrence in frequency corresponding to breathing frequency at rest. To get to useful data for this process it is needed to decompose signal using discreet wavelet transform up to level 6, which mean we will get to frequency accuracy of 0.156 Hz per part. To simplify the process even more, we decorrelate signal from nasal airflow and abdomen effort using the principal component analysis.

Severity of sleep apnea is divided by number of occurrences per hour. The mild severity is from 5 to 15 airflow drops per hour of sleep, the moderate severity is from 15 to 30 occurrences per hour and the severe severity is from 30 or more airflow drops per hour.

3.1 Signal Processing Using Energy of Frequency Parts

Decomposition of signal using Haar wavelet transform up to 6th level will result in frequency precision of approximately $10 \times 2^{-6} = 0.15625\ Hz$ with the sampling frequency of 10 Hz. The most interesting part of signal with respect to breathing is between 0–0.7 Hz (0–42 breaths per minute). This partition will lead in 5 signals representing different frequency parts. To get uniform results from different subjects, it is possible to transfer this signal using Parseval's theorem to ratio of signal energy in each decomposed part to energy of original signal.

The average respiratory rate at rest [7, 17, 15] is:

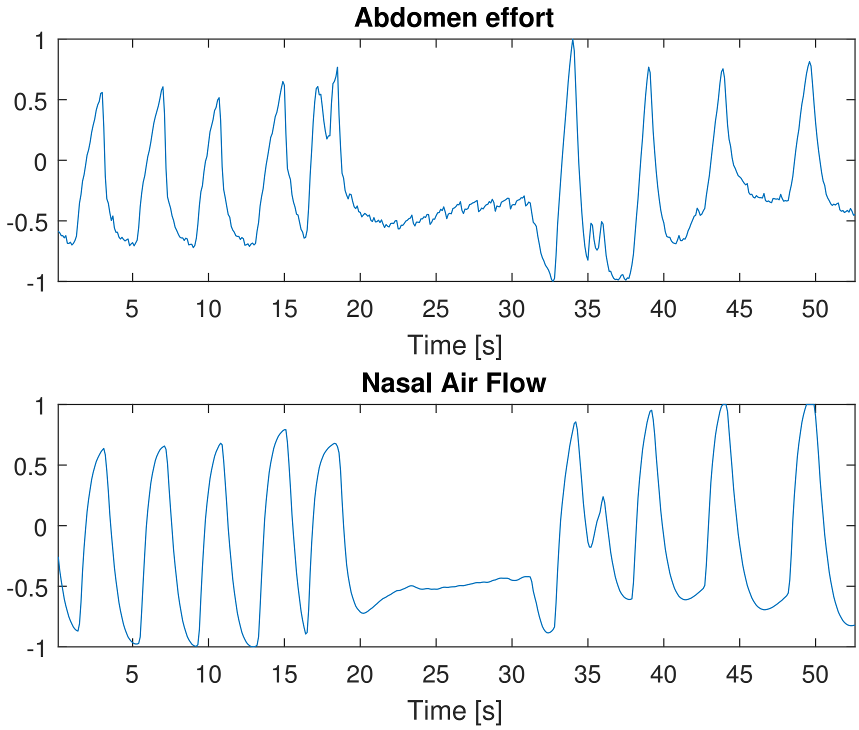

Figure 3: Breathing signals during central apnoa. Patient completely stops to breathe.

- within 6 weeks: 0.5–1 Hz (0 to 60 breaths per min.)
- 6 months: 0.41–0.66 Hz (25-40 breaths per min.)
- 3 years: 0.33–0.5 Hz (20-30 breaths per min.)
- 6 years: 0.3–0.41 Hz (18-25 breaths per min.)
- 10 years: 0.2–0.25 Hz (12-15 breaths per min.)
- Adult: 0.26–0.33 Hz (16-20 breaths per min.)[2]
- $\geq$ 65 years: 0.2–0.46 Hz (12-28 breaths per min.)[23]

Figure 5 presents the breathing signal with the central apnoa event and its decomposition of using Haar wavelet transform. We can see a significant decrease of signal energy during this event. Figure 6 presents a normal breathing during sleep period for comparison.

The principal component analysis show that the majority of information is in the first channel of DWT decomposition (80 %), and nearly all of the remaining information are in the second (12 %) and the third (7 %) channel which means that 99 % of relevant information is in the range of 0–0.4688 Hz.

As non-automatic analysis of whole night recordings of multimodal data is very time consuming, results of classification does not always indicate all events. Such can happen when there is more apnea events in sequence. It would not be wise to try to apply classifier that would learn with teacher, so unsupervised learning on competitive neural network with 2 classes was applied.

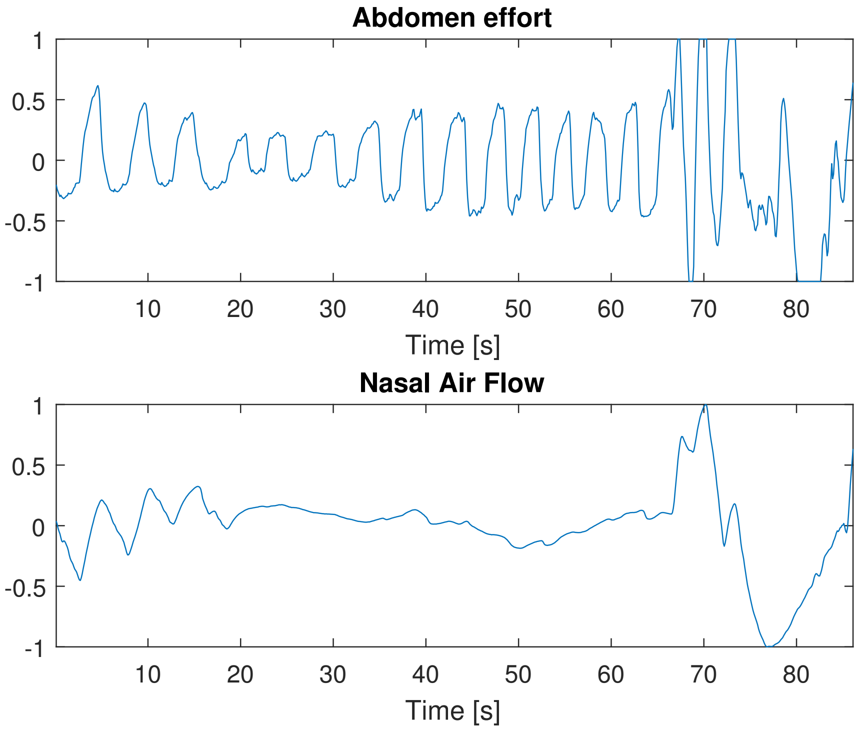

Figure 4: Breathing signals during obstructive apnoa. Patient tries to breathe, but he is not able to inhale.

4 Results

As the classification of breathing signal was done by unsupervised competitive neural network (CNN), it is necessary to evaluate its results in two ways. The first approach is to evaluate outputs as comparison to manual classification by doctor and the second approach is to evaluate results with respect to all events of apnea in a selected signal. Output of a competitive neural network is in Figure 7, with selected detailed part in Figure 8. The CNN was trained on 13 apnea events from 10 patients.

Unfortunately it seems that not all apnea events are included in original classification of polysomnographic data by doctor. That is probably because some of the events have to be detected manually in the whole night records and it is more useful to know about areas when the apnea happened than to manually detect every single one. Even so, it is possible to evaluate result of our competitive neural network by comparison to original classification of sleep apnea. Our approach has accuracy of 94.2 % versus classification of original data with respect to every data point in discrete signal the sampling frequency of with 10 Hz.

The evaluation of the whole output of competitive neural network is more complicated, as the CNN was trained without target data. But with respect to events in signal where the breathing cycle stops, it detects these events from the length of 5 seconds. Best example is in Figure 8 where can be clearly seen (in the third part of Figure 8) that the CNN can detect apnea events that are identical to events classified by doctor (the second part of Figure 8), but that are missing in the original classification by doctor.

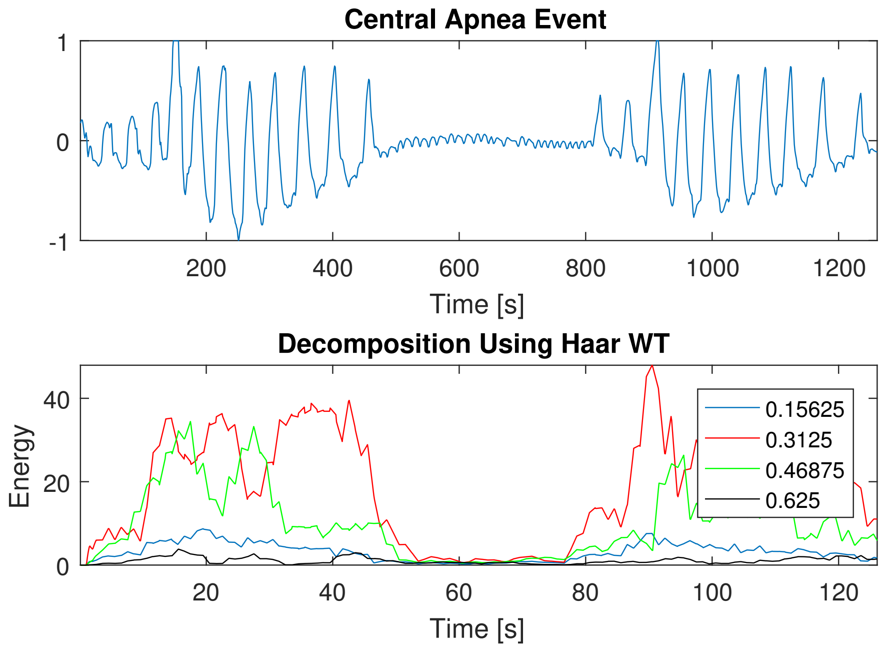

Figure 5: An event of central apnea represented as decorrelated signal, with wavelet decomposition using Haar wavelet up to the 6th level. Each signal is representation of frequency part of breathing signal as energy with respect to energy of the whole analyzed window. The drop of energy in all channels during central apnea event is visible in the middle of the signal.

5 Conclusion

The tested multimodal signal processing approach shows a promise of very precise apnea detection. All original classification of polysomnographic data are manual, so the error of 6.8 % corresponds to error of 0.1 s. That means error around one data sample, which can be unintentionally done during manual selection by doctor. The whole process presented in this paper forms the first step in a more complex approach of sleep apnea detection and classification.

The future aim of this research will be testing current approach to a larger data set of 57 whole night records, from which 25 records are from patient with diagnosed sleep apnea and 32 records are from healthy patients. The additional distinction between all types of apnea will be added, and possibility to detect hypopnea will be tested.

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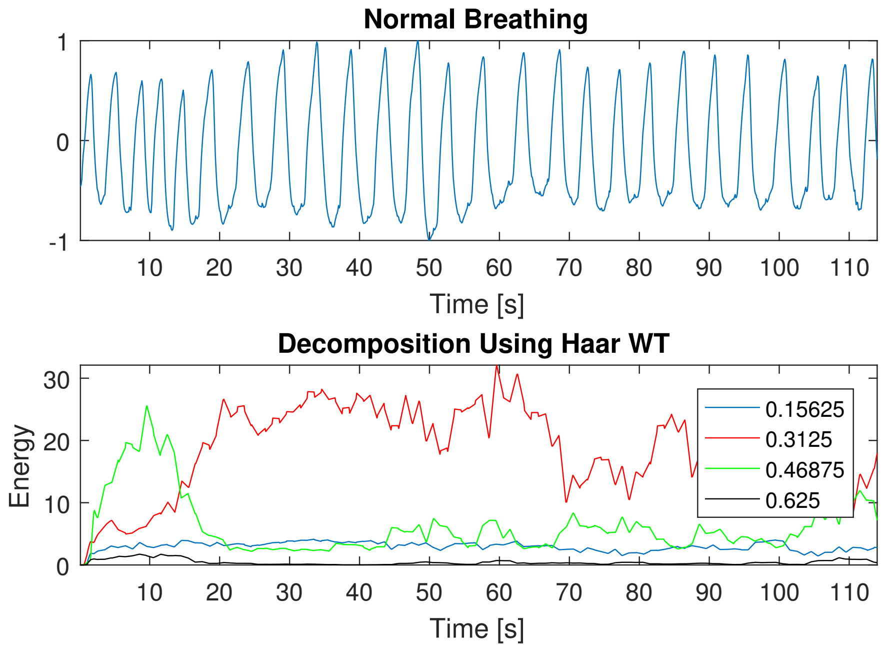

Figure 6: Part with normal breathing represented as decorrelated signal, with wavelet decomposition using Haar wavelet up to the 6th level. Each signal is representation of frequency part of breathing signal as energy with respect to energy of the whole analyzed window.

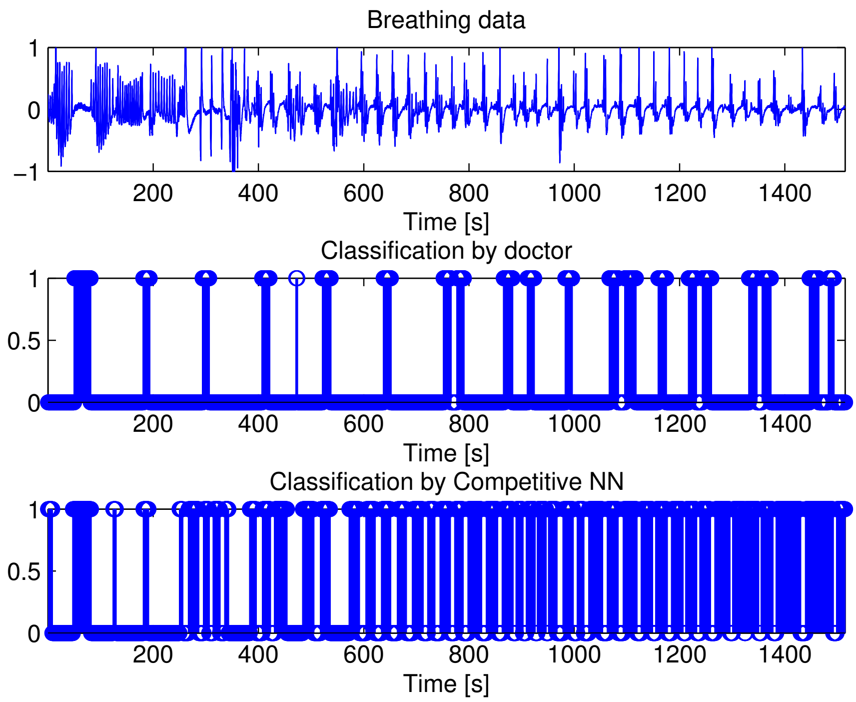

Figure 7: Decorrelated breathing signal with classification of sleep apnea by doctor and classification by competitive neural network.

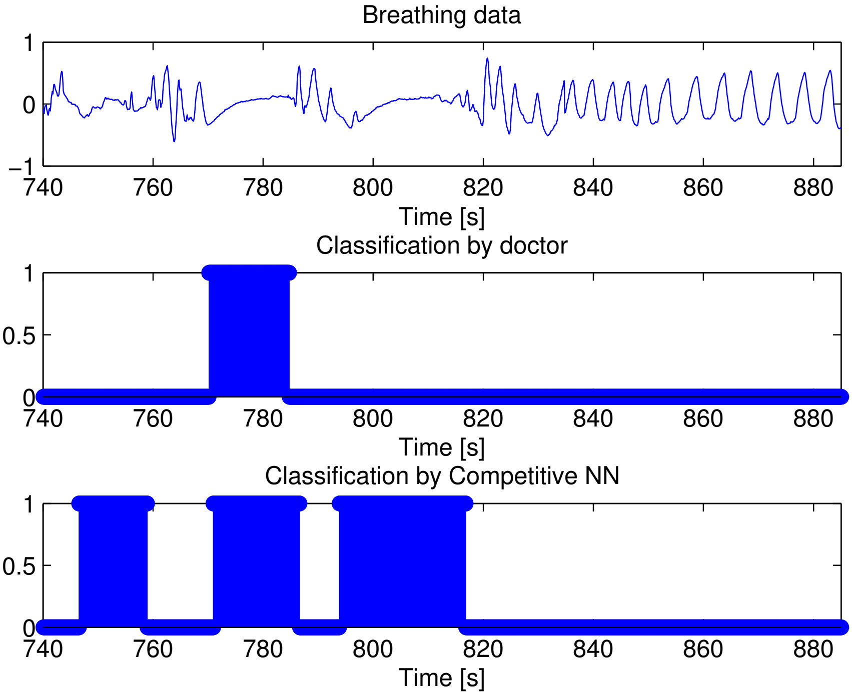

Figure 8: Selection of decorrelated breathing signal from Figure 7 with classification by doctor and classification by competitive neural network.

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