Harmonic Spectrogram for the Analysis of Semi-periodic Physiologic Signals

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Abstract- **We describe a new method of power spectral density (PSD) estimation that improves frequency resolution of non-sinusoidal semi-periodic signals. Our method estimates the total power spectral density at each frequency that includes the power of the fundamental and harmonic components. This is a useful tool for the analysis of physiologic signals such as the electrocardiogram and blood pressure. We demonstrate the method on several biomedical signals.**

Keywords - **Fast Fourier transform (FFT), spectrogram, scaleogram, time-frequency analysis, semi-periodic signals.**

I. INTRODUCTION

Time-frequency estimation of power spectral density (PSD) is a common step in the analysis of nonstationary signals. The spectrogram is arguably the most popular technique, though the scaleogram and Wigner-Ville distribution are also common [1]. The spectrogram estimates the PSD by applying the modified periodogram to windowed signal segments separated by a fixed interval [2]. The user-specified length of the window controls the trade-off between time and frequency resolution of the image.

A disadvantage of the spectrogram is that it displays multiple horizontal bands for semi-periodic non-sinusoidal signals. This is especially problematic for signals such as the electrocardiogram that contain semi-periodic impulses because the majority of the signal power is located in the higher harmonics, as illustrated in Fig. 1. This confounds time-frequency visualization at the frequencies that are generally of physiologic interest (say 0 – 3 Hz) because a much wider range of frequencies must be displayed for the user to see the power of the harmonics. This is also cumbersome for the user who must visually combine the power at each of the harmonics in order to get a complete picture of the spectral content of the semi-periodic signals at different frequencies.

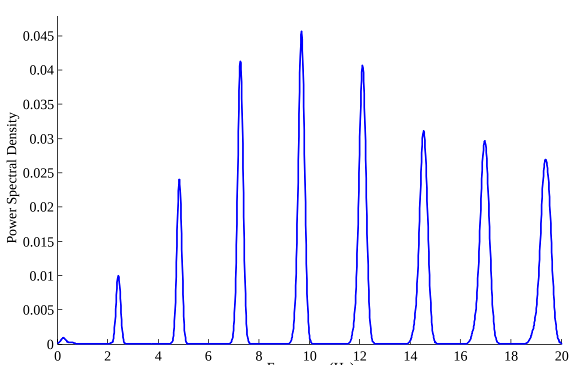

Fig. 1. Power spectral density of an electrocardiogram (ECG) signal recorded from a pediatric patient. The heart rate was approximately 2.4 Hz. This plot illustrates that the majority of the signal power of ECG signals is located in the higher harmonics well above the heart rate. We estimated the PSD using Welch's method of spectral estimation with a window length of 8.192 s and 50% overlap of windows.

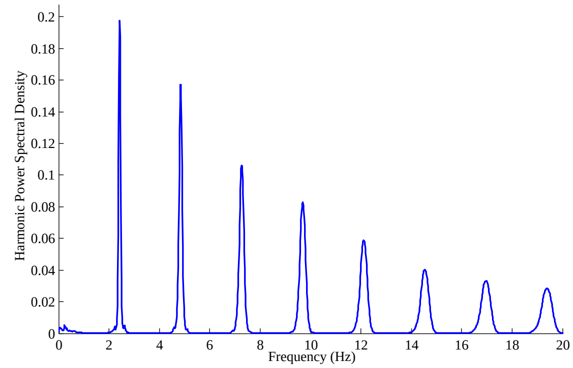

Fig. 2. Harmonic PSD estimate of the same ECG signal used in Fig. 1. For this example n=11 harmonics were combined. This demonstrates the improved frequency resolution of this spectral estimation technique.

II. METHODOLOGY

In this paper we describe a simple method of spectral estimation that adds the power of a user-specified number of harmonics (n),

$$h(\omega) = \sum_{k=1}^{n} p(k\omega), \qquad (1)$$

where $p(\omega)$ is the estimated PSD and $h(\omega)$ is total estimated power in the first n harmonics of the signal.

One of the problems with this approach is that it can cause sub-harmonics of the signals of interest to appear in the estimate $h(\omega)$. For example, if the signal of interest is at 2 Hz and the user specifies n = 2, then significant spectral power will appear at 1 Hz because this estimate will include the PSD component at 2 Hz. To eliminate this problem we combined n spectral components using the following expression,

$$h(\omega) = \sum_{k=1}^{n} \min\left(\alpha\, p(\omega), p(k\omega)\right), \qquad (2)$$

where α ensures that the power of the harmonics added to $h(\omega)$ does not exceed the power at the fundamental by more than a factor of α.

The harmonic PSD improves frequency resolution of the lower harmonics. This is a direct consequence of using the signal harmonics to help estimate the power at the fundamental frequency. For example, if the kth harmonic is known to have a frequency range of $k\omega \pm \delta$, then we can conclude the fundamental is in the range $\omega \pm \delta/k$.

For all of the examples reported here α was set equal to 2, a Blackman window was used to reduce sideband leakage, and zero padding was applied so that the harmonic PSD could be evaluated at many frequencies. The spectrograms show the square root of the PSD to emphasize the low power components. The color scale was chosen to range from 0 to the 99th percentile of the spectrogram.

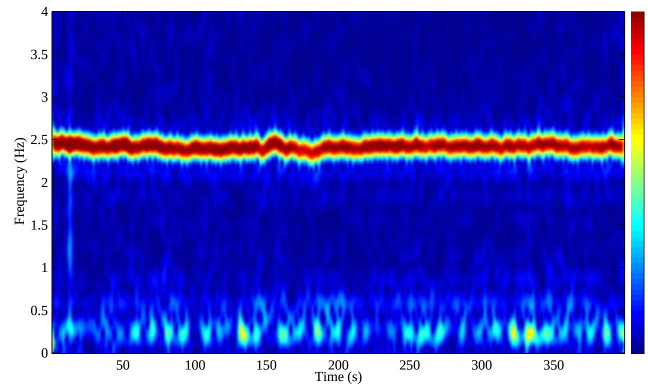

Fig. 3. Spectrogram of an ECG signal recorded from a pediatric patient with traumatic brain injury. The window length was 10 s.

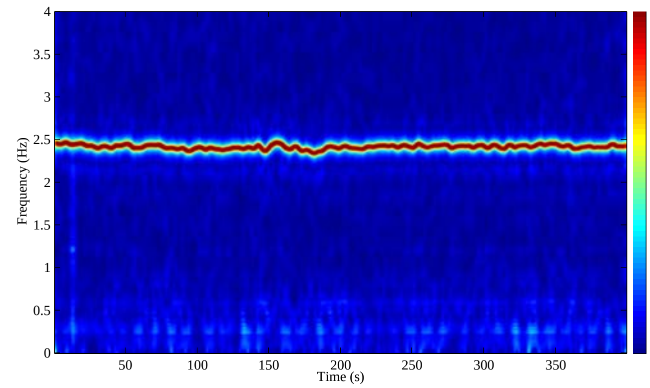

Fig. 4. Harmonic spectrogram of the same ECG signal shown in Fig. 3. The window length was 10 s and n=10 harmonics were used.

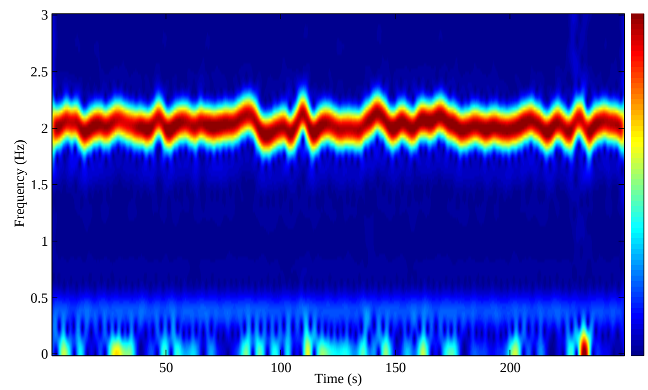

Fig. 5. Spectrogram of an arterial blood pressure (ABP) signal recorded from a pediatric patient with sepsis. The window length was 8 s.

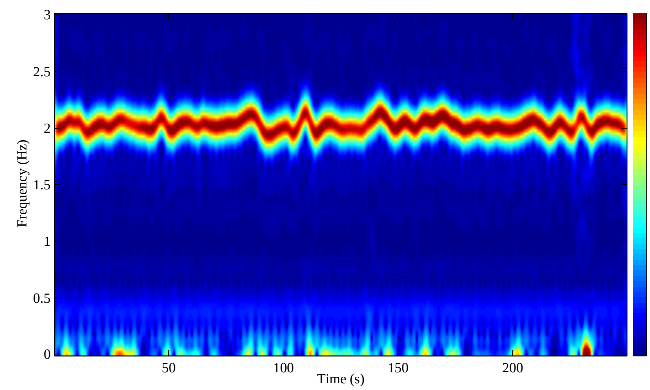

Fig. 6. Harmonic spectrogram of the same ABP signal shown in Fig. 5. The window width was 8 s and n=3 harmonics were used.

III. Examples and Discussion

The ECG signal is one of the most difficult to analyze with the spectrogram because the majority of the signal power is located in the higher harmonics of the signal. Fig. 1 shows the estimated PSD of an ECG signal using Welch's method [2]. Fig. 2 shows the harmonic PSD with $n = 11$. Note that the harmonic PSD has the largest amplitude at the heart rate and the width of the estimate is narrower. This demonstrates the improved frequency resolution of our method.

Figs. 3 and 4 show the spectrogram and harmonic spectrogram, respectively, of the same ECG signal. The patient was mechanically ventilated at a fixed rate of approximately 0.29 Hz. The frequency and time resolution of the harmonic spectrogram is significantly better than the spectrogram even though the same window size was used for both estimates. A slight additive component is visible at approximately 0.29 Hz in the harmonic spectrogram.

Figs. 5 and 6 show the spectrogram and harmonic spectrogram, respectively, of an ABP signal recorded from a pediatric patient with sepsis. As in the previous example, the harmonic spectrogram shows slightly better time and frequency resolution of the cardiac component. The effect is less dramatic than the previous example because only the first few harmonics of the cardiac component have significant signal power.

IV. Conclusion

We described a method of estimating the harmonic power spectral density that combines the power of the fundamental and harmonic components. This method has many benefits. It is less sensitive to signal morphology than traditional PSD estimates because it accounts for variations in the power distribution among harmonic frequencies. It is simple and can be easily implemented with modern methods of PSD estimation. It achieves better frequency resolution by leveraging the relatively better resolution at the harmonic frequencies.

We demonstrated the method on electrocardiogram and arterial blood pressure signals recorded from two different pediatric patients. We are currently investigating more advanced methods of estimating the harmonic power spectral density (HPSD) of non-sinusoidal semi-periodic signals. A MATLAB implementation of the HPSD is available on the web at *http://bsp.pdx.edu/Toolbox*.

References

[1] S. Qian, *Introduction to Time_Fequency and Wavelet Transforms*, New Jersey: Prentice Hall, 2002.

[2] M. H. Hayes, *Statistical Digital Signal Processing and Modeling*, New York: John Wiley & Sons, 1996, pp. 408-412.