Using Wavelet Transform to Detect R-peaks in ECG Signal

1st Chandrakishor Singh
Department of Information Technology
Indian Institute of Information Technology, Allahabad
mit2021117@iiita.ac.in

2nd Dablu Chauhan
Department of Information Technology
Indian Institute of Information Technology, Allahabad
mit2021115@iiita.ac.in

3rd Madhu Donipati
Department of Information Technology
Indian Institute of Information Technology, Allahabad
mit2021116@iiita.ac.in

***Abstract*—This paper presents a fundamental introduction to the wavelet and wavelet transform. We begin with the discussion on what a wavelet is and how it is different from a wave. We then define the wavelet transform as a transformation which retains both the local spectral and temporal information which makes it a better alternative than Fourier transform for finding the characteristics of the signal that has a low frequency. Finally, we demonstrate the usage of wavelet transform to detect the R-peak, which is the highest amplitude point in an ECG signal. The demonstration is done through Octave and a time series dataset of electrical signals of the heart.**

***Keywords*—Wavelet, Wavelet Transformation, QRS complex, R-peak, ECG**

I. Background

A. Wavelet

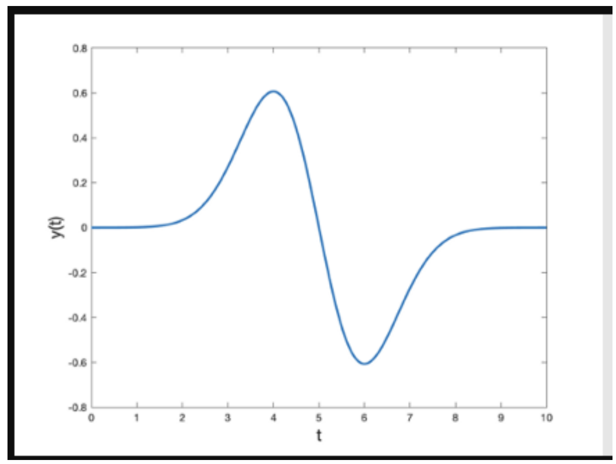
In Fourier Transform, a wave is defined as a quantity that has amplitude and frequency. A wavelet is similar to a wave but it has 2 properties that makes it different from a wave defined for the Fourier transform. [2]

A wavelet is a wave-like oscillation that has "scale" property and "location" property. The scale, which is also referred to as dilation, defines the stretch of the wave and is related to the frequency which is defined for the wave. And the location property defines where the wavelet is located with respect to time or space. [2]

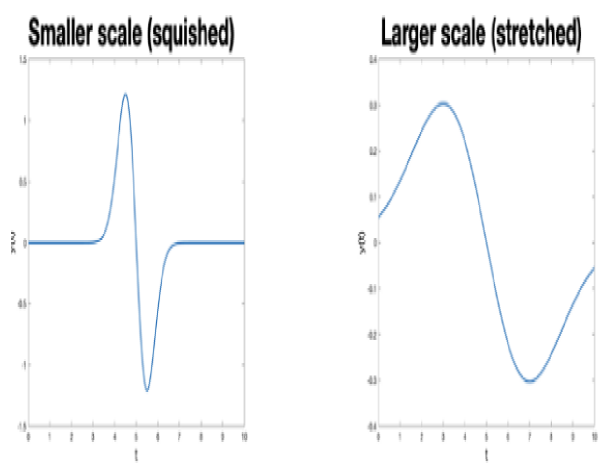
A simple wavelet can be defined with the help of the derivative of the Gaussian function as follows.

$$f(x) = ae^{-(x-b)^2/2c^2}$$

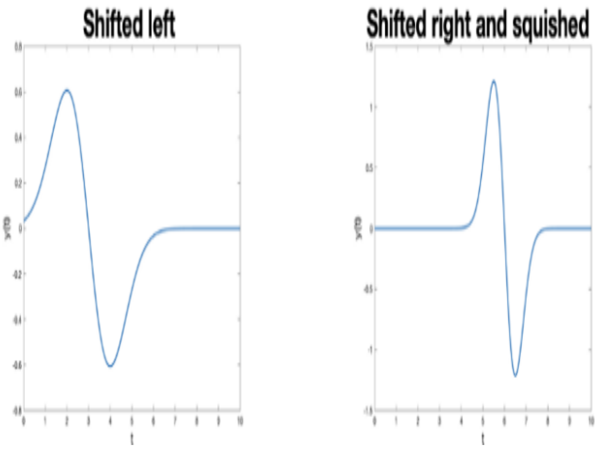
Its plot will look something like the below image.



The parameter "a" defines how much the wavelet is stretched. If we increase the value of a then the wave will look more stretched in the horizontal direction. On the other hand, if we decrease the value of "a" then the wave will look more squeezed in the horizontal direction.



And the other parameter b defines the location of the wavelet in time or space. Increasing the value of b will result in the wavelet to be shifted to the right side as follows. While decreasing the value of b will shift the wavelet in the left side.



B. Wavelet Transform

Wavelet transformation is a type of transformation which is similar to Fourier transformation but the only difference is that instead of using an infinite sum of sinusoidal function, Wavelet transform tries to find out the extent to which a wavelet(defined for this particular transformation) is present for a given scale and location. [4]

This is similar to convolution of the wavelet over the entire signal. Practically, this is calculated by selecting a wavelet of a particular scale. It is then passed to the entire signal by varying its location. At each point in the location the wavelet is multiplied by the signal and this gives the coefficient for that wavelet at that particular location of the signal. Then the same process is repeated by increasing the scale of the signal. [4]

There are two kinds of wavelet transformation. These are Continuous Wavelet Transform(CWT) and Discrete Wavelet Transform(DWT).

- Continuous Wavelet Transform(CWT): In continuous wavelet transform, the "Mother(or basis)" wavelets are defined everywhere. Its equation is as follows.

$$T(a,b) = 1/\sqrt{a}\int_{\infty}^{-\infty} x(t)\psi^*((t-b)/a)dt$$

- Discrete Wavelet Transform(DWT): In discrete wavelet transform, the "Mother(or basis)" wavelets are defined everywhere. Its equation is as follows.

$$T_{m,n} = \int_{\infty}^{-\infty} x(t)\psi_{m,n}(t)dt$$

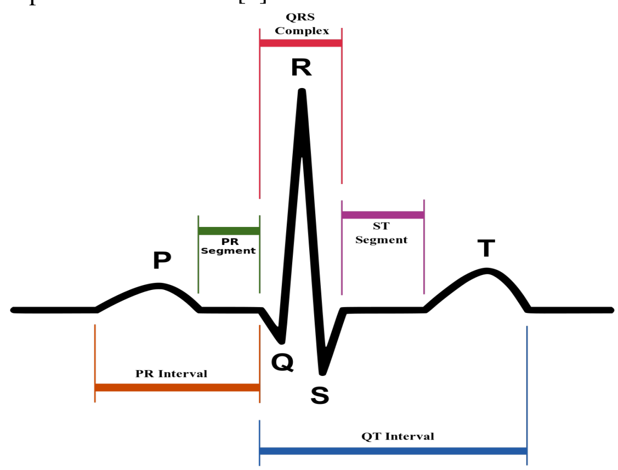
C. Comparison with Fourier Transform

The Fourier transform represents a signal as a sum(possibly infinite) of sinusoidal waves. This can be viewed as a special case of the Wavelet Transform where the mother wavelet is $\psi(t) = e^{-2\pi\iota t}$. The Fourier transform is only localized in frequency domain while the Wavelet transform is localized both in frequency and time domain. [4]

A variant of Fourier transform called Short-time Fourier transform is similar to wavelet transform because in this transformation, the Fourier transform is only applied on a segment of the entire signal.

II. QRS COMPLEX

The QRS complex is the combination of 3 seemingly different signals of an electrocardiogram. This is the central and most visible part of the signal and it corresponds to the contraction and inflation of the heart. A diagram of the QRS complex is as follows. [5]



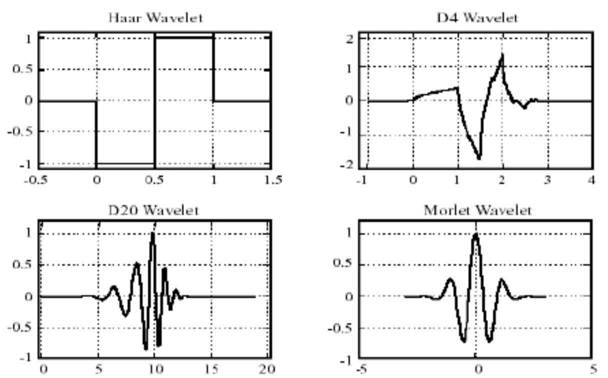
We can see that the R section of the complex has the highest peak. The time duration of the QRS complex is about 80 to 100ms. Hence its frequency is relatively high.

A. Why Wavelet Transform over Fourier Transform ?

In this paper, we attempt to detect the R-peak of this QRS complex. It is closely related to heart activity. Detecting the R-peak and thus heart rate activity is very important in finding the Heart Rate Variability(HRV).

To detect the R-peak, Wavelet transform is used instead of Fourier transform. This is because of the following reasons. [5]

- The QRS complex duration is very small(about 80 to 100ms). Fourier transform is applied over the entire signal which won't give good results as these waves are localized and live for very small duration. We could use a variant of Fourier transform called Short-Time Fourier transform which is essentially a Fourier transform but is applied over a segment of the entire signal rather than the complete one. However, this will require us to apply the transform multiple times as there will be many QRS complexes in one signal and hence creating multiple segments of the signal and then applying Fourier transform will result in poor performance.
- There are many shapes(obtained by choosing different scales) of wavelets that can be selected to best suit the requirement of the application. Since, here we want to detect the R-peak which has a shape of a sharp bell curve, it is preferable to have a wavelet with similar shape. Some of the common wavelets are as follows.



B. Maximal Overlap Discrete Wavelet Transform(MODWT)

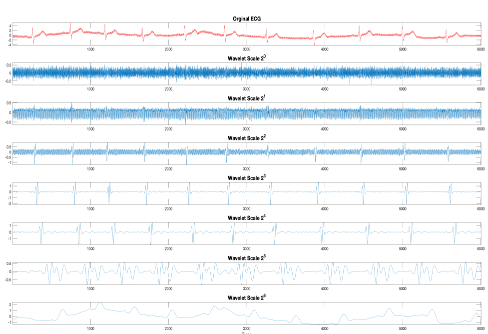
The real world ecg signal of QRS complex is usually very noisy. The common peak finding algorithms will fail to find the R-peak as it will become difficult to find them when data becomes noisy. Hence, it is important to convert the signal into a more "cleaner" form that will be easier for the peak finding algorithm to work with. [5]

Here, we are using a wavelet called Symlet with 7 different scales that has 4 vanishing moments. This wavelet is derived from the Daubechies wavelets with increased symmetry and the name of the transform with this particular wavelet is Maximal Overlap Discrete Wavelet Transform(MODWT).

III. Experimental Analysis

A. Analyzing the Data

Below is a plot of the original ECG data along with the wavelet coefficients for each scale.

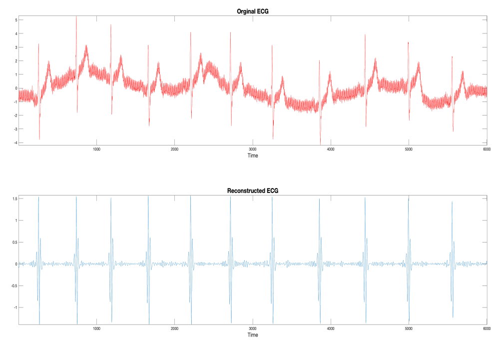


We can see that for the smaller scale like 20, 21 the frequency is high and also the noise. As the scale is increased, we can see the peaks of the signal which correspond to R-peaks. For the high scales, the frequency becomes very low and the peak becomes very small.

B. Reconstructing the Original Signal

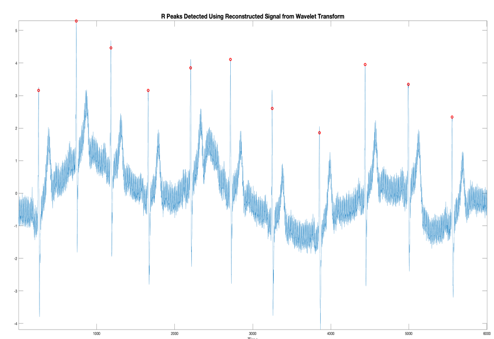
Now, we will reconstruct the original image from a subset of the wavelet scales that we have chosen above. The scale of 23 looks promising as the peaks are very similar to how the QRS complex looks like. Also, we can use the fact that these signals persist for only 80 to 100ms to find the best subset of scales to choose from.

The original ECG signal and the reconstructed one are plotted below.



We can clearly see that the peaks of the original signal and those of reconstructed ones are in sync with each other. Therefore, now we can give the reconstructed signal to a peak finding algorithm to find the peaks rather than the original one.

Lastly, we will use the reconstructed signal to find peaks using the findpeaks function of octave.



IV. Applications

Some other important applications of the wavelet transform are as follows.

- **Audio Compression:** Wavelet Transform is widely used in audio compression. In audio compression, we use the discrete wavelet transform it is a very useful tool for signal compression. Speech compression is mainly used in mobile communication to reduce the transmission time. Effective speech and audio compression algorithms use knowledge of human hearing. Human hearing is associated with critical bands. In audio compression, the audio signals can be divided into voice and unvoiced sounds. Voiced sounds have mainly low-frequency content, whereas unvoiced sounds have energy in all frequency bands. Human hearing is associated with nonuniform critical bands, which can be approximated using a four-level dyadic filter bank.
- **Image and video compression:** Wavelet transform is used in image and video compression. In this, we extract low frequencies of image and video are extracted by high scale wavelet function. In image compression, JPEG image compression is well-known image compression, in which the image is transformed by performing the

discrete wavelet transform in the vertical and horizontal direction. After the discrete wavelet transform, all coefficients are quantized.
- **Speech Recognition:** Wavelet transform has become a popular tool for speech processing, such as speech analysis, pitch detection, and speech recognition. In speech recognition wavelets are successful front-end processors for speech recognition, by exploiting the time resolution of the wavelet transform. For speech recognition, the recognition performance depends on the coverage of the frequency domain. The goal for good speech recognition is to increase the bandwidth of a wavelet significantly affecting the time resolution. This can be done by wavelet transform.

V. Conclusion

This report draws attention towards Wavelet and Wavelet transform. We have demonstrated the reason and use of wavelet transform in detecting the R-peak of ECG signals using Octave. Along with that, some other existing applications of wavelet transform are also discussed.

Contributors

- Chandrakishor Singh : Research & Writing on Wavelet, Wavelet Transform, Comparison with FT, QRS complex, Coding & Analysis
- Dablu Chauhan : Research & Writing on Applications Wavelet Transform
- Madhu Donipati : Research & Writing on QRS complex

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References

[1] P.S. Addison. The Illustrated Wavelet Transform Handbook. IOP Publishing Ltd, 2002. ISBN 0-7503-0692-0.

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[4] Wikimedia Foundation. (2021, October 3). Wavelet Transform. Wikipedia. Retrieved October 22, 2021, from en.wikipedia.org/wiki/Wavelet_transform

[5] Wikimedia Foundation. (2021, October 13). QRS Complex. Wikipedia. Retrieved October 22, 2021, from https://en.wikipedia.org/wiki/QRS_complex

VI. Appendix

Octave code used in the paper is as follows.

```
load('ECG_data.mat');

levelNumber = 6;
wt = modwt(ECG, 'sym4', levelNumber);

[numScales, ~] = size(wt);

fig = figure(1);
fig.Units = 'normalized';
fig.Position = [0 0 1 1];

subplot(numScales+1,1,1)
plot(ECG, 'r-')
title('Orginal ECG', 'FontSize', 14)
axis tight

for i=2:numScales+1

    subplot(numScales+1,1,i)
    plot(wt(i-1,:))
    title(strcat('Wavelet Scale 2^', string(i-2)),
    axis tight
end

xlabel('Time', 'FontSize', 14)

print('waveletTransform_signal_decomposition', '-d

fig = figure(2);
fig.Units = 'normalized';
fig.Position = [0 0 1 1];

recwt = zeros(size(wt));

recwt(4,:) = wt(4,:);

recECG = imodwt(recwt,'sym4');

subplot(2,1,1)
plot(ECG, 'r-')
title('Orginal ECG', 'FontSize', 16)
xlabel('Time', 'FontSize', 14)
axis tight
subplot(2,1,2)
plot(recECG)
title('Reconstructed ECG', 'FontSize', 16)
xlabel('Time', 'FontSize', 14)
axis tight

print('waveletTransform_reconstructed_signal', '-d

t = 1:length(ECG);

recECG = abs(recECG).^2;
[qrspeaks,locs] = findpeaks(recECG, t, 'MinPeakHei

fig = figure(3);
fig.Units = 'normalized';
fig.Position = [0 0 1 1];
```

```
plot(t,ECG)
hold on
plot(locs,ECG(locs),'ro', 'LineWidth',2)
xlabel('Time', 'FontSize', 14)
title('R Peaks Detected Using Reconstructed Signal from Wavelet Transform', ...
    'FontSize', 16)
axis tight
print('waveletTransform_rpeak_annotation', '-dpng');
```