EKG De-noising using 1-D Wavelets Techniques

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Abstract

The electrocardiogram (ECG or EKG) is a graphic recording or display of the time- variant voltages produced by the myocardium during the cardiac cycle. The P, QRS, and T waves reflect the rhythmic electrical depolarization and re-polarization of the myocardium associated with the contractions of the atria and ventricles. The electrocardiogram is generally used clinically in diagnosing various diseases and conditions associated with the heart. It also serves as a timing reference for other measurements. Hence its accurate measurement is a must.

A normal EKG waveform consists of common mode noises such as dc electrode offset potential and 50 or 60 Hz ac-induced interference. This paper presents the study of filtering these noises using 1-Dimensional wavelets theory. Wavelets are mathematical functions that cut up data into different frequency components, and then study each component with a resolution matched to its scale. They have advantages over traditional Fourier methods in analyzing physical situations where the signal contains discontinuous and sharp spikes.

1. Introduction to EKG

The electrocardiogram (ECG or EKG) is a graphic recording or display of the time-variant voltages produced by the myocardium during the cardiac cycle. [1] It is the physiological measurement of the cardiovascular systems. Cardiovascular system is the transport system of the body, by which food, oxygen, water and all other essentials are carried to the tissues and cells and their waste products are carried away. It comprises of blood, blood vessels (arteries, capillaries and veins), and the heart. ECG was originally observed by Waller in 1889 using his pet bulldog as the signal source and the capillary electrometer as the recording device. In 1903, Einthoven enhanced the technology by employing the string galvanometer as the recording device and using human subjects with a variety of cardiac abnormalities [2].

1.a Basic Waveform

The record of the bio-potentials generated by the muscle of the heart is the electrocardiogram and the basic waveform recorded for a normal person is shown below:

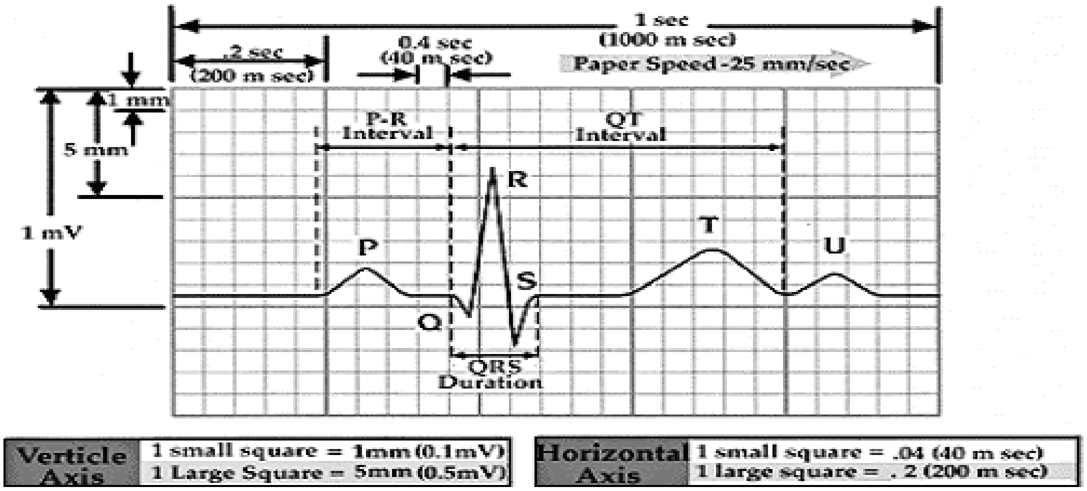


Figure 1: Electrocardiogram waveform [1]

1.b Noises in ECG

The main noises found in an ECG waveform are the common mode signals. The common mode voltage (CMV) in ECG is composed of two components: [3]

- DC electrode offset potential
- 50 or 60 Hz ac induced interference

This 50 or 60 Hz interference also known as *Hum* interference is caused by magnetic and electric fields from power lines and transformers cutting across ECG electrodes and patients. Hum currents flow in signal, common, and ground wires via capacitive coupling between the field and the system.

There have been many researches on removing these noises which seem to be ever-present.

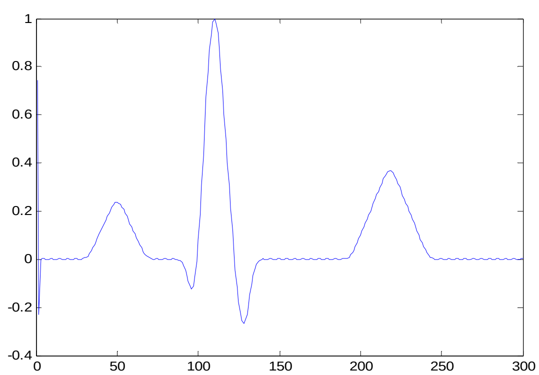


Figure 2a: Pure ideal EKG signal

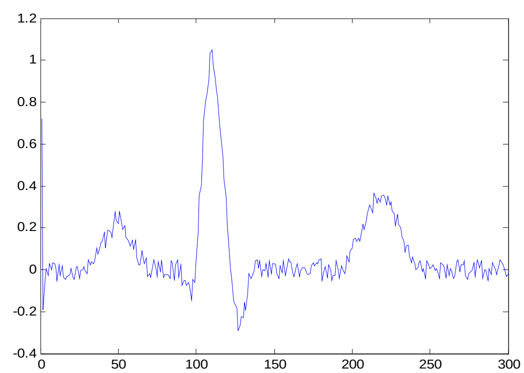


Figure 2b: EKG signal + Noise

2. Introduction to Wavelets

2.a History

A wavelet is a waveform of effectively limited duration that has an average value of zero. The concept of wavelets developed when the attention of researchers gradually turned from frequency-based analysis to scale-based analysis and when it started to become clear that an approach measuring average fluctuations at different scales might prove less sensitive to noise. The present theoretical form of wavelet concept was first proposed by Jean Morlet and the team at the Marseille Theoretical Physics Center working under Alex Grossmann in France.[4]

2.b Comparison with Fourier analysis

Wavelets are mathematical functions that cut up data into different frequency components, and then study each component with a resolution matched to its scale. They have advantages over traditional Fourier methods in analyzing physical situations where the signal contains discontinuities and sharp spikes. Compare wavelets with sine waves, which are the basis of Fourier analysis. Sinusoids do not have limited duration as they extend from minus to plus infinity. And where sinusoids are smooth and predictable, wavelets tend to be irregular and asymmetric.

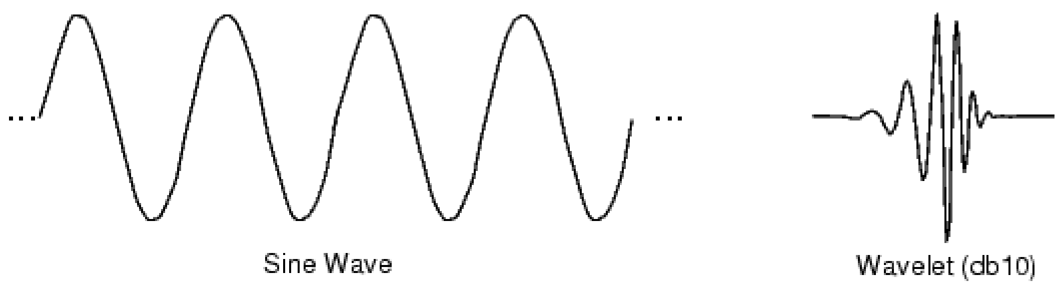


Figure 3: Comparing a wavelet with a sine wave [4]

Fourier analysis consists of breaking up a signal into sine waves of various frequencies. Similarly, wavelet analysis is the breaking up of a signal into shifted and scaled versions of the original (or *mother*) wavelet. Just looking at pictures of wavelets and sine waves, we can see that signals with sharp changes might be better analyzed with an irregular wavelet than with a smooth sinusoid.

2.c Wavelet Analysis

Wavelet analysis represents a windowing technique with variable-sized regions. Wavelet analysis allows the use of long time intervals where we want more precise low-frequency information, and shorter regions where we want high-frequency information.

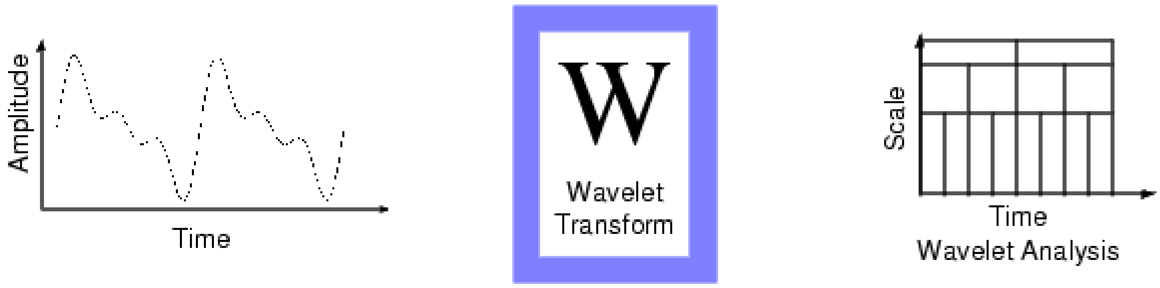


Figure 4: Comparing a wavelet with a sine wave [4]

Here's what this looks like in contrast with the time-based, frequency-based, and STFT views of a signal:

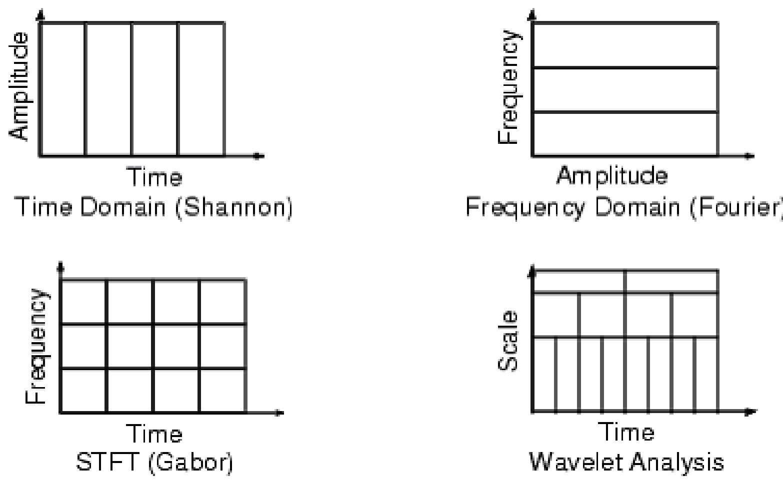


Figure 5: Time-based, frequency-based, and STFT views of a signal [4]

The wavelet analysis does not use a time-frequency region, but rather a time-*scale* region. A major advantage afforded by wavelets is the ability to perform *local analysis* -- that is, to analyze a localized area of a larger signal. Consider a sinusoidal signal with a small discontinuity -- one so tiny as to be barely visible. Such a signal easily could be generated in the real world, perhaps by a power fluctuation or a noisy switch.

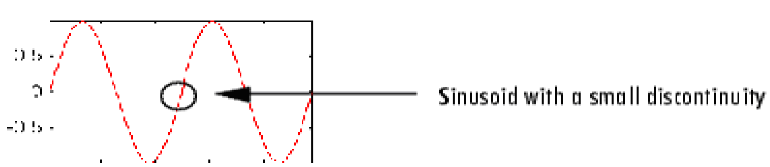
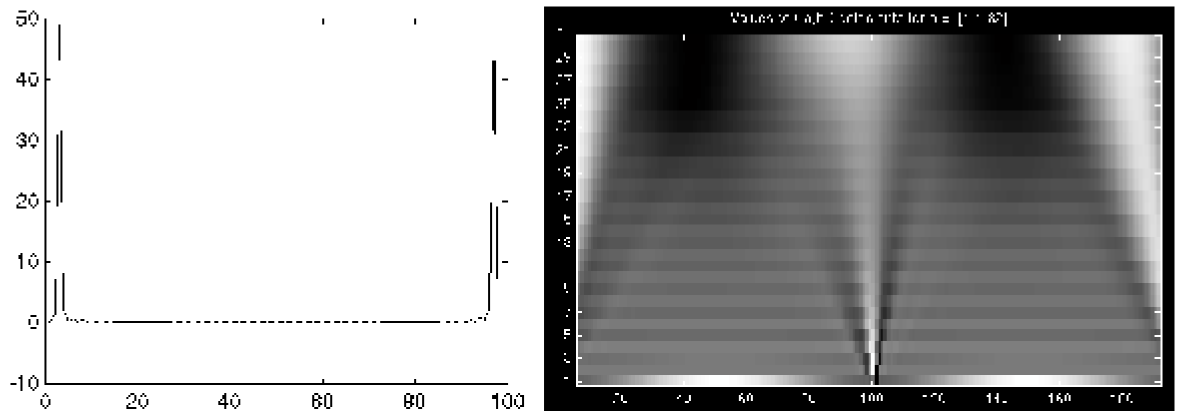


Figure 6: Sinusoid with a small discontinuity [4]

A plot of the Fourier coefficients (as provided by the fft command) of this signal shows nothing particularly interesting: a flat spectrum with two peaks representing a single frequency. However, a plot of wavelet coefficients clearly shows the exact location in time of the discontinuity.



Fourier Coefficients   Wavelet Coefficients

Figure 7: Fourier coefficients plot and wavelet coefficients plot [4]

Wavelet analysis is capable of revealing aspects of data that other signal analysis techniques miss, aspects like trends, breakdown points, discontinuities in higher derivatives, and self-similarity. Furthermore, because it affords a different view of data than those presented by traditional techniques, wavelet analysis can often compress or de-noise a signal without appreciable degradation.

3. Wavelet Windows

3.a Symlets

The symlets are nearly symmetrical wavelets proposed by Daubechies as modifications to the db family. The Daubechies family wavelets were compactly supported orthogonal wavelets, which made discrete wavelet analysis practicable. The wavelet functions psi are shown below.

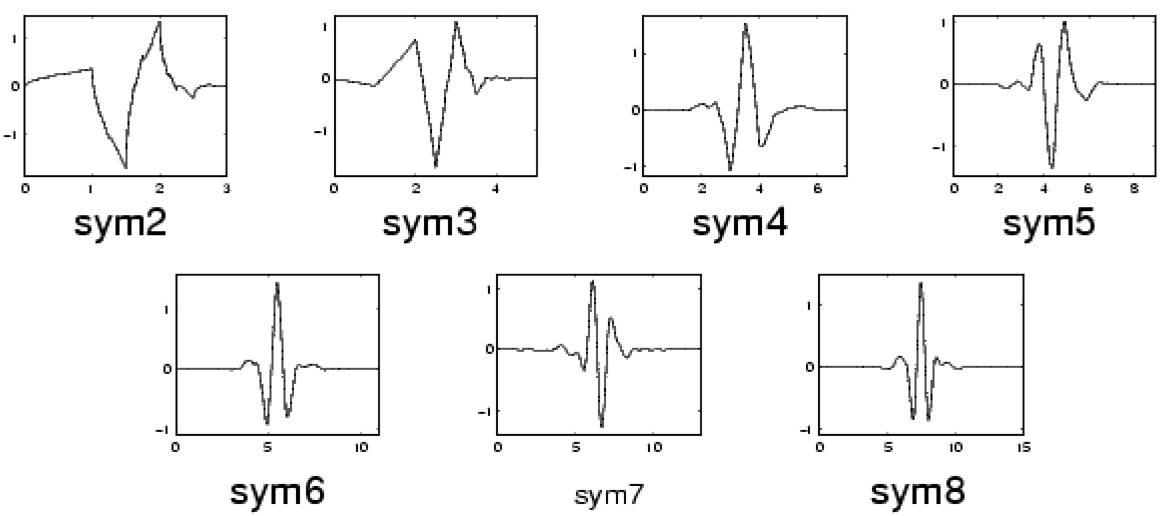


Figure 8: Wavelet functions psi [4]

3.b Wavelet Filtering Methods

The wavelet is defined by the scaling filter - a low-pass finite impulse response (FIR) filter of length 2N and sum 1. In biorthogonal wavelets, separate decomposition and reconstruction filters are defined.

The concept of denoising

Denoising procedure can be explained clearly as this. Assume that the measured signal is $X(t) = S(t) + N(t)$ where $S(t)$ is the uncorrupted EKG signal with additive noise $N(t)$. Let $W(.)$ and $W^{-1}(.)$ denote the forward and inverse wavelet transform operators.. Let $D(.,\alpha)$ denote the denoising operator with threshold α. We intend to denoise $X(t)$ to recover $S'(t)$ as an estimate of $S(t)$. The procedure can be summarized in three steps:

$Y = W(X)$

$Z = D(Y, \alpha)$

$S' = W^{-1}(Z)$

$D(.,\alpha)$ being the thresholding operator and α being the threshold. [5]

We have used symlets, decomposition and reconstruction methods to filter out the noise from the EKG signal. The sections below show the different methods along with the results.

3.b.1 Filtering using Soft Threshold

A soft threshold is a denoising technique that reduces the intensity (original signal + noise) in an input signal, so that samples with intensity values below the threshold value are reduced. Figure 9a and 9b show input and output EKG signals using Soft Threshold technique.

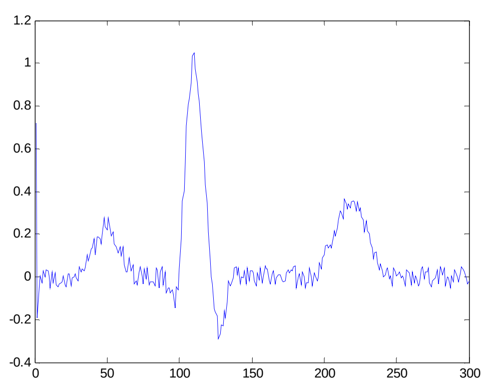


Figure 9a: EKG signal + Noise

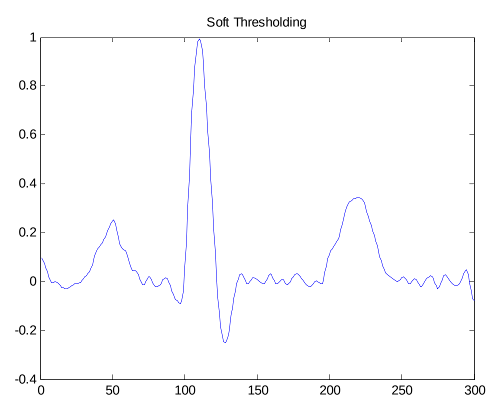


Figure 9b: Cleaned output

3.b.2 Filtering using Fixed Threshold

In fixed threshold, the values above the threshold are kept, values below it are deleted. This can also be referred as ‘all or nothing’ technique. Figure 10a and 10b show input and output EKG signals using Fixed Threshold technique.

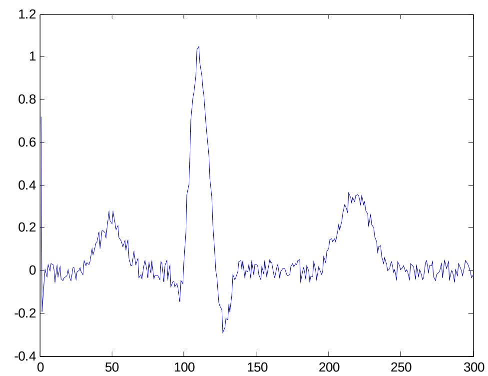


Figure 10a: EKG signal + Noise

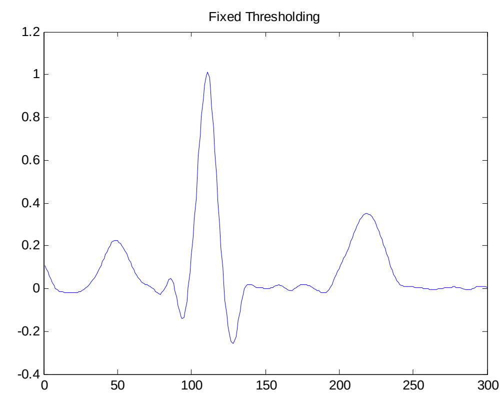


Figure 10b: Cleaned output

3.b.3 Filtering using Min-Max Estimation

In this thresholding technique, the value of the threshold is calculated using the Min-Max estimation algorithm. Figure 11a and 11b show input and output EKG signals using Min-Max Estimation technique.

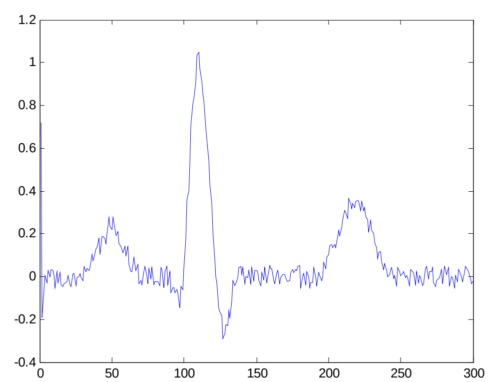


Figure 11a: EKG signal + Noise

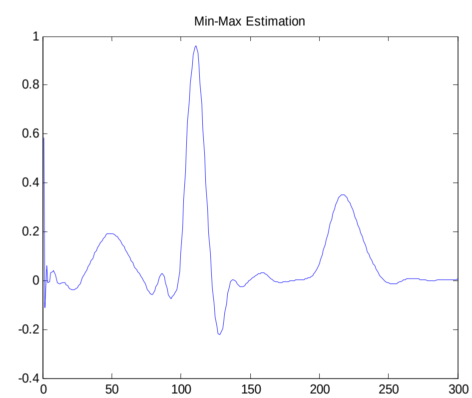


Figure 11b: Cleaned output

3.b.4 Filtering using Adaptive Threshold

In this thresholding technique, a different threshold is used for different levels of the decomposed signals. This can also be referred as local or dynamic thresholding. Figure 12a and 12b show input and output EKG signals using Min-Max Estimation technique.

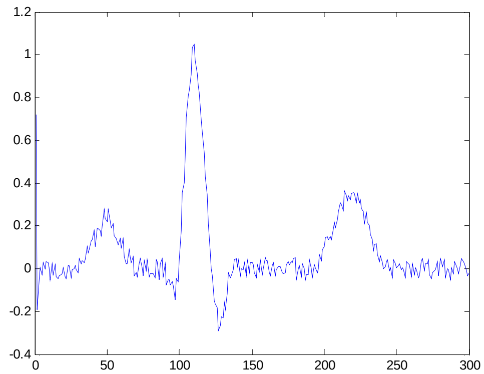


Figure 12a: EKG signal + Noise

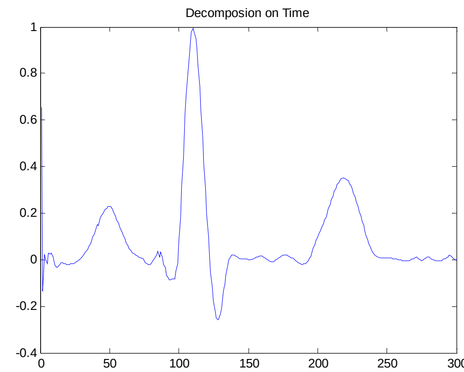


Figure 12b: Cleaned output

4. Conclusion

Legacy digital filters such as FIR and IIR have been long used to clean up signals. In this paper, we have experimented with using wavelet theory on 1-Dimensional signal such as EKG. This work describes the application of different wavelets, levels and thresholding techniques on the noisy EKG waveform. Best results were obtained using the 'sym4' and fixed thresholding. Fine tuning of the filter w.r.t. the number of levels and thresholding technique is required to optimize the results.

References

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[2] Edward J. Berbari, Indiana University/Purdue, University at Indianapolis, "Principles of Electrocardiography" URL: http://deis1.dei.uminho.pt/outraslic/lebiom/cardio/ch013.pdf

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[4] The Mathworks, URL: http://www.mathworks.com/

[5] Image Denoising Using Wavelets — Wavelets & Time Frequency, Raghuram Rangarajan, Ramji Venkataramanan, Siddharth Shah, URL: http://sitemaker.umich.edu/rangaraj/files/551report.pdf

Biographies

Manan Joshi has received his MS degree in Electrical Engineering from University of Bridgeport in Dec 2006. Currently he is pursuing his PhD in Computer Science & Engineering at the University of Bridgeport. His research interests are in the field of Analog Electronics, Medical Electronics, Computer Networking and Wireless Communications.

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Lawrence V. Hmurcik is Professor and Chairman of Electrical Engineering at the University of Bridgeport, Bridgeport, CT. He earned his Ph.D. in semiconductor devices at Clarkson University in 1980. He worked in Diamond Shamrock's research division for 3 years before joining the University of Bridgeport in 1983. Dr. Hmurcik has 50 publications and 5 grants. He is also a professional consultant with 240 case entries, including 14 appearances in Court and Legal Depositions. Dr. Hmurcik's interests have changed over the years: starting in Solar Cell technology in 1977, Dr. Hmurcik is currently pursuing work in Medical Electronics and Electric Safety.