Obstructive Sleep Apnea Classification Based on Spectrogram Patterns in the Electrocardiogram

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Abstract

In this paper we describe the findings of an exploratory study of the effect of obstructive sleep apnea (OSA) on the electrocardiogram (ECG) signal. Episodes of sleep apnea are characterized by periodic cycles of breathing cessation and restoration. Our analysis was guided by the hypothesis that these cycles synchronously alter the ECG. We discovered several characteristic indicators of apnea in the ECG signal.

Our study focused on data sets provided for the Computers in Cardiology (CINC) 2000 apnea classification competition. After careful QRS detection, artifact removal, and preprocessing, we found that we could recognize sleep apnea by visually inspecting spectrograms of various features of the ECG such as the heart rate (HR), S-pulse amplitude, and pulse energy. As part of this study we entered both CINC competitions. We were able to correctly classify 28 out of 30 subjects in our initial competition entry and 30 out of 30 in our third entry. Once each signal was classified as a whole, we were able to correctly classify each minute in 13,626 out of 17,268 cases in our initial entry and 15,994 cases in our fourth entry.

1. Introduction

Our study of obstructive sleep apnea (OSA) was motivated by the *Computers in Cardiology (CINC) 2000 apnea classification competition*. Standard methods of diagnosing OSA are based on respiration monitoring which is intrusive and expensive. Screening for OSA using the ECG alone would save time, money, and discomfort. The premise of the competition was that "the major obstacle to the use of such methods is that careful quantitative comparisons of their accuracy against that of conventional techniques for apnea detection have not been published." While we have not developed an algorithm to do it, we believe that the work we present here demonstrates that it is possible to screen for OSA using the ECG alone.

In the competition data we first observed the large oscillations in O_2Sat. that results from the periodic obstruction of respiration. We noticed that R-R intervals seemed to shorten when respiration was obstructed, and we hoped that the effect was real and could be used to detect OSA. A hasty literature search confirmed that respiration and hypoxia are known to effect heart rate (HR) and ECG pulse energy. A. Patwardhan studied the effect of respiration on heart rate [1]. Tanaka *et al.* studied the response of the heart rate to the cessation of respiration and found the relationship to be nontrivial; at first HR increases and it later decreases [2]. Hirsch and Bishop quantified the "relationship of respiratory sinus arrhythmia amplitude (RSA) to tidal volume and breathing frequency." and noted that the appearance of the respiratory cycle in the HR signal, called RSA, has been known for at least 150 years [3, 4].

2. QRS detection

As a first step in our analysis we implemented our own QRS detection algorithm to extract a number of features in each pulse including the time and amplitude of each element of each PQRST complex and an overall characterization of the amplitude of the complex which we will refer to as the ECG pulse energy (see Figure 1).

3. Preprocessing

After QRS detection, we implemented several stages of preprocessing to remove artifacts and the effect of noise. For the first stage, we eliminated any portion of the signal that was above or below a specified percent of the median.

Second, we effectively low-pass filtered the signal and resampled it at a fixed rate of 100 samples per minute by applying a Gaussian kernel smoother with a standard deviation of 0.3 seconds.

Finally, we applied an anti-aliasing filter and downsampled the signal by a factor of two. This eliminated high frequency noise and reduced the computation required to estimate the spectrogram over the frequency range of interest.
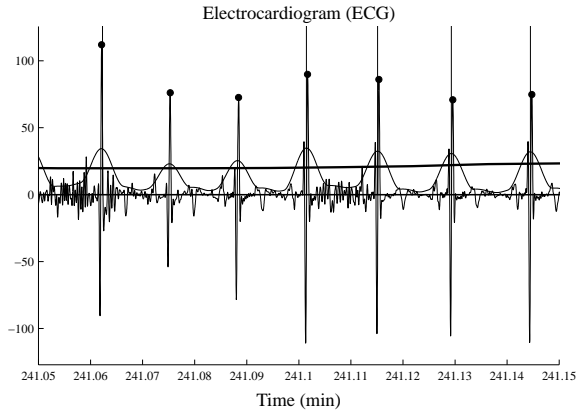
Figure 1. Example of our QRS detection algorithm. The times of the R pulses provided with the data set, shown by the vertical lines, did not include the second and third pulses shown here. The horizontal line shows heart rate. The amplitude and times of the R pulses detected by our algorithm are shown by the dots at the top of each pulse. The ECG pulse energy is shown as a series of bumps centered at each pulse.

4.   Spectrogram estimation

We estimated spectrograms using an FFT applied to a series of signal segments multiplied by a Blackman window. The window length was 256 points (5.12 minutes) and the power spectrum was estimated every 30 seconds.

We also calculated and plotted two estimates of the signal energy. One estimate was the average weighted energy in the same window used to estimate the power spectrum. The second estimate was calculated for only the portion of the signal in the frequency range of 0.50 to 3.50 cpm (cycles per minute), the approximate frequency range of apnea-induced breathing cycles.

We plotted the spectrogram for each signal along with the signal energies and the signal under study.

5.   Discussion

We examined many features of the ECG signals including the intervals between various pulses, the amplitudes of each pulse, the difference between pulse amplitudes, and the ECG pulse energy. We found that the heart rate (R-R intervals) was the most useful for identifying episodes of apnea. We also found that when it was hard to see an OSA signature in the HR, it could sometimes be seen in spectrograms of the amplitude of the S pulses or the ECG pulse energy.

The characteristics of apnea were similar in all of the signals we examined. Figure 2 shows a typical pattern in the heart rate signal during an episode of apnea. This example illustrates several characteristics of the signals that
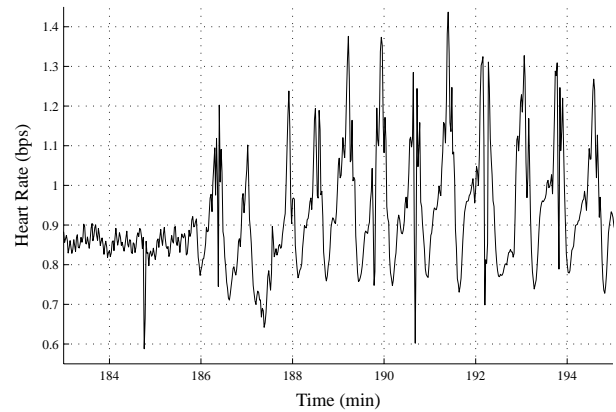

Figure 2. Example of the heart rate during the onset of apnea (£le a03). The expert estimated that apnea began at 186 minutes.
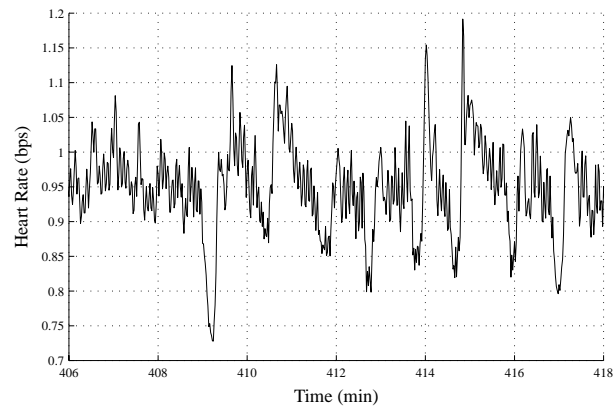

Figure 3. Example of the heart rate during the onset of apnea (£le a05). The expert estimated that apnea began at 410 minutes.

we analyzed. The data contained many glitches, partially due to beats that were not detected by our QRS detection algorithm. In this example, apnea is characterized by slow rises in the heart rate followed by a rapid decrease. Figure 3 shows another typical pattern in the heart rate signal during the onset of apnea. Unlike Figure 2, the episodes of apnea in this signal are characterized by a rapid increase in heart rate followed by a slow decline. However, both signals are non-sinusoidal and have a similar fundamental frequency of 0.5–2.0 cpm. In some cases, third and fourth harmonics of the fundamental frequency could also be observed.

We also observed that the ECG often has transient characteristics at the onset of apnea. Figure 4 shows a typical onset of apnea in the heart rate. After approximately 40 minutes a clear oscillation appears with growing amplitude and decreasing frequency. After minute 70 the amplitude stops growing and the frequency stabilizes.

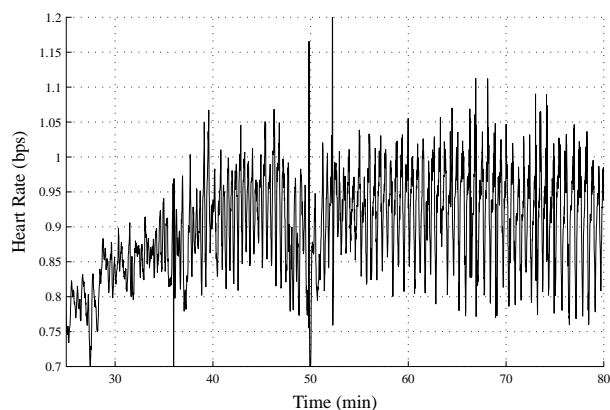Figure 5 shows the spectrogram of the heart rate for the

Figure 4. Example of the onset of apnea (£le a04). The expert estimated that apnea began at 35 minutes and continued throughout the duration of the segment shown.
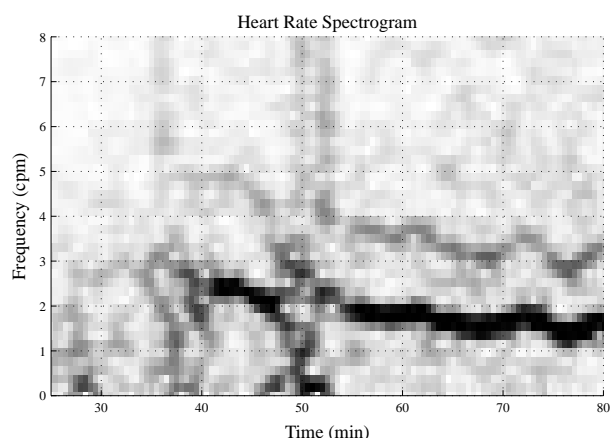

Figure 6. Example of several transitions in the S-pulse amplitudes between apnea and normal respiration (£le a06). The expert classi£ed minutes 260–267 and 306–315 as apnea states.

Figure 5. Example of the spectrogram of the heart rate during the onset of apnea. This is over the same time segment as Figure 4.

Figure 7. Example of normal respiration detected by the spectrogram. This is the same segment as in Figure 6. Note that four harmonics are clearly visible in the £rst apnea segment.

same segment as in Figure 4. The decreasing frequency and growing amplitude are clearly visible in the spectrogram. The glitch that occurs at approximately 50 minutes causes a vertical stripe in the spectrogram. The transients at the onset of OSA limit the effectiveness of methods that rely on stationarity.

We found that intervals of normal respiration are sometimes characterized by a periodic signal at the rate of respiration. The expert consistently labeled these segments as non-apnea states. Figure 6 shows this type of segment in the S-pulse amplitude signal. Figure 7 shows the spectrogram of the same segment. For this subject, episodes of non-apnea are characterized by a strong periodic respiration signal at approximately 14 cpm.

Although the HR (R-R intervals) was generally more accurate for detecting apnea than the S-pulse amplitudes or the ECG pulse energy, occasionally the heart rate was
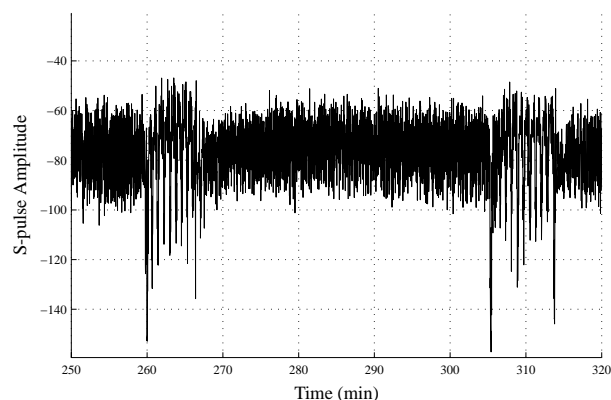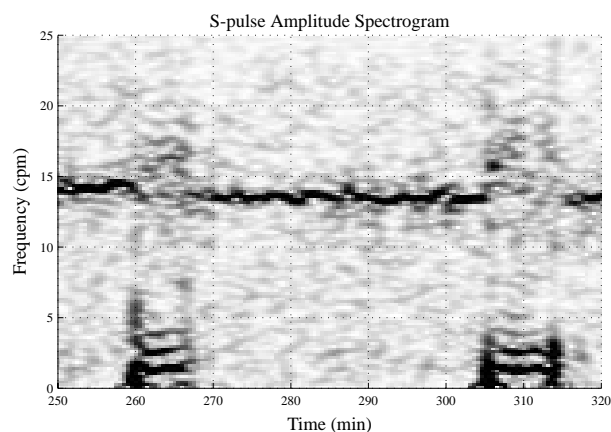
misleading (See Figures 8 and 9).

6.　　Results

We initially tried to classify each minute by estimating how much energy was in the frequency range of 0.5–2.2 cpm of the heart rate. Although we were able to consistently classify the labeled data set with an accuracy of approximately 83–86%, we found that this method often mislabeled segments that were apparent to us visually.

Second, we tried hidden Markov models (HMM's) methods developed for speech recognition. Although we were able classify the labeled data set with an accuracy of 80–87%, we found again that the mislabeled segments were apparent visually.
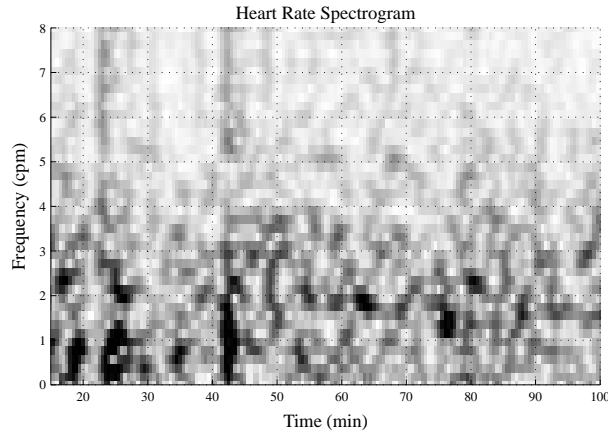
Heart Rate Spectrogram

Figure 8. Example of the heart rate spectrogram displaying a false signature of apnea. The expert estimated that apnea began at 33 minutes and continued throughout the duration of the segment shown.
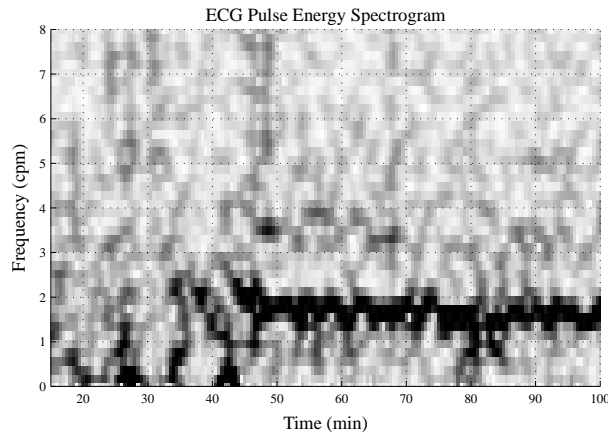
ECG Pulse Energy Spectrogram

Figure 9. Example of the ECG pulse energy spectrogram displaying a strong signature of apnea. This is the same segment as shown in Figure 8.

Finally, we tried labeling the segments manually based on the signatures in the spectrogram and we found that we could do this with an accuracy of approximately 90–93%. We decided to submit an entry to the competition based on our manually labeled signals. In our fourth attempt we achieved an accuracy of 92.6% on the test set. Table 1 summarizes the methods we used to generate each entry and our corresponding scores.

7.   Conclusions

In this paper we described our £ndings from an exploratory study of how sleep apnea affects the electrocardiogram. We found that episodes of apnea could be characterized by a periodic oscillation in the electrocardiogram with a fundamental frequency of 0.5–

Table 1. Summary of methods used to generate competition entries and the corresponding results.

Apnea Screening	
Method	Score
Inspection of heart rate signal	28/30
Inspection of heart rate spectrograms	29/30
Inspection of heart rate and S-amplitude spectrograms	30/30

Quantitative Assessment of Apnea	
Method	Score
Energy above manual threshold	13,626
Hidden Markov Models	14,474
Inspection of heart rate and S-amplitude spectrograms	15,668
Inspection of heart rate, S-amplitude, and ECG pulse energy time series and spectrograms	15,994

2.0 cpm. There was signi£cant variation in the shape of this pattern among subjects and affected different elements of the ECG including the heart rate (R-R intervals), S-pulse amplitude, and the ECG pulse energy. Due to complexity of the patterns and variation among subjects, we found that we could manually classify the ECG more accurately than the algorithms that we developed.

References

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