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Detection of the electrocardiogram P-wave using wavelet analysis*

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ABSTRACT

Since wavelet analysis is an effective tool for analyzing transient signals, we studied its feature extraction and representation properties for events in electrocardiogram (EKG) data. Significant features of the EKG include the P-wave, the QRS complex, and the T-wave. For this paper the feature that we chose to focus on was the P-wave. Wavelet analysis was used as a pre-processor for a backpropagation neural network with conjugate gradient learning. The inputs to the neural network were the wavelet transforms of EKGs at a particular scale. The desired output was the location of the P-wave. The results were compared to results obtained without using the wavelet transform as a pre-processor.

1. INTRODUCTION

The wavelet transform has emerged as an effective tool for analyzing transient signals with short-time behavior. Comparisons between the wavelet transform and more conventional methods such as the Fourier transform have been discussed extensively in the literature.[1,2,3] The localization properties of the wavelet transform are particularly attractive, especially for problems involving feature extraction. The feature that this research is interested in is the P-wave of the EKG. The P-wave is an important indicator of atrial activity in the heart.[4] However, its detection is sometimes made difficult by its relatively small amplitude and its nearness to the QRS complex. We seek in this paper to answer the following question:

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Will taking the wavelet transform of the EKG help in locating the P-wave? In the remainder of this section we define the wavelet transform, give a brief description of the structure of the EKG, and then discuss applications of the wavelet transform to the EKG.

1.1 Definition of the wavelet transform

The wavelet transform of a signal $f(t)$ with respect to the wavelet $g(t)$ is defined as:

$$W_g f(a, b) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{\infty} f(t)\, g^*\left(\frac{t-b}{a}\right) dt \tag{EQ 1}$$

where $g\left(\frac{t-b}{a}\right)$ is obtained from the "mother" wavelet $g(t)$ by dilation a and translation b operations.[5] Unlike the Fourier transform where sinusoids of infinite duration are the basis functions, the basis functions (wavelets) utilized in the wavelet transform decay rapidly to zero. In addition, they are oscillatory and have zero-mean. Stated mathematically, the "mother" wavelet should satisfy the following *admissibility condition*:

$$\int_{-\infty}^{\infty} \frac{|G(\omega)|^2}{|\omega|} < \infty \tag{EQ 2}$$

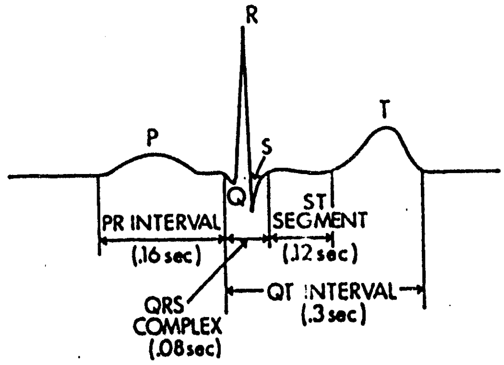
where $G(\omega)$ is the Fourier transform of $g(t)$.

Looking at the wavelet as a windowing function, we see that the scale a and the size of the window are dependent on each other (in contrast to the short-time Fourier transform where ω and window size are independent of each other). The window used in the short-time Fourier transform is fixed, thus all frequency behavior is not treated equally. On the other hand, the window used in the wavelet transform is flexible, it narrows (small a) for high frequency behavior and widens (large a) for low-frequency behavior. Another important feature of the wavelet transform is that the analyzing wavelet can be arbitrarily chosen to fit the particular application. For an in-depth look at wavelet theory the reader is referred to the books by Chui[6] and Daubechies[7].

1.2 Brief description of the EKG

Due to its short-time transient nature, the EKG is a good candidate for study using the wavelet transform. The EKG represents the electrical activity of the heart where its primary features are the P-wave, the QRS complex, and the T-wave (see Fig. 1). The P-wave represents the electrical activation of the atria, which initiates atrial contraction. The QRS complex, the most identifiable feature of the EKG, represents the electrical activation of the ventricles, which initiates ventricle contraction. There is a delay between the end of the P-wave and the beginning of the QRS complex which represents the conduction time of the atrioventricular node. Ventricular repolarization is represented by the T-wave.[8,9] The amplitude, duration, and rhythm of these features (particularly the P-wave and the QRS complex) are used to aid in identifying abnormalities.

FIGURE 1.



Primary features of the EKG[9]

1.3 The EKG meets the wavelet transform

The use of the wavelet transform for EKG analysis has been studied by several groups.[10,11] Some of the most promising results have involved the detection of very late potentials (VLP).[12,13] In fact, the success of the wavelet transform in detecting VLP provided the motivation for using it in locating P-waves. Our approach uses the wavelet transform as a pre-processor for a backpropagation neural network with conjugate gradient learning.[14] The goal is for the network, using a wavelet decomposition of an EKG cycle as input, to be able to locate the P-wave.

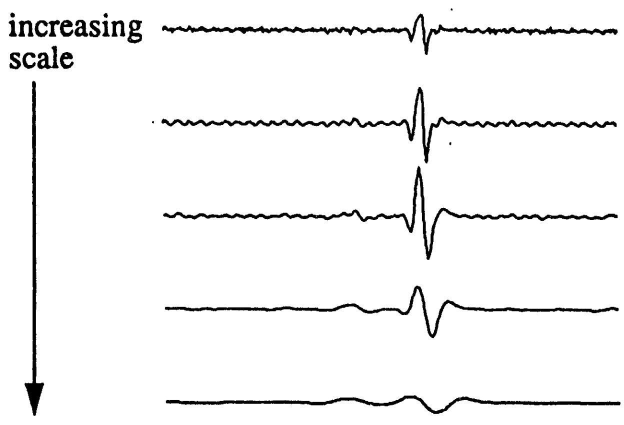
2. PROCEDURE

The data used was taken from a resting EKG sampled at 1 kHz for approximately 4 minutes. This data was divided into 300 individual cycles and then each of these cycles was subsampled by 2 and truncated, so that we ended up with each cycle containing 316 points. The cycles could have been subsampled further, but there was concern about retaining important features of the signal. The intact P-wave and QRS complex were randomly moved to different positions in the cycle. This was done 5 times for each cycle resulting in 1500 different EKG cycle files.

The next step was to obtain a wavelet decomposition of each of these cycles. This was accomplished with Mallat and Zhong's XWAVE1 package. The particular wavelet used in this package is a quadratic spline of compact support and is illustrated and defined in one of their recent papers.[15] We took decompositions at five different scales (Fig. 2) and it was found that one particular scale (2nd from bottom in Fig. 2) seemed the most appropriate to use as input to the neural network. Reasons for choosing only one scale were (1) to keep to a minimum the amount of input data, and (2) the other scales did not seem to contain strong information about the P-wave.

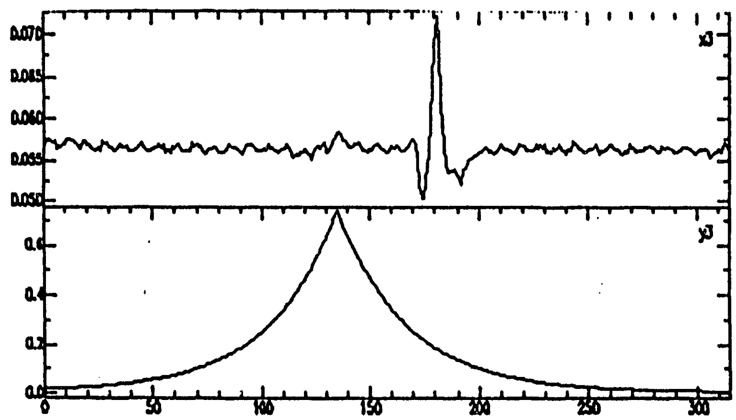
Thus, each of the 1500 cycles was wavelet transformed and the one scale mentioned above was kept as input. 1200 of these were used for the training set. The desired output was a function that indicated the location of the highest point in the P-wave (see Fig. 3). It was found that the width of this locator function was an important factor in training of the network. Using a narrower function made it more difficult (requiring more iterations) to train the network. The neural network that was trained had a 316 node input layer, one 5 node hidden layer, and a 316 node output layer. After training, the network was tested with a set of 100 cycles that were not part of the training set.

FIGURE 2.



Wavelet decomposition of one EKG cycle at five scales.

FIGURE 3.



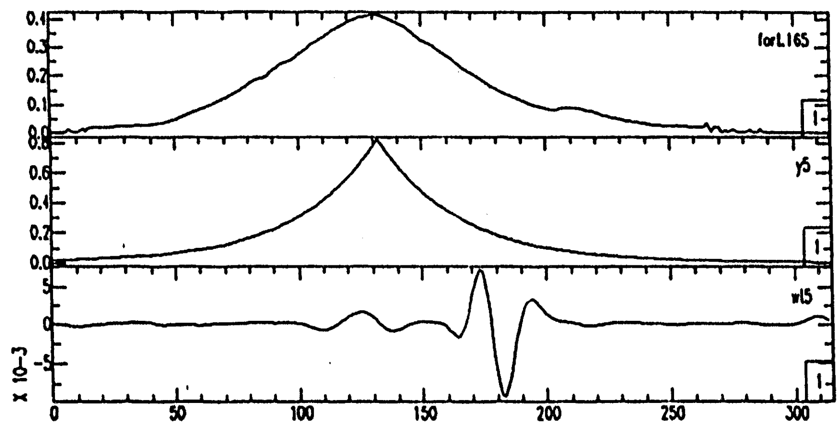
EKG cycle and its P-wave locator function

3. RESULTS

A network trained for 3600 iterations with the wavelet decomposition at one scale as input, was able to locate the P-wave peak to within 10 data points for 70 cases of the test set, where for 48 cases the P-wave peak was located to within 5 points. Now, when instead the original EKG signal was used as input (for training and testing), the network was able to locate the P-wave peak to within 10 points for 52 cases of the test set, where for 30 cases the P-wave peak was located to within 5 points. An example of an output from the network for one of the test set (wavelet decomposition as input) is contrasted to the desired output in Figure 4.

These preliminary results were promising in that by using the wavelet decomposition instead of the original EKG signal to test and train the network, the network located the P-wave more often. We then increased the number of iterations to train the network to 5400. The performance of the network using the wavelet decomposition as input did not change significantly from the results stated in the previous paragraph, however, the performance of the network using the original EKG signal as input increased to the point where it was performing better than that using the wavelet decomposition as input.

FIGURE 4.



From bottom to top: test input to network, desired output, actual output from network

4. DISCUSSION

From the results, it would seem that if one is concerned with computation time (in our case, training for the extra iterations was computationally expensive), then using the wavelet transform as a pre-processor did indeed help in locating the P-wave more accurately. However, if one is not concerned about computation time then it seems that given enough iterations the network can be trained well enough by just using the original EKG signal. Overall, the results would seem to be inconclusive regarding the effectiveness of using the wavelet transform as a pre-processor for this application.

In terms of further study, it would be interesting to try to locate other features of the EKG (such as the T-wave) using the same methodology. In addition, we are currently investigating using different "mother" wavelets as basis functions when taking the wavelet transform of the EKG. Another option being considered is inputting more than one scale of the wavelet transform to the neural network. The problem with this option is that the input vector size would increase by at least two times, thereby increasing the size of the required training set.

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