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# Hand Tremor Detection via Adaptive Empirical Mode Decomposition and Hilbert-Huang Transform

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## Abstract

Involuntary human hand motions, or tremors, are normally regarded as a non-stationary process. Due to its nonlinear and non-stationary nature, we need the amplitude and frequency information of a tremor at a specified time for accurate and real-time suppression. Research to date only approximates tremor as stationary processes and predominant methods such as Fourier Transform used to analyze tremor signals completely lose time resolution, therefore, loosing accuracy of tremor treatments.

Our research uses a new mathematical method called Empirical Mode Decomposition (EMD) to analyze tremor signals. In general, EMD is a time-frequency analysis method that is capable of extracting amplitude and frequency information of a signal at a given time incident. Because of this, the severity and frequency range of tremors can be identified; hence treatment priority can be determined. Since this method can be implemented in a small-sized, low-power, fast processing Digital Signal Processor (DSP), low-cost and practical detector can be developed.

In this paper, we present our research results using EMD and Hilbert-Huang Transform (HHT). The EMD is modified by adaptively changing its stopping criteria and therefore more accurately extract a tremor signal's amplitude, frequency, and time information. The results are expected to be helpful for real-time tremor detection and suppression.

## Introduction

Tremor is the most common movement disorder and manifests as involuntary, rhythmic, oscillatory movements produced by reciprocally innervated antagonist muscles. Most often, the hand and forearm are involved. The bulk of research has focused on scientific understanding, specific diagnosis, pharmacologic and surgical therapies. Treatment of tremor remains symptomatic and many options have side effects and inherent risks. A number of mechanical means for restoring functionality to tremulous forearms and hands have been developed, though no device is yet generally available. While available treatments help many, many others still experience distressing and disabling tremor [1], [2]. Most recent approaches approximate tremors as stationary processes, when they are nonlinear, non-stationary in nature. The conventional Fourier Transform used to analyze tremor signals reveals frequency content in a tremor signal. However, because the transform averages the signal over time, it completely loses time resolution and therefore loosing real-time treatments of tremors. An example will be given in the later section of this paper.

A recent DSP approach models tremors as AR(3) (third-order AutoRegressive) processes, and an linear predictor is developed for adaptive processing of tremor signals.[3] Though the results based on Levinson-Durbin algorithm (LD algorithm) show faster convergence than LMS (Least Mean Square) and RLS (Recursive Least Squares) algorithms, however, it does not detect amplitude and frequency range of a tremor at a specific time. In addition, no effort to date specifically addresses tremors in different frequency bands, though it has been shown that different kinds of tremor have different characteristics that range from 3 – 15 Hz [4], [5].

Due to its nonlinear and non-stationary nature, accurate suppression of tremor demands knowledge of its amplitude and frequency at any given time incident. In this research effort, the latest mathematical method called Empirical Mode Decomposition is employed to extract tremor amplitudes and frequencies at any time incident, hence uniquely determines treatment priority at that time and consequently significantly improves treatment quality. This method provides great potentials of characterizing the levels of severity and helps locate tremors in different frequency bands. Because this method can be implemented in a small-sized, low cost Digital Signal Processor, a low-profile, wearable electro-mechanical system to detect and suppress tremor can be developed as a potentially effective, safer, less expensive treatment option [6]. In the results presented in [6], the stopping criteria for EMD were fixed, and therefore, optimal results may or may not be obtained depending on the nature of the tremor signals. Further research was conducted to adaptively adjusting the stopping criteria for this algorithm, and more accurate results can be obtained and are presented in this paper.

Tremor signal is a time series. For any arbitrary time series $x(t)$, an analytic function $Z(t)$ can be constructed as:

$$Z(t) = x(t) + jx_h(t) \tag{1}$$

where $x_h(t)$ is the Hilbert Transform of $x(t)$.

In order to extract the instantaneous bandwidth and instantaneous frequency information of the signal, The analytic signal is alternatively expressed as:

$$Z(t) = a(t)e^{j\theta(t)} \tag{2}$$

and the instantaneous bandwidth and instantaneous frequency of the analytic signal can be obtained by equations (3) and (4), respectively:

$$BW_{inst} = \left|\frac{da(t)/dt}{a(t)}\right| \tag{3}$$

$$\omega(t) = \frac{d\theta(t)}{dt} \tag{4}$$

In the case of hand tremors, these parameters provide crucial information that helps tremor suppression. However, due to its nonlinear, nonstationary nature, instantaneous information of tremor signals may not be extracted accurately or on a real-time basis. Empirical Mode

Decomposition (EMD) provides a powerful means of decomposing nonlinear, nonstationary signals into the sum of a series of stationary signals (AM-FM signals) and hence makes real-time tremor detection possible.

## Empirical Mode Decomposition and Hilbert-Huang Transform

### *A. Empirical Mode Decomposition Method*

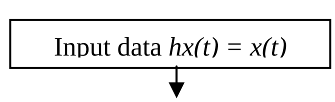
Empirical Mode Decomposition method was first proposed by N. E. Huang in 1998 [7]. The basic concept of EMD is to identify proper time scales that reveals physical characteristics of the signals, and then decompose the signal into modes intrinsic to the function, which are referred to as Intrinsic Mode Functions (IMF). IMFs are signals satisfying the following conditions:

1) in the whole dataset, the number of extrema and the number of zero crossings must either be equal or differ at most by one,
2) at any point, the mean value of the envelope defined by local maxima and the envelope defined by the local minima is zero.

The first condition is similar to the traditional narrow band requirements for a stationary Gaussian process. The second condition is new – its locality is necessary so that the instantaneous frequencies will not have unwanted fluctuations induced by asymmetric waveforms. An IMF is not limited as a sinusoid in the classical sense (such as in Fourier Transforms), it can be an amplitude and frequency modulated signal and, can even be a non-stationary signal. This method enables us to eliminate the drawback of a traditional time-domain to frequency-domain transformation where frequency contents are observed by sacrificing time resolution. Instead, IMFs provide amplitude and frequency information of a signal at any given time.

*Adaptive EMD Procedures:* EMD is an iterative or "sifting" process. EMD procedures are described in figure 1.

1) Upper and lower envelopes of the signal $hx(t)$ are constructed with its maxima and minima using cubic spline function.
2) Mean of the envelopes $m_i$ is subtracted from the signal $hx(t)$ to obtain a new signal $h_i(t)$.
3) Determine if $h_i(t)$ is an IMF using the criteria described above.
4) If $h_i(t)$ is an IMF, it is subtracted from the original signal $hx(t)$, and the resulted new signal $hx(t)$ goes through the above procedures until another IMF is obtained.
5) When the last IMF is obtained, it is checked to determine if this IMF is in the tremor frequency band (3 – 15 Hz). If not, the algorithm adaptively adjusts the stopping criteria until the in-band IMF representing a tremor is detected.



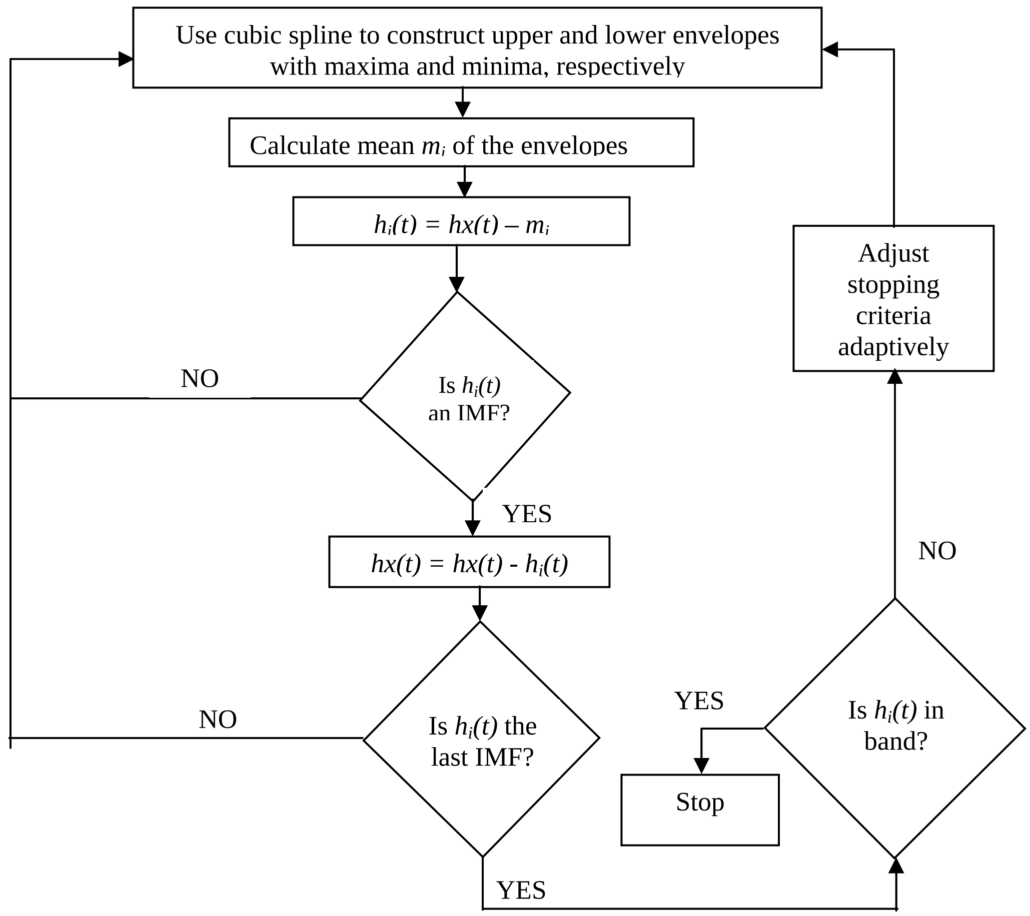



Figure 1: EMD Procedures

The stopping criteria consist of several important parameters including the absolute amplitude of the remaining signal, the mean value of the envelope, the cross-correlation coefficient between the remaining signal and the original signal, and the Standard Deviation (SD) between two consecutive results in the sifting process. SD can be expressed by the following equation (5) and our simulation results have shown that the reasonable values for SD are between 0.25 – 0.3.

$$SD = \sum_{t=0}^{T} \left[ \frac{\left| h_{1(k-1)}(t) - h_{1k}(t) \right|^2}{h_{1(k-1)}^2(t)} \right] \tag{5}$$

As shown in figure 1, the stopping parameters are adjusted adaptively based on the quality of the extracted IMFs. The main quality measures of an IMF include the amplitude (to determine the severity of a tremor) and the frequency range of the IMF (to determine if the IMF is in the desired detection frequency band of 3 – 15 Hz). It is worth noting that the extracted IMFs may not be single frequency components, instead, they may be amplitude-frequency modulated signals. Determining the exact frequency of the signal is impossible.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Whether or not the IMF is in the desired frequency band is determined by counting the number of maxima and minima for a known detection time period.

*B. Hilbert-Huang Transform (HHT)*

Suppose we obtained $N$ IMFs through the above EMD process. Let $z_i(t)$ be analytic function constructed with the $i^{th}$ IMF and equation (2), then $z_i(t)$ can be expressed as:

$$z_i(t) = a_i(t)e^{j\theta_i(t)} = a_i(t)e^{j\int \omega_i(t)dt} \tag{6}$$

and the original signal $x(t)$ can be expressed as a linear combination of the real parts of $z_i(t)$ and a residue term $r_n$:

$$x(t) = \mathrm{Re}\left\{\sum_{i=1}^{N} a_i(t)e^{j\int \omega_i(t)dt}\right\} + r_n \tag{7}$$

The residue term $r_n$ can be used to indicate the trend of the signal. Equation (7) enables us to represent amplitude as a function of frequency and time. The frequency-time distribution of the amplitudes is designated as the Hilbert spectrum, $H(\omega, t)$ and can be contoured on a frequency-time plane. To obtain a measure of total amplitude (or energy) contribution from each frequency, the marginal spectrum is defined as:

$$h(\omega) = \int_0^T H(\omega,t)dt \tag{8}$$

In addition to $h(\omega)$, Instantaneous Energy (IE) is defined in equation (9) and can be used to check the energy fluctuations.

$$IE(t) = \int_\omega H^2(\omega,t)d\omega \tag{9}$$

The following is a classical example that shows how this algorithm works. Although the process is not non-stationary, however, the example illustrates the basic concepts of EMD:

$$x(t) = 0.3\cos(2\pi 3t)+0.5\cos(2\pi 5t)+0.7\cos(2\pi 8t)+\cos(2\pi 12t) \tag{10}$$

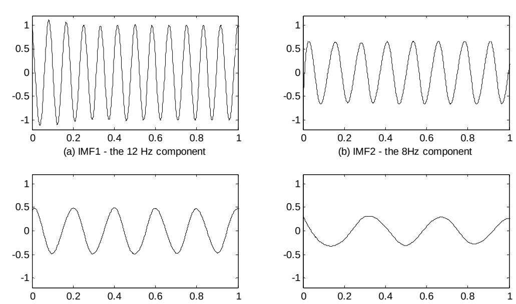


Figure 2: The IMFs of equation (10)

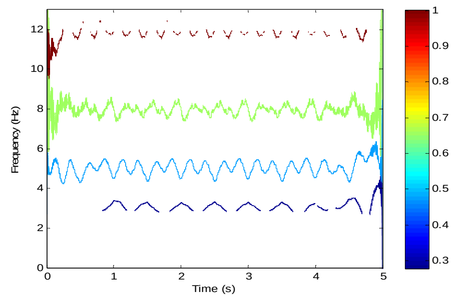


Figure 3: The HHT spectrum of the IMFs

The signal is so chosen that it contains various frequencies within the tremor signal frequency band. The goal of this experiment is to test if the amplitude and frequency contents of the signal can be accurately extracted by the method proposed. As expected, the information of interests was obtained with extreme accuracy. Figure 2 shows the extracted IMFs, and figure 3 shows the HHT results.

Figure 3 shows the amplitude of each IMF contoured on the time-frequency plane. As can be observed from this figure, all frequency contents (12 Hz, 8 Hz, 5 Hz, and 3 Hz) were extracted by the EMD algorithm. The amplitude of each frequency component can be determined by comparing with the color bar, which is 1, 0.7, 0.5, and 0.3, respectively. This indicates the fact that at each point of time of interest, the frequency contents and their respective amplitudes can be determined and hence made it possible for real-time suppression of hand tremors.

**Test platform and data collection**

The test-bed consists of three major subsystems: a hand tremor simulator, a sensor network interface, and a data acquisition device. The simulator generates simulated human hand tremors by composite movements of hand and arm, and detected by a 3-axis accelerometer sensor network. Data is collected via a LabView USB DAQ device. Each subsystem will be explained in the following sections.

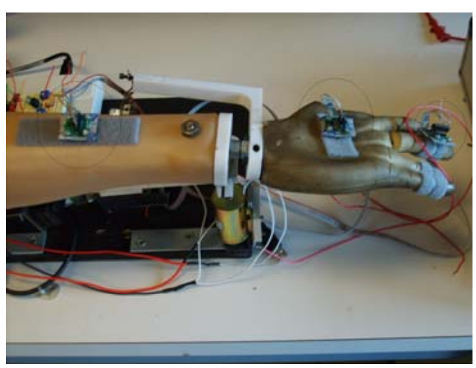

Figure 4: Human Hand Tremor Simulation Test-bed

*A. Hand Tremor Simulator*

Figure 4 shows the hand tremor simulator. This device was constructed using an arm and a hand from a military training dummy. Solenoids were used to move the hand and the arm at low frequencies. Tremor motion in the arm was simulated using a push-type solenoid attached near the wrist. To simulate tremor motion in the hand, an assembly was developed to house a ball bearing, which allowed smooth motion for the hand to pivot. This assembly was attached to the forearm and another push-type solenoid. This allowed the wrist to pivot from side to side to simulate a hand shaking during a tremor. The final assembly allows a realistic simulation of tremors by moving the arm up-and-down and the hand sideways simultaneously at different frequencies.

*B. Detection and Data Acquisition*

Signal detection was accomplished using an ADXL330 3-axis accelerometer network. As shown in figure 4, three accelerometers were used, one on the middle finger, one on the hand, and one on the forearm, respectively. Because of involuntary vibrations, the movements on the middle finger best depict the nature of a tremor signal which in most cases is a non-stationary process. The measured results are the time-series of acceleration on X. Y, and Z directions and filtered with 50 Hz low pass filters on each direction. The acceleration can then be translated into distances travelled that represent the amplitude of the tremor signals. The tremors are sampled at 200 samples/sec. Total 6000 samples were acquired for one complete test cycle of 30 seconds. Data were collected via a designed LabView Virtual Instrument (VI) user interface and an NI-USB 6008 DAQ device.

## Results

This section provides two examples of applying the proposed method for tremor detection. The data used were collected directly from the aforementioned test platform. The first example used a single frequency to move the arm and the aim was to demonstrate the superiority of the EMD to the traditional Fourier transform. The second example used a composite signal to drive the arm and the hand simultaneously, and the purpose was to show the results similar to a real-world situation.

In the first example, a 6Hz signal was used to move the arm. It was expected that the sensors would detect 6Hz signals in all directions. Sensor A, B, and C represent sensors located on the hand, arm, and the middle finger, respectively. Figure 5 shows the original data collected at AX, BX, and CY, where the first letter indicates the sensor, and the second letter indicates the direction of movement (e.g., AX represents data from sensor A along X direction).

As shown in figure 6, a Fourier analysis revealed the expected frequency contents in all directions. It can be observed that 6Hz signal is dominant in all directions and locations, along with its higher ordered harmonics. It can also be observed that the data collected from sensor B (arm) shows clearly the 2$^{nd}$ and the 3$^{rd}$ order harmonics, sensor A (hand) shows a clear 2$^{nd}$ order harmonic, and sensor C (middle finger) mainly shows the fundamental frequency at 6Hz. However, from Fourier analysis, one can only observe the frequency contents and their respective amplitude, no information is available as to when the frequencies occurred. This is due to the very nature of Fourier analysis that the information is averaged over time.

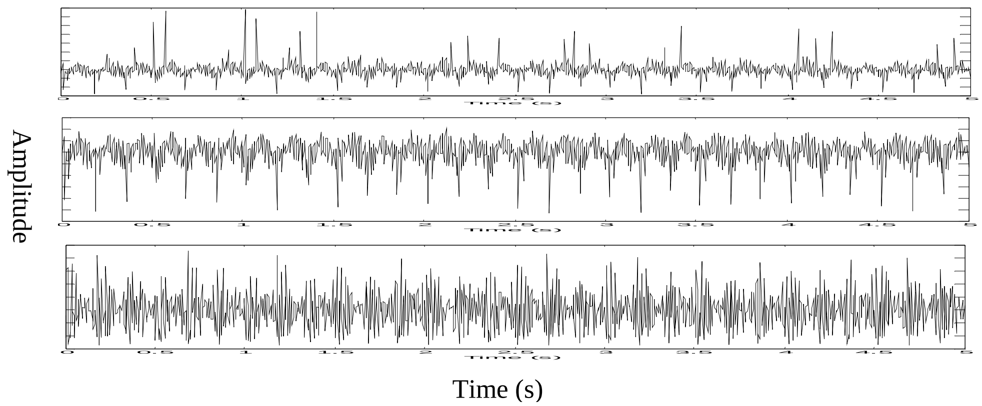


Figure 5: Original data collected from AX, BX, and CY with 6Hz driving signal

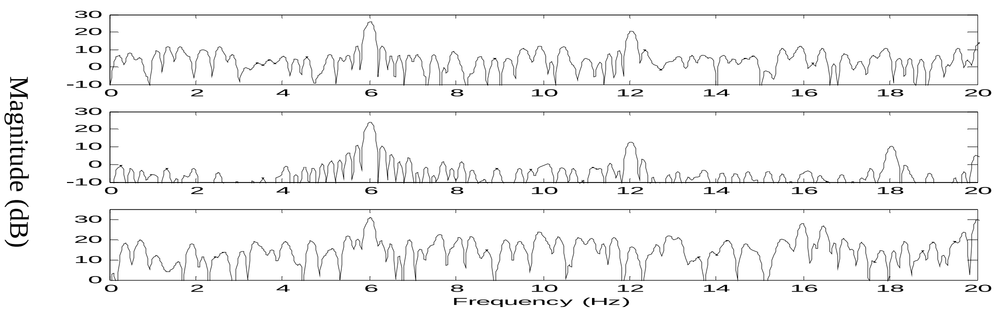


Figure 6: Fourier analysis of AX, BX, and CY signals

Figure 7 shows the IMFs obtained from EMD of AX, BX, and CY signals. As can be observed from these plots, more detailed information of the motions was provided. Each subplot shows an average frequency of 6Hz, however, amplitude change is also clearly sown in each subplot. These IMFs can be viewed as AM-FM modulated signals. Intuitively, tremor signals are not expected to be composed of single-frequency fixed-amplitude components. Therefore, EMD results intuitively better explains the nature of any tremor signals.

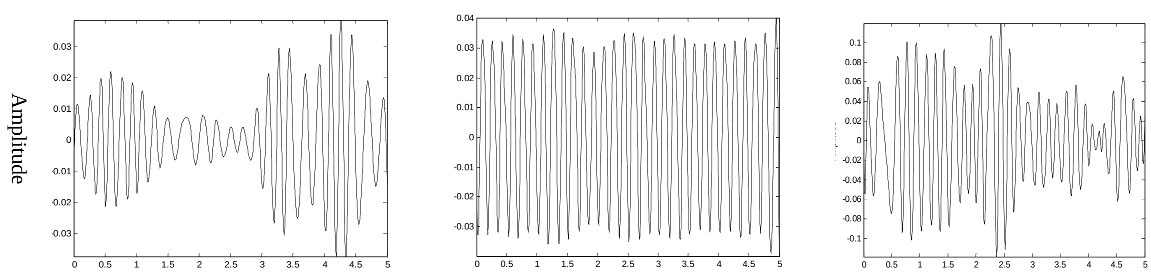


Figure 7: IMFs for AX, BX, and CY signals

Figure 8 shows the HHT spectrum of the above signals. As can be seen in the plots, the amplitudes are displayed as functions of time and frequency. From these plots, one can easily find the amplitude and the frequency of the tremor at a certain time of interest. For example, the subplot in the middle shows the HHT spectrum of the data collected by sensor B in the X direction. This subplot shows an average frequency over time is around 6Hz, but the signal does cover a frequency band from 4.5 – 7.5 Hz or so. In addition, the subplot shows the time a specific frequency occurs. It can be seen from this subplot that between 1.8s and 2.2s time period, there was no 6Hz signal present at sensor B at its X direction. Moreover, the amplitudes of the signals are contoured on the time-frequency plane, and make it possible for the researchers to investigate the magnitude of a certain frequency signal at a specific given time. This can be easily observed from the first and the third subplots where higher frequency contents presented at lower (in blue color) amplitudes. These results are consistent with those obtained from the Fourier analysis shown above. Unlike Fourier analysis where time resolution is completely lost, EMD method well preserves time information of the tremors.

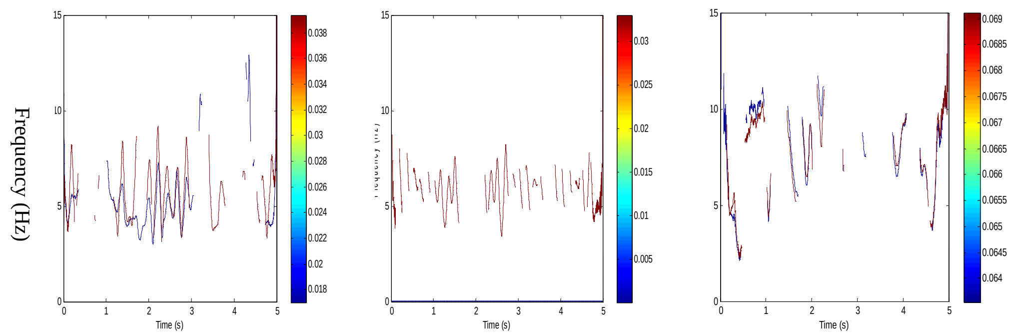


Figure 8: HHT spectrum of AX, BX, and CY signals

In the second example, a 4Hz signal was used to move the arm, and a 6Hz signal was used to move the hand. Due to similarities of data on the x, y, and z directions, only tremor signals on the z-direction from each sensor are presented in figure 9. Figures 10-12 show IMFs and their Hilbert spectrum of each data set. Exact frequencies at 4Hz and 6Hz are not expected due to the complex nature of movements and signal modulation property. One needs to be careful when interpret the results. IMFs are not single frequency signals, rather, they are AM-FM modulated signals reflecting the amplitude and the frequency at a given time point. The Hilbert spectral plot contours the amplitude on a time and frequency plane, with x-axis being the time axis and y-axis being the frequency axis. The amplitude is presented with color match the magnitude indicated in the color bar. The time-frequency plane plots provide information on the frequency of the signal propagates over a certain time periods. Amplitudes provide information on the magnitudes of predominant tremor signals that need to be suppressed and hence help decide treatment priority.

As can be observed from figure 10, there are three IMFs associated with the data collected along the z-direction of the sensor mounted on the middle finger. These IMFs are AM-FM modulated signals with frequencies span over 4-10 Hz range, and amplitude from 0.02-0.1 (normalized).

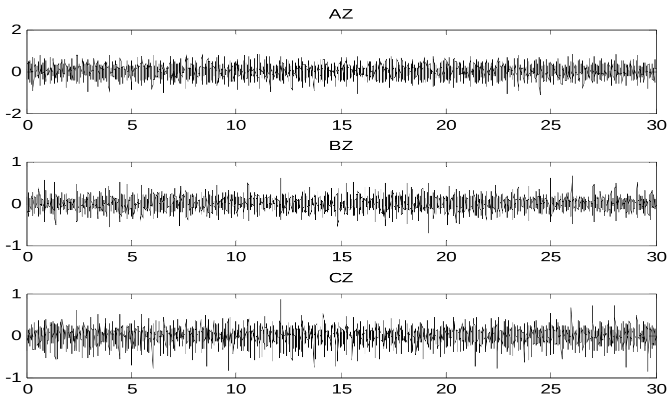


Figure 9: Collected data from sensors A, B, and C, all along Z-direction

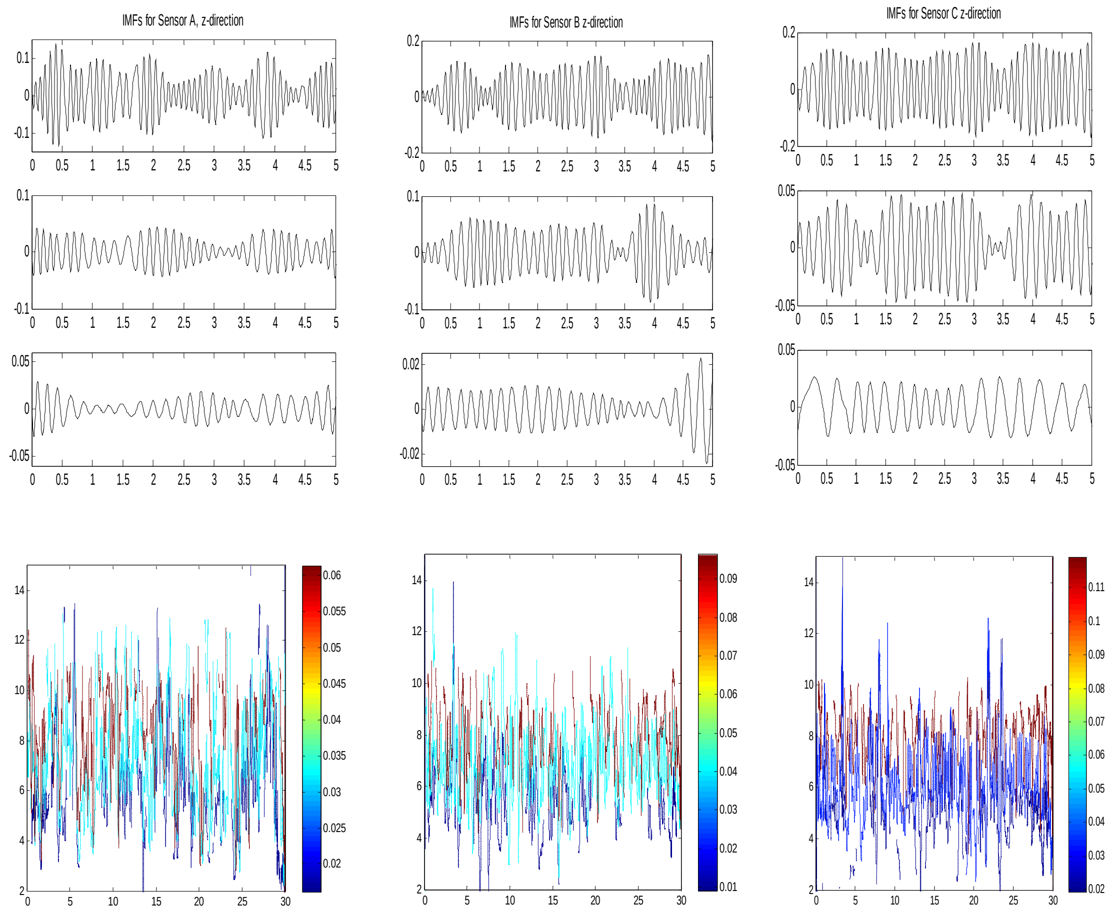


Figure 10 (middle finger) Figure 11 (arm) Figure 12 (hand)
Figures 10-12: IMFs and HHT Spectrum

The last IMF has an average frequency at around 6Hz, which is the fundamental frequency used to move the hand. Similar frequency range can be observed on the signal collected from the sensor mounted on the arm, as shown in figure 11. It is interesting to observe the last IMF extracted from the data collected from the sensor mounted on the hand. It shows an average frequency at about 4 Hz, which is the fundamental frequency to move the arm. Because the sensor is mounted close to the solenoid that moves the arm, the result showed expected detection accuracy.

## Conclusion

This paper showed our results of analyzing human hand tremor signals using EMD method. The novelty of using this method is the identification of magnitude of a tremor signal on a time-frequency plane. The increased time resolution of this analysis enables the treatment of tremor of a certain frequency at a frequency within a much shorter time interval, and therefore, provides possibility of real-time treatments. Further investigation relies on a simultaneous multi-dimensional detection of tremor at all directions and a suppression mechanism based on the detected IMFs.

## References


[1] A. Anouti and W. C. Koller, “Tremor Disorders Diagnosis and Management,” *Western Journal of Medicine*, Vol. 162, No. 6, June 1995, pp.510-513.

[2] J. Raethjen and G. Deuschl, “Tremor,” *Ther Umsch*, Vol. 64, No. 1, 2007, pp. 35-40.

[3] J. Zhang and F. Chu, “Real-time Modeling and Prediction of Physiological Hand Tremor,” *IEEE ICASSP*, 2005, pp. 645-648.

[4] J. Jakubowski, K. Kwiatos, A. Chawaleba, and S. Osowski, “Higher Order Statistics and Neural Network for Tremor recognition,” *IEEE Transactions On Biomedical Engineering*, Vol. 49, No. 2, Feb. 2002, pp.152-159.

[5] P. S. Slack and X. Ma, “Time dependency assessment of muscular fatigue index and hand tremor under operating conditions,” *Proceedings of the 29th Annual International Conference of the IEEE EMBS*, August 2007, pp. 4822-4825.

[6] J. Z. Zhang, B. Price, R. Adams, K. Burbank, and T. Knaga, “Detection of Involuntary Human Hand Motions Using Empirical Mode Decomposition and Hilbert-Huang Transform,” *Proceedings of the IEEE International 51st Midwest Symposium on Circuits and Systems*, August, 2008. pp. 157-160.

[7] N. E. Huang, Z. Shen, S. R. Long, M. C. Wu, H. H. Shih, Q. Zheng, N. C. Yen, C. C. Tung, and H. H. Liu, “The empirical mode decomposition and the Hilbert spectrum for nonlinear and nonstationary time series analysis,” *Proc. Roy. Soc. Lond. A*, 1998, pp. 903-1005.


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