Neural Net based arrhythmia analysis software

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Abstract

Many studies have shown a strong link between cardiovascular disease and sleep disorders. A new, innovative, neural network based analysis software, capable of accurately detecting heart rate variability and many cardiac arrhythmias for the sleep specialist, was developed and tested. The wave analysis section, that detects heartbeats, has a 98.7% accuracy and the neural network based section has greater than a 96% success categorizing heartbeats as normal or to a specific arrhythmia.

Introduction

A new method for accurately detecting heart rate variability and many cardiac arrhythmias for the sleep specialist, was developed and tested. Many studies have shown a strong link between cardiovascular disease and sleep disorders (1). Therefore, it is important for sleep monitors to accurately detect cardiac events during Polysomnography to identify those patients who need a referral to a cardiologist for further diagnosis.

The newly developed CleveMed heartbeat and arrhythmia analysis software is designed to analyze electrocardiogram (ECG) signals, calculate the heartbeat and detect heartbeat arrhythmia. The software consists of a wave analysis section, to detect the waveform specifics and heartbeat, and a neural network based section, to classify the arrhythmia. We found the wave analysis section to have a 98.7% accuracy and the neural network based section to have greater than a 96% success rate.

Methods

The heartbeat database used for the CleveMed heartbeat and arrhythmia analysis software is a collection of the 48 ECG recordings from the MIT-BIH Arrhythmia Database (2). The database consists of over 108,000 heartbeats and textual annotations concerning each heartbeat, and was used to validate the wave analysis software (WAS). The WAS matched an annotation from the database if the heartbeat detected by the algorithm was within +/- 0.0416 s (15 samples) of the annotation. The number of matches was also used as a measure of how well the WAS correctly identified heartbeats.

Subsequently, the detected heartbeats were used as inputs for the arrhythmia detection neural network (ADNN). The ADNN uses 13 waveform specific inputs to classify each heartbeat into an arrhythmia group. The ADNN then outputs classification groups associated with one or more particular arrhythmias. Ideally, each classification would have a 100% association with a single arrhythmia (or normal). The ADNN identified normal, left and right bundle branch block, atrial, aberrated atrial, nodal and supraventricular premature, ventricular contraction, atrial, nodal and ventricular escape beat, and non-conducted P-wave types of heartbeats.

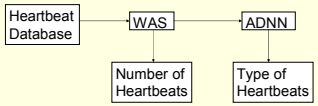

Fig. 1. The analysis software consists of two steps, the wave analysis software (WAS) and the arrhythmia detection neural network (ADNN).

Conclusions

A new heartbeat and arrhythmia analysis software was developed. The software includes a wave analysis section to detect the heartbeat waveform and a neural network based section to classify the arrhythmia. This analysis software promises to generate an accurate heart rate variability and cardiac arrhythmia detector. Future work will include additional testing and further neural network training.

Literature cited

1. Roux F, D'Ambrosio C, Mohsenin V. Sleep-related breathing disorders and cardiovascular disease. Am J Med. 2000 Apr 1;108(5):396-402.
2. http://www.physionet.org/physiobank/database/html/mitdbdir/mitdbdir.htm

Acknowledgments

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For further information

More information on this and related projects can be obtained at www.CleveMed.com.

Results

We found the wave analysis section to have a 98.7% accuracy and the neural network based section to have greater than a 96% success rate. The cardiac event analysis software displays data in three different ways. The heartbeats are detected and the R-R interval is calculated for each heartbeat (Fig 2). The ECG trace is plotted with the abnormal heartbeats labeled (Fig 3). A histogram shows the number of heartbeats detected in each of 20 different types (Fig 4).

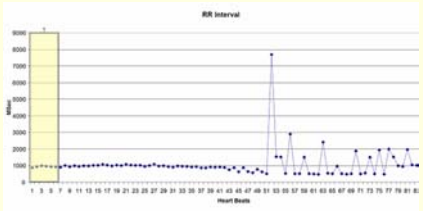

Fig. 2. The R-R interval is calculated for each heartbeat.

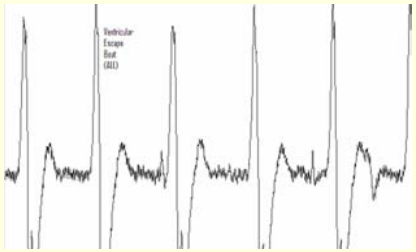

Fig.3. The ECG trace is plotted with any abnormal heartbeats marked.

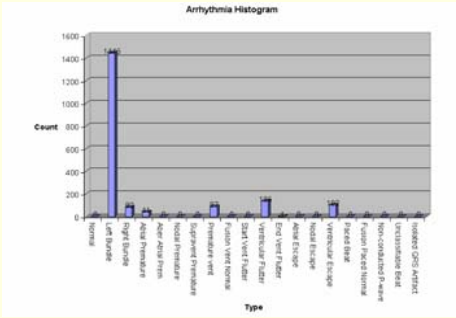

Fig. 4. A histogram is generated for each patient to give a summary of any abnormal ECG activity.

Of the 5,512 annotations from the database without a heartbeat detected by the WAS, 960 were excluded as lead in and lead out phases, and another 2,316 were comments (not heartbeats). The remaining 2236 MIT annotations (2.1%) without an identified CleveMed heartbeat seem to be genuine misses. Two typical errors conditions include when there is no identifiable heartbeat pattern (wild, random signals) and when a heartbeat bordered between being normal (upward) or inverted (downward). Based on an estimated 692 missed heartbeats being due to a difference in the interpreted direction of the QRS complex, the number of annotations without an identified CleveMed heartbeat is only 1544.

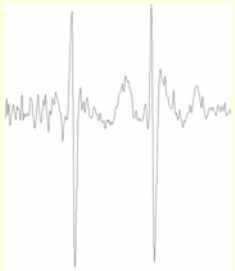

Fig. 5. The similar positive and negative deflection amplitude of these heartbeats makes using a threshold to detect R ineffective. Additional wave characteristics must be used. However, additional characteristics may not be clearly defined.

If one adds the 108,486 heartbeats identified by CleveMed, the 1544 MIT annotations without an identified CleveMed heartbeat and the 960 purposely missed heartbeats, the total count of MIT heartbeats becomes 110,990. Separate references mention that there are approximately 110,000 heartbeats in the MIT database. It seems our numbers are consistent with this observation.

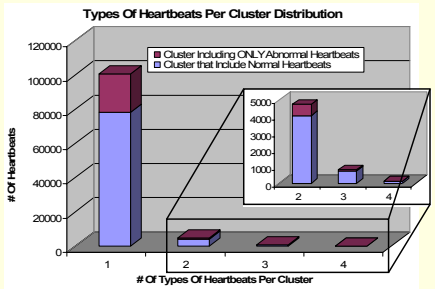

Fig. 6. Over 96% of the heartbeats were correlated with 100% confidence to one type of heartbeat.

The ADNN created 7,117 clusters of heartbeats. 5,866 of the clusters were 100% correlated to one type of heartbeat. The remaining 1251 clusters, approximately half of the clusters showed a mixture of arrhythmia and half showed a mixture of arrhythmia and normal heartbeats. Typically, the mixed types within a cluster were limited to two types. The 1,251 non-100% correlated clusters consisted of 4,233 heartbeats. Therefore, the ADNN correlated over 96% of the heartbeats with 100% confidence.

In order to not confuse the end user, the output software would reduce the complexity of the output. In other words, if clusters 5, 12, 18, 25, 44 and 78 produced high concentrations of "premature ventricular contraction" and the output cluster for the incoming waveform was cluster 12, the end user would just be told that there was a high probability that the waveform was of the type "premature ventricular contraction".