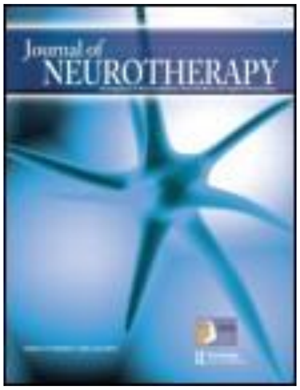

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Developments in EEG Analysis, Protocol Selection, and Feedback Delivery

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LETTER TO THE EDITOR

DEVELOPMENTS IN EEG ANALYSIS, PROTOCOL SELECTION, AND FEEDBACK DELIVERY

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It stands to reason that the better the extracted information from the electroencephalogram (EEG), the better the data analysis and subsequent EEG biofeedback. At the core of digital signal processing used in our field is a linear filtering technology that discards significant EEG features. Brainwaves are nonlinear, nonstationary, and noisy signals. The purpose of this letter to the editor is to illuminate the Hilbert-Huang Transform's (HHT's) (Huang et al., 1998) ability to empirically quantify nonlinear, nonstationary signals such as the EEG. I demonstrate how this technique can detect and extract a tiny noisy complex waveform from a raw signal while preserving the majority of the important information from the original source. I contrast and compare the HHT to other quantitative techniques.

Linear filters, such as Fourier-based Transforms (FFTs), measure brainwaves as if they were a series of tuning forks ringing in various volumes. What happens when the tuning forks are quickly changing in frequency? The FFT can no longer accurately read them because the FFT assumes that the signal section being analyzed (the sample) is repeated over and over again. The FFTs requires linearity and the data must be stationary—it provides information on microvolt levels over a selected frequency range but discards information about the varying frequency changes and microvolts at every point in the sample across time. This results in an unnatural uniformity. By contrast, when using the Hilbert-Huang Transform (HHT), all the different shapes of the waves forms, also known as morphology, are represented. More specifically, the HHT preserves the morphologies peak broadness, peak spacing, and tangents from the zero point to peak envelope angles. This information may represent a normal versus abnormal distribution curve of power. Consequently, any information related to the signal morphology is lost (Klimesch, 1999). Using the short-time Fourier transform instead assumes the stationarity of the signal within the time frame; however, this is not practical when inspecting naturally occurring signals such as the electroencephalogram (EEG) (Walker & Kozlowski, 2005).

It is worth mentioning a few additional transforms that have become standards in an attempt to more accurately detect changes in time-frequency analysis. Wavelet transforms can analyze finite length signals, but they are

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not adaptive (Huang et al., 1998). This makes time-frequency analysis possible, but the energy that escapes from the wavelet transform causes the time-frequency representation to appear broader and less variable than the actual spectrum. Wavelet analysis is linear whether it is distinct or continuous, so it doesn't work well for nonlinear data, but it can be used for nonstationary data. The distribution in the Wigner-Ville transformation is Fourier-based, but it introduces the idea of negative energy (Klimesch, 1999). Likewise, the Gabor transform is somewhat similar to the short-time Fourier transform, but it uses fixed windows (Saeid & Chambers, 2007). Independent component analysis is currently a popular method for blind source separation of linear or mildly nonlinear mixtures unlike the EEG. However, nonlinear independent component analysis does not necessarily lead to nonlinear blind source separation. Nonlinear blind source separation is impossible without prior knowledge of the mixing model (Jutten & Taleb, 2000). In summary, there are problems with all of these transforms when applied to nonlinear and nonstationary data.

What is the HHT? It begins with what is called Empirical Mode Decomposition (EMD), which is an algorithm based on the local properties of the signal, at each point of the signal (Huang et al., 1998). In each section of signal we first find a local maximum (highest point above zero) and a local minimum (lowest point below zero). This is an approximation of the left half of the wave of the highest frequency contained in that section of the wave. Halfway between them is an approximation of the middle (minimum + maximum/2) about which that highest frequency wave is oscillating. By joining up the local maxima and local minima with a natural cubic spline, the local middles are found. Now the highest local frequency can be subtracted from the wave and is replaced by the local middles. The product of this initial iteration is called the first Intrinsic Mode Function (IMF). The local middles are then treated as a new wave. The whole procedure is then repeated using the local middles curve as a starting point, again locally, to extract the next lowest local frequency. This process is repeated until the last IMF becomes a monotonic function, which means it fails to complete more than one full cycle. When these intrinsic oscillations are summed they equal the original signal. Having obtained the IMF components, we can subject them to the HHT to obtain the time-frequency-power distribution. When these intrinsic oscillations are summed they equal the original signal (see Figure 1).

Empirical Mode Decomposition Steps

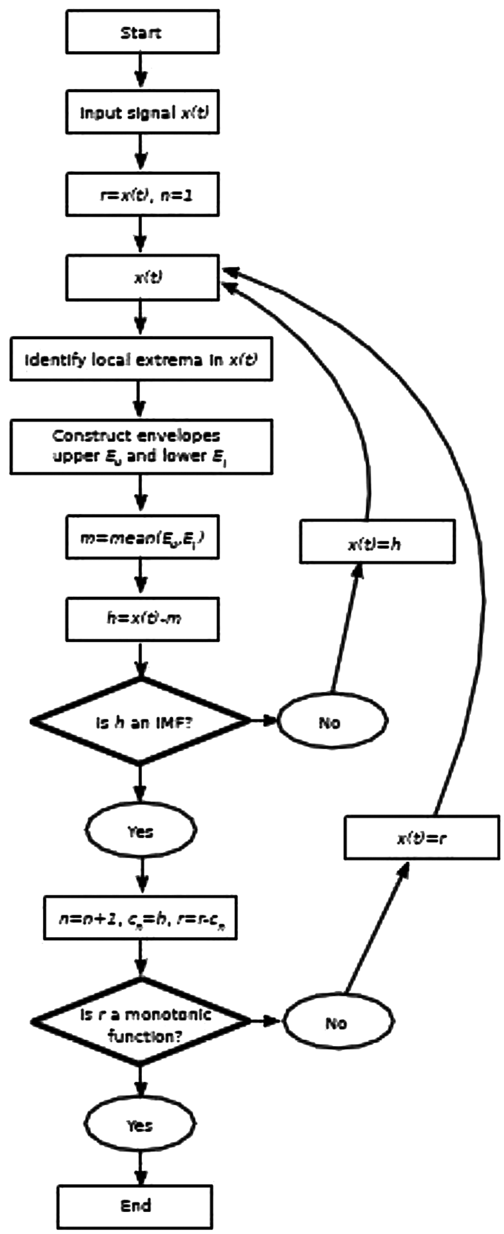

FIGURE 1. Flowchart of the Empirical Mode Decomposition procedure.

Figure 2 is the actual output of raw data followed by four iterations derived from the sifting process that extracts the first IMF. This 1-s epoch of EEG was sampled at 256 samples/second from a subject's session. The local minima and maxima are connected with the natural cubic splines and are, respectively, blue and red. The emerging IMF is green. The black line straightening out across the iterations is the mean envelope. When the standard deviation of the mean envelope is less than 0.3, the iteration function is stopped. That mean envelope is then used as the input signal to decompose the next IMF.

When 60 Hz notch filters are applied, the first IMF is in the gamma range from 38 to 45 Hz. This subject's gamma during that second

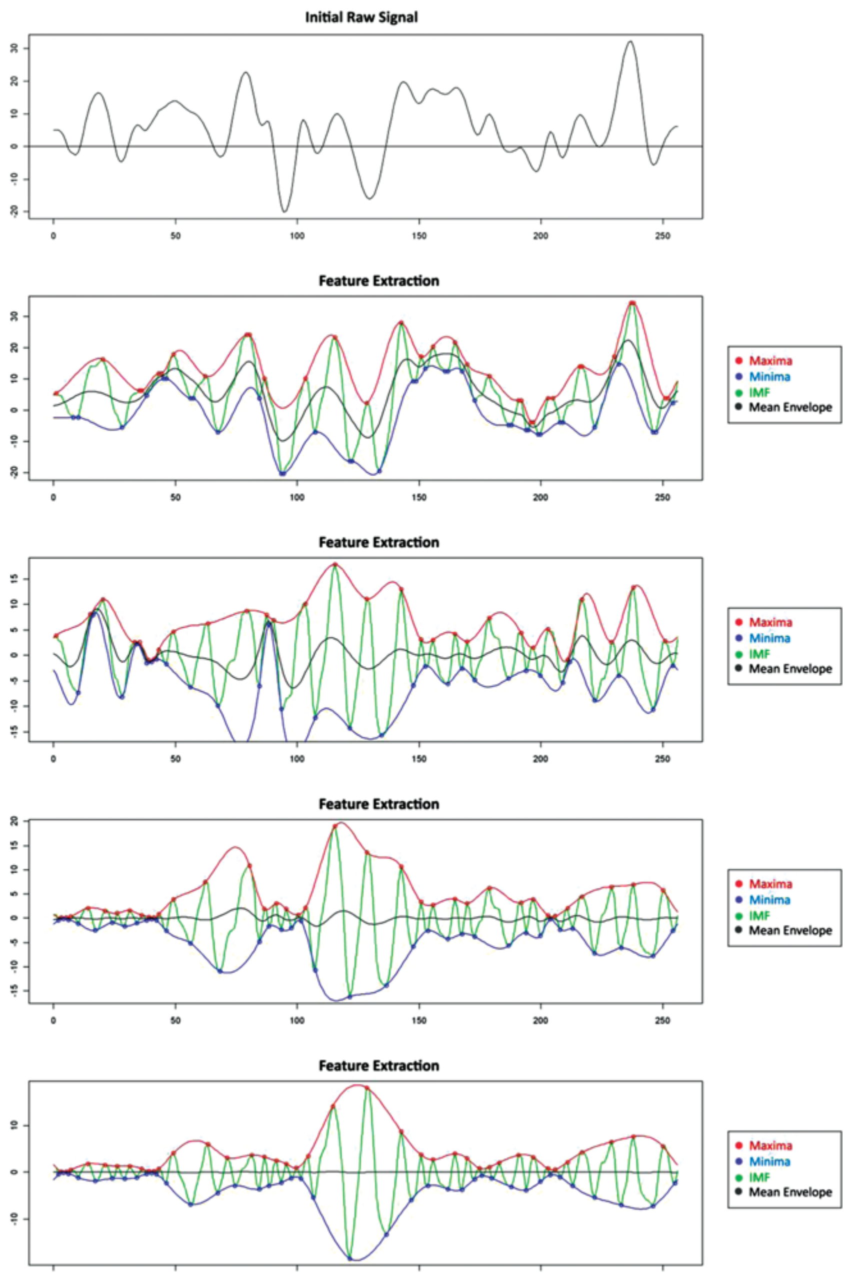

FIGURE 2. The extraction iterations for the first 1-s Intrinsic Mode Function (IMF). (Color figure available online.)

was 38 Hz. Figure 3 shows subsequent IMFs revealing his beta (16 Hz), alpha (9 Hz), theta (4 Hz), and delta (3 Hz). We performed the HHT on each IMF to reveal its instantaneous amplitude as well.

In a typical 10-s EEG sample, there could be 100 microstates, each with a potentially different alpha, beta, theta, gamma, and delta content. In the HHT, each IMF may have a significant change of frequency 100 times, but it is possible that the highest local frequency is just ''noise'' and only some of the lower local frequency IMFs will reflect the changing microstate.

Figure 4 demonstrates how a small complex noise signal can be extracted from the rapidly changing complex signal. The noisy signal comprised the fourth instantaneous amplitude of the Hilbert spectrum. It was subtracted from the raw signal creating a correlation coefficient of .99 between the raw signal and the raw signal minus the artifact.

Figure 5 is a demonstration of the Hilbert Spectrum revealing the expected alpha increase in instantaneous amplitude in an eyes-open versus eyes-closed condition.

The HHT was first used by NASA in 1998 and uses the EMD method to decompose a signal into IMFs. Then it applies the Hilbert spectral analysis method to get instantaneous frequency and amplitude data. It evolved

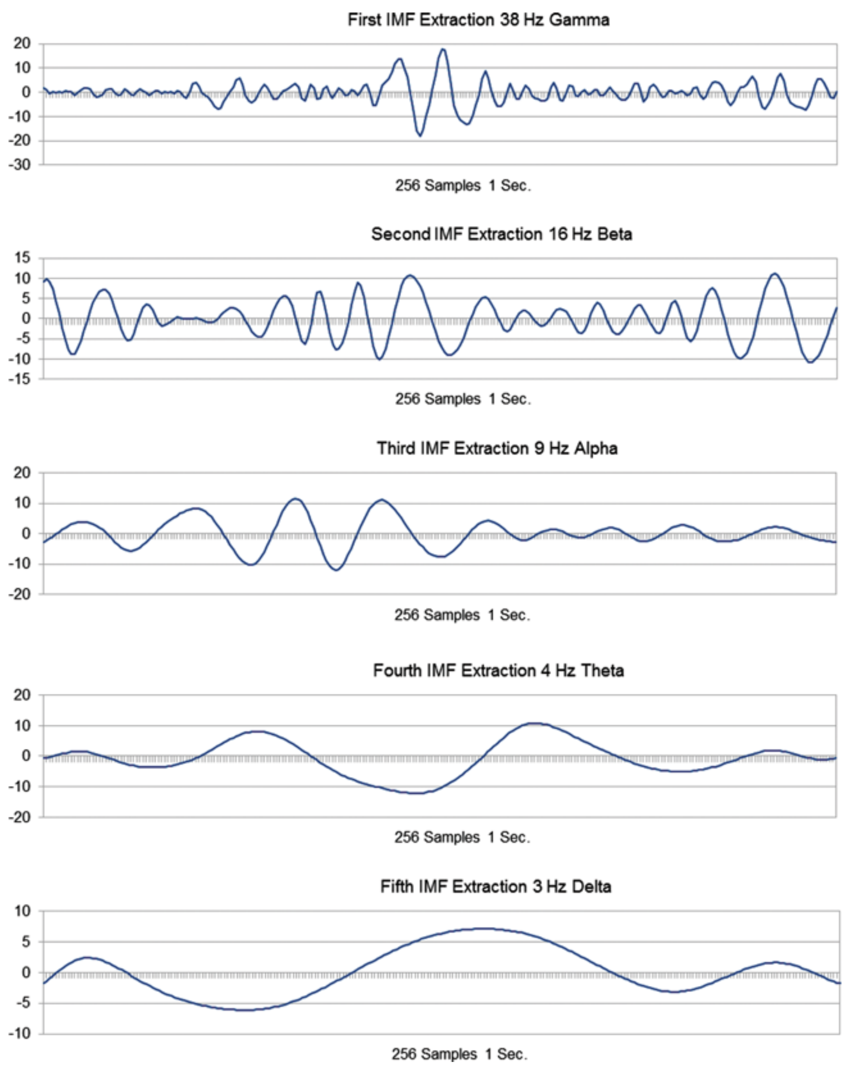

FIGURE 3. Five frequency bands were decomposed from 1 s of raw data. *Note*. IMF = Intrinsic Mode Function. (Color figure available online.)

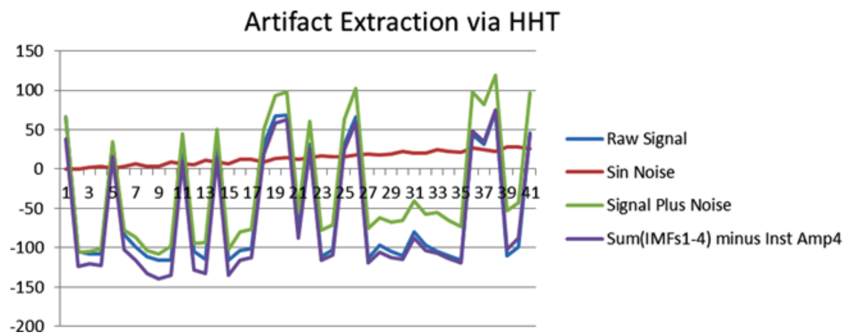

FIGURE 4. Artifact removal demonstration via Hilbert-Huang Transform (HHT). *Note*. IMF = Intrinsic Mode Function. (Color figure available online.)

from the need to analyze nonstationary and nonlinear time series data. The advantages HHT presents in processing EEG signals is really only beginning. The reason for this is that it is such a different point of view, and it has taken some time to develop schemes to recognize the really important IMFs in signals that are being compared.

In just the last 12 months, three EEG studies using the HHT methodology have reported findings quite relevant to the field of EEG biofeedback. The first study (Chia-Lung, Hsiang-Chih, Chi-Hsun, & Po-Lei, 2010) looked at event-related potentials from a finger movement exercise. They found that extracting the relevant IMFs gave excellent noise reduction compared to other methods. For example, there is so much noninformation in the signal-to-noise ratio in the FFT-based methods of information extraction that multiple averages of the physical response are needed to average out the noise from the signal. The adaptive nature of the EMD method automatically extracts the signal in an IMF and places the noise in other IMFs. This happens in a single trial. The second study (Chien-Chang & Jie, 2010) used the HHT with a radial basis function neural network to diagnose the kind of obstructive sleep apnea from electroencephalography. They classified three types with 92% to 97% accuracy. Finally IMFs subjected to higher order crossings and subsequent quadric discriminant analysis classified six different emotions with 85% accuracy. It was found that an EMD-based classifier gave significantly greater emotion recognition than the most commonly used classifiers (Petrantonakis & Hadjileontiadis, 2010). The last study may be relevant in many clinical situations involving anxiety, depression, and attention deficit because IMF is subjected to higher order crossings and subsequent quadric discriminant analysis classified six different emotions with 85% accuracy. The six specific emotions were happiness, surprise, anger, fear, disgust, and sadness.

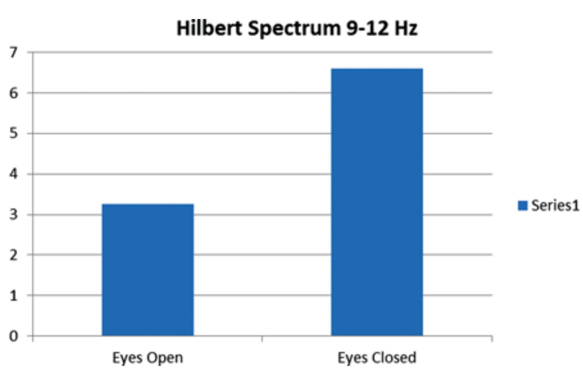

FIGURE 5. Eyes open and eyes closed result in 9–12 Hz alpha increase in instantanious amplitude of the Hilbert spectrum. *Note*. We revealed the expected alpha decrease in a parietal region in an eyes-open versus eyes-closed condition. (Color figure available online.)

When the HHT is used in feedback, it should convey better information about brain states, which would translate into better results. We are using a hybrid method of the HHT (HHHT) in the BrainPaint software whereby information on changes in the morphology is translated into fractal image movement. In addition, we are providing the standard amplitude feedback with thresholds, inhibits, and rewards through graphs, text, and audio indicators of various movement and muscle tension artifacts. A randomized controlled trial is under way on attention-deficit/hyperactivity disorder ($n = 75$) using BrainPaint. The preliminary results (which still include outliers) suggest that the FFT training group is replicating the 2005 ($n = 121$) randomized controlled trial results on the Test of Variables of Attention (Scott, Kaiser, Siderhoff, & Othmer, 2005). Yet the HHHT group is improving significantly faster than the FFT-based training group and a waitlist control group. We had not been capturing the data from the HHHT in a meaningful form but have begun the process for a new study.

CONCLUSION

An EEG signal consists of multiple superimposed oscillatory components that represent different underlying physical components of brain activity. The true nature of this signal is highly nonlinear and nonstationary, making linear time-frequency analysis not the ideal method to analyze brainwaves. EEG signals can be analyzed with advanced mathematical methods in order to separate the most essential components from the rest. HHT is a new method to construct a sharp and clean time-frequency spectrum of a nonlinear and nonstationary signal. It consists of empirical mode decomposition, which translates the signal into intrinsic mode functions, and Hilbert transforms, which is then used to obtain the spectrum. The ability of EMD to decompose nonlinear signals and retain their intrawave modulation makes it very suitable for quantitative EEG analysis.

Extracting the components of the EEG makes interpreting the signal much easier. The underlying idea is that a signal is high oscillations superimposed on low oscillations. This makes separating the details from the trend, and the noise from the signal, possible. For example, artifacts show up in separate IMFs and can be easily subtracted from the original signal without disturbing much of the remaining temporal structure. Although the HHT is a superior digital processing tool, it has room for improvement, which perhaps could be covered in a future article.

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