International Journal of Image Processing and Vision Science

Volume 2 | Issue 2 Article 1

October 2013

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WORK MODELING FOR CATEGORIZATION OF LATE POTENTIALS IN ECG SIGNALS BY WAY OF WAVELETS

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Abstract: Late potentials in ECG take place in the terminal portion of the QRS complex and are characterized by tiny amplitudes and larger frequencies. The occurrence of late potentials may signify underlying distribution of electrical activity of the cells in the heart, and provides a substrate for production of arrhythmias. The conventional Fourier transform does not readily localize these features in time and frequency. Short Time Fourier Transform (STFT) is added useful because the concentration of the signal energy at various times in the cardiac cycle is more readily identified. This STFT suffers from the problem of selecting the proper window function as a window width can determine whether high temporal or high spectral resolution is achieved. The Wigner-Ville distribution, which produces a composite time – frequency distribution but suffers from the problem of interference from cross-terms. The problem of late potentials causes high levels of signal power to be seen at frequencies not representing the original signal. The present work describes the application of Wavelet Transform to provide a more accurate picture of the localized time-scale features indicative of the late potentials. The first step includes generating mathematical equations for various cases by developing a program in Matlab. Compared the signal under consideration with all those signals in the database by developing an identification code in Matlab. Analyzed the late potentials in the signal under consideration and identified the case. The second step includes generating mathematical equations for various specimen cases for the same type category by developing a program in Matlab. Compared the signal under consideration with all those signals in the database by developing an identification code in Matlab. Analyzed the late potentials in the signal under consideration and identified the case along with the specimen case.

***Keywords**: Fourier transforms, Short-Time Fourier Transform, Continuous Wavelet Transform, Wigner-Ville Distribution, Wavelet Transform, ECG, Late Potentials, Arrhythmia, PAF Prediction challange database (afpdb), T-Wave Alternans challange database (twadb)*

INTRODUCTION:

A number of time-frequency methods are currently available for the high resolution decomposition in the time-frequency plane useful for signal analysis, including the short time Fourier transform (STFT), Wigner-Ville transform (WVT) and the continuous wavelet transform (CWT).

Continuous Wavelet Transform (CWT) has emerged as the most favored tool by researchers as it does not contain the cross term inherent in the Wavelet while processingfrequency-dependent windowing which allows for arbitrarily high resolution of the high frequency signal components (unlike the STFT).

The Fourier transforms are probably by far the most popular. Most of the signals in practice are TIME-DOMAIN signals in their raw format. No frequency information is available in the time-domain signal, and no time information is available in the frequency-domain signal in the Fourier transformed signal. The Fourier analysis transforms a signal into frequency domain by breaking the signal into constituent sinusoids. But in doing so, the information in the time domain is lost. If a signal is a stationary signal this drawback isn't very important. However, most interesting, signals contain numerous non-stationary or transitory characteristics: drift, trends, abrupt changes, and beginnings and ends of events. These characteristics are often the most important part of the signal, and Fourier analysis is not suited in detecting them.

The Short-Time Fourier Transform (STFT), maps a signal into a two-dimensional function of time and frequency. It provides some information about both when and at what frequencies a signal event occurs. In STFT, the signal is divided into small enough segments, where these segments (portions) of the signal can be assumed to be stationary. For this purpose, a window function "w" is chosen. The width of this window must be equal to the segment of the signal where its stationary is valid. The drawback with STFT is that once you choose a particular size for the time window, that window remains same for all frequencies.

Narrow window ==>good time resolution, poor frequency resolution.
Wide window ==>good frequency resolution, poor time resolution.

The Wigner-Ville Distribution has much better resolution than STFT but gives rise to cross term calculations and aliasing effect.

The Continuous Wavelet Transform:

The continuous wavelet transform has emerged as the most favored tool by researchers as it does not contain the cross terms inherent in the WVT while possessing frequency-dependent windowing which allows for arbitrarily high resolution of the high frequency signal components (unlike the STFT). 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.

A wavelet is a waveform of effectively limited duration that has an average value of zero. 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, you can see intuitively that signals with sharp changes might be better analyzed with an irregular wavelet than with a smooth sinusoid. The result of the CWT is many wavelet coefficients C, which are a function of scale and position.

The continuous wavelet transform (CWT) is a time–frequency analysis method which differs from the more traditional short time Fourier transform(STFT) by allowing arbitrarily high localization in time of high frequency signal features.

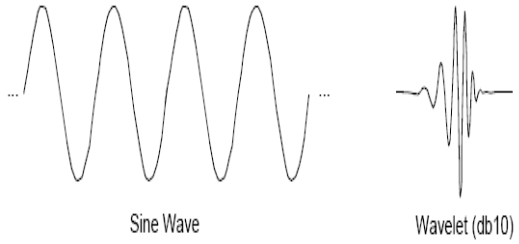

Fig.1

The CWT does this by having a variable window width, which is related to the scale of observation a flexibility that allows for the isolation of the high frequency features. Another important distinction from the STFT is that the CWT is not limited to using sinusoidal analyzing functions. Rather, a large selection of localized waveforms can be employed as long as they satisfy predefined mathematical criteria.
The wavelet transform of a continuous time signal, x (t), is defined as:

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

Where $\psi*$ (t) is the complex conjugate of the analyzing wavelet function ψ (t), a is the dilation parameter of the wavelet and b is the location parameter of the wavelet.

The continuous wavelet transform is the sum over all time of the signal multiplied by scaled, shifted versions of the wavelet. This process produces wavelet coefficients that are a function of scale and position.

Scale and Frequency:

It must be noted that there is an important correlation between scale and frequency.

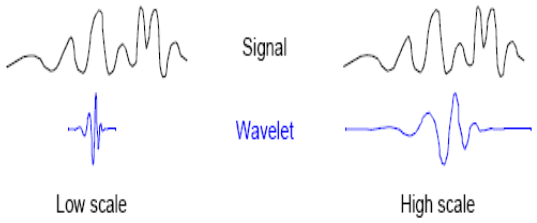

Fig.2

We can see that as we lower the scale the wavelet gets more compressed and it has a better ability to track the rapidly changing details of a signal i.e. high frequency components of signal. Similarly as we increase the scale the wavelet gets expanded and has the ability to track the slowly varying details of a signal i.e. low frequency component of a signal.

Overview of an ECG signal:

As the heart undergoes depolarization and repolarization, the electrical currents that are generated stretch not only within the heart, but also throughout the body. This electrical activity generated by the heart can be measured by an array of electrodes placed on the body surface. The recorded tracing is called an electrocardiogram.

On a standard ECG, only three physiological events usually show up as deviations from the base line. The depolarization of the atrial myocardium produce a deflection called the P wave. The depolarization of the ventricular myocardium produces the QRS complex. The repolarisation of the ventricular myocardium produces the T wave.

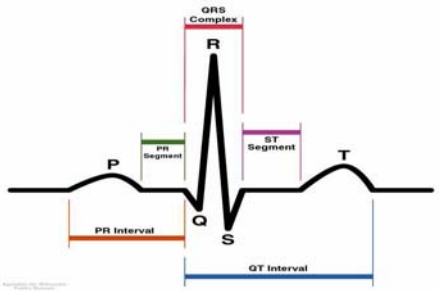

Fig. 3: ECG Signal

CASE 1: MIT-BIH Normal Sinus Rhythm

The normal rhythm of the heart is a regular pattern with a rate of between 60 to 100 beats per minute. This rhythm is called normal sinus rhythm because a collection of heart cells called the sinus node controls the rate and rhythm.

The above signal has been taken from the MITBIH Normal Sinus Rhythm Database of the Physio Bank. The first subplot shown in Fig. 4 represents the equation plot superimposed on the original plot for the purpose of knowing the difference between actual signal and generated signal. Second subplot represents original plot and the third subplot represents the Equation plot.

The Wavelet coefficients of the above signal have been plotted in MATLAB as shown in Fig. 5.

The coefficients are plotted in terms of scales on the y-axis and the time on x-axis, the wavelet coefficient at that point is represented by a color with the varying intensity. The intensity of the color at any point is directly proportional to the magnitude of the wavelet coefficient at that point.

As shown in fig.5, the brighter the color at a point the larger the wavelet coefficients for a given scale. And we can also see that at the terminal portion of the QRS complex, as we increase the scale (i.e. the higher scale) the intensity of the color is also increasing. We know that the higher the scale more

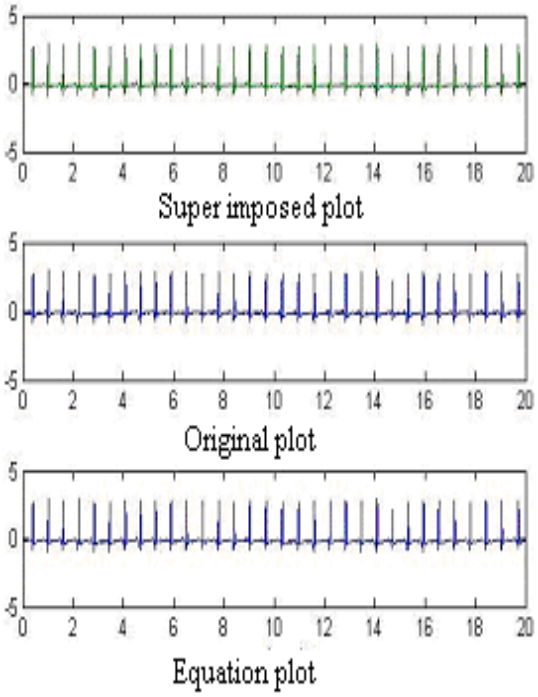

Fig. 4: MIT-BIH Normal Sinus rhythm Database, duration: 0-20 sec.

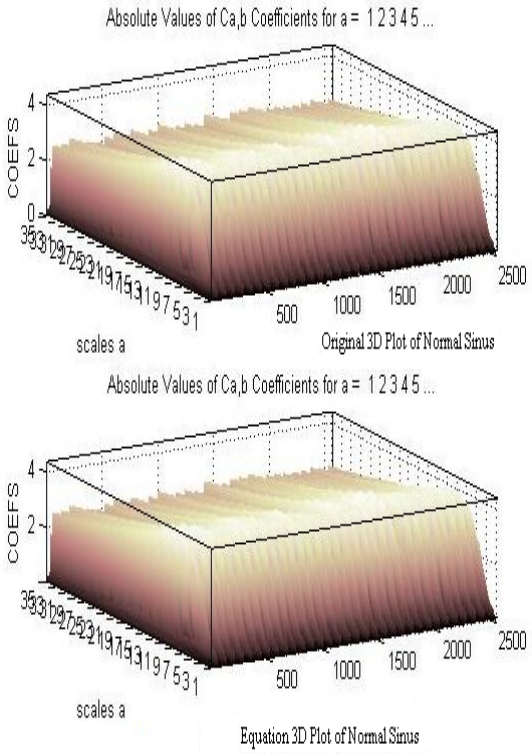

Fig. 5: 3D Plot of Wavelet coefficients of Normal Sinus Rhythm signal in case 1.

expanded the wavelet and it can track the coarse low frequency component of a signal. This indicates the absence of high frequency components at the terminal portion of the QRS complex or late potentials in the ECG signal chosen for analysis which very much is the characteristics of the signal chosen as it is a normal sinus rhythm.

CAS 2: PAF Prediction challange database (afpdb)
The Report includes PAF (paroxysmal atrial fibrillation) Prediction challange database (afpdb). For this case the ECG signal for the analysis has been taken from the PAF Prediction challange database (afpdb) of the Physio Bank.

The mathematical expressions for PAF Prediction challange database (afpdb) are for a time limit of 20sec.

This database consists of 100 record sets, each including a pair of 30-minute excerpts from a long-term ECG recording. Approximately half of the subjects have PAF (paroxysmal atrial fibrillation) immediately following one of the two 30-minute excerpts.

Among the 50 record sets in the learning set, the PAF can be studied by referring to 5-minute continuation records that accompany each 30-minute record. In the 50 record sets belonging to the test set, the challenge is to identify which records immediately recede PAF

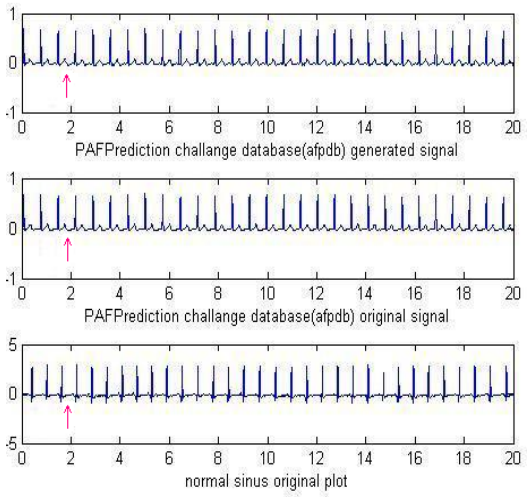

Fig.6: Prediction challange database (afpdb), duration 0-20 sec

The first subplot shown in Fig. 6 represents the generated signal plot of Prediction challange database (afpdb), which is identical to the original signal plot. Second subplot represents original signal plot and the third subplot represents the normal sinus signal plot.
Prediction challange database (afpdb), describes an irregular and often rapid heart rhythm. The irregular rhythm, or arrhythmia, results from abnormal electrical impulses in the heart. The irregularity can be continuous, or it can come and go. Normal heart contractions begin as an electrical impulse in the right atrium. This impulse comes from an area of the atrium called the sinoatrial (SA) or sinus node, the "natural pacemaker."

The order of the equations P1, P2 …P 120 is 10 and the coefficients are arranged in decreasing order. The total numbers of samples 2561 are shaped into 120 parts for better accuracy in matching points.

Part 1:

P 1= (6.489575025872059e+013)*x^10
+ (-3.381336292302121e+013)*x^9
+ (7.390904167532784e+012)*x^8
+ (-8.805328010645812e+011)*x^7
+ (6.231704692116696e+010)*x^6
+ (-2.688424903910296e+009)*x^5
+ (7.015406938086893e+007)*x^4
+ (-1.061421146245077e+006)*x^3
+ (8.388436118066935e+003)*x^2
+ (-2.583207457208573e+001)*x^1
+ (-1.507645443529759e-002)*x^0
. . . . .
Part 120:
P 120= (-1.137587470071633e-002)*x^10
+ (4.403211572581235e-001)*x^9
+ (4.817811408369041e+000)*x^8
+ (-3.661505846420457e+002)*x^7
+ (2.991512750711263e+003)*x^6
+ (1.638718574822748e+004)*x^5
+ (3.336038213839260e+005)*x^4
+ (-8.651008797540121e+006)*x^3
+ (1.190673955789470e+007)*x^2
+ (1.777094900403925e+008)*x^1
+ (-3.351273125821933e-023)*x^0
The time intervals for these parts are:
P 1 is 0 < t < 0.1090
P 120 is 19.9140 < t < 20.0000

The Wavelet coefficients of the above signal when plotted in MATLAB look as shown in Fig.7

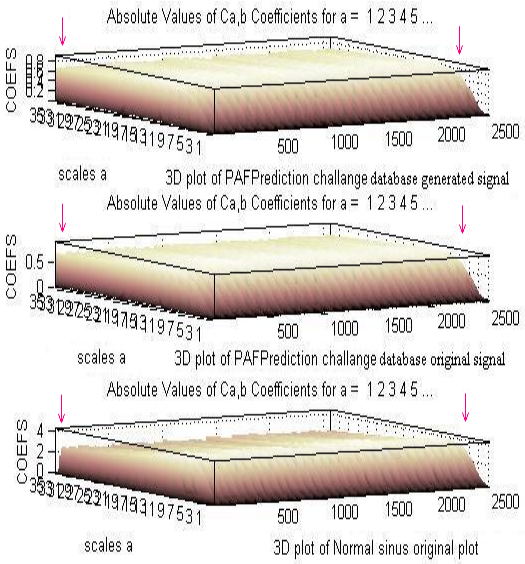

Fig. 7: Prediction challange database (afpdb),duration 0-20 sec

CASE 3: T-Wave Alternans challange database (twadb)

The Report includes T-Wave Alternans challange database (twadb). For this case the ECG signal for the analysis has been taken from the T-Wave Alternans challange database (twadb) of the Physio Bank. The mathematical expressions for T-Wave Alternans challange database (twadb) are for a time limit of 20sec.

This database contains 100 multichannel ECG records sampled at 500 Hz with 16 bit resolution over a ± 32 mV range. The subjects include patients with myocardial infarctions, transient ischemia, ventricular tachyarrhythmias, and other risk factors for sudden cardiac death, as well as healthy controls and synthetic cases with calibrated amounts of T-wave alternans. Specific information about individual records will be posted here after the conclusion of the Challenge in September 2008. Since these records come from a variety of sources, some of them have been resampled and scaled from original recordings sampled at higher or lower resolution in order to present them in a uniform format here. In most cases, each record contains the standard 12 diagnostic ECG signals, but a few contain only 2 or 3 signals. Each record is approximately two minutes in duration

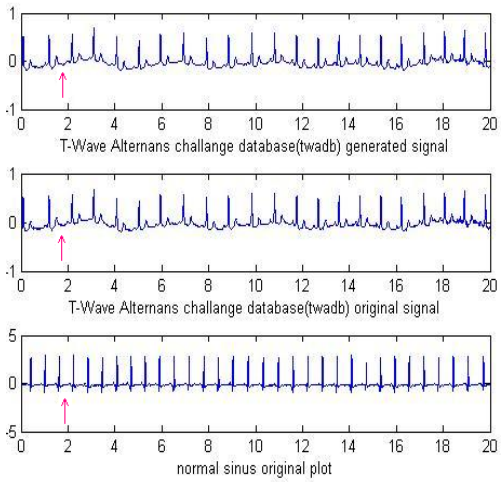

Fig.8: T-Wave Alternans challenge database (twadb) duration: 0-20 sec

The first subplot shown in Fig. 8 represents the generated signal plot of T-Wave Alternans challange database (twadb), which is identical to the original signal plot. Second subplot represents original signal plot and the third subplot represents the normal sinus signal plot.

T-Wave Alternans challange database (twadb), describes an irregular and often rapid heart rhythm. The irregular rhythm, or arrhythmia, results from abnormal electrical impulses in the heart. The irregularity can be continuous, or it can come and go. Normal heart contractions begin as an electrical impulse in the right atrium. This impulse comes from an area of the atrium called the sinoatrial (SA) or sinus node, the "natural pacemaker."

The order of the equations TW 1, TW 2 …TW 637 is 10 and the coefficients are arranged in decreasing order. The total numbers of samples 10001are shaped into 230 parts for better accuracy in matching points
Part 1:

TW 1= (2.420800387473729e+013)*x^10
+ (-1.057679520193558e+013)*x^9
+ (1.926696273607374e+012)*x^8
+ (-1.900653276708516e+011)*x^7
+ (1.102410795752514e+010)*x^6
+ (-3.807868864552987e+008)*x^5
+ (7.530155352872325e+006)*x^4
+ (-7.603951880812219e+004)*x^3
+ (2.977833156604613e+002)*x^2
+ (2.308484970693869e-001)*x^1
+ (-1.487332126429163e-001)*x^0
. . . . .
Part 230:
TW 230= (1.348553578448897e-010)*x^10
+ (3.355132580275681e-009)*x^9
+ (-2.433415556695129e-007)*x^8
+ (2.713679728568084e-006)*x^7
+ (-1.445353426992520e-005)*x^6
+ (-6.006860393010462e-005)*x^5
+ (4.122932193101818e-003)*x^4
+ (9.688870084907882e-005)*x^3
+ (-7.588435213826041e-002)*x^2
+ (7.217493507166546e+000)*x^1
+ (7.664148622631943e-082)*x^0
The time intervals for these parts are:
TW 1 is 0 < t < 0.0980
TW 230 is 19.9980 < t < 20.0000

The Wavelet coefficients of the above signal when plotted in MATLAB look as shown in Fig.9

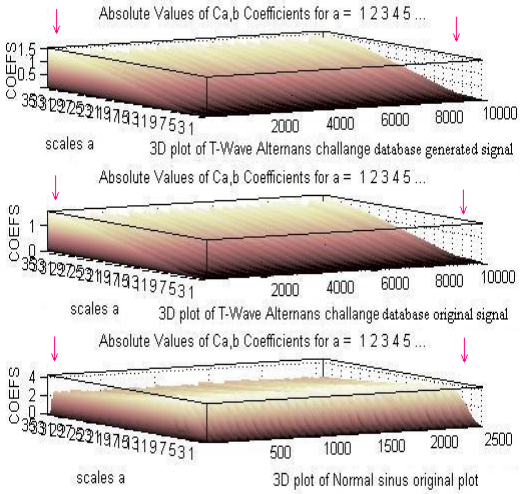

Fig. 9: T-Wave Alternans challange database (twadb) duration: 0-20 sec

Comparisons:
Late Potentials in ECG occur in the terminal portion of the QRS complex and are characterized by small amplitudes and higher frequencies. In figure 5 it can be seen that at higher frequencies the strength of coefficients is relatively small which indicates that we do not have any Late Potentials. The presence of low frequency component or the absence of Late Potentials, which complies with the nature of the signal chosen.

Now consider figure 6. In this figure at around 2 second's time as indicated with arrows it is the imperative summit to learn. The signal strength is swerve in subplots 1 &2 from 3rd subplot but it is as good as minuscule which can swindle to infer erroneous diagnosis. But it is not in the case shown in figure 8. As arrows indicated in figure 7 at higher frequency scale, the coefficients strength is matching in subplots 1 &2 and is veer off from 3rd subplot. At stumpy frequency scale it is awfully tricky to identify the disparity, hence likelihood for erroneous diagnosis. But it is not in the case shown in figure 9. At higher frequencies if the strength of coefficients is relatively large which do indicates the presence of Late Potentials. This high frequency, low amplitude components at the terminal portion of QRS complex are the Late Potentials.

CONCLUSIONS:

Prediction challange database (afpdb) and T-Wave Alternans challange database (twadb) in the Late Potentials has been used as a marker to identify patients at risk from certain types of life menacing arrhythmias. There is an important link between SCD (Sudden Cardiac Death) and arrhythmias. The vast majority of cases of Sudden Cardiac Death have been accredited to the occurrence of sudden fatal arrhythmias. Many of the people who suffer SCD are not recognized to have heart disease prior to their death. Among those who have heart disease, a large proportion will not die suddenly. Identifying those people who are at peril for SCD before an episode of serious arrhythmia is a major defy for the cardiologist. The above work used cases where the late potentials are very manifest, however in most cases the late potentials are not as distinct as in the cases chosen for this work. By analyzing the ECG signals of the diseased patients who have suffered SCD by the above method we can establish a model to predict an episode of a serious arrhythmia and prevent SCD by taking deterrent measures.

The signals have shown in figures 6, 7, 8, and 9 are so analyzed using the developed scientific programs and categorize the case exclusive of any individual erroneous diagnosis. Studying the signals discretely and communally one can wrap up a superior diagnosis.

The ECG so analyzed can be premeditated by an expert sitting at aloofness through internet thereby enabling long distance diagnoses possible. Most prominently it eliminates the soul boo-boo which may be allied with a doctor in the ECG Psychoanalysis, thus edifice medical diagnosis safer and robust.

Coming up Circulation and Expansion:

The ECG so analyzed can be deliberate by an expert session at a distance through internet thereby enabling long distance diagnoses doable. In the deficiency of a doctor, the program can itself give the report of the stipulation of the patient.

Emergent an embedded system it is quite possible to assist the medical practitioners in making further precise and swift diagnosis.

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