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PAPER

# Frontal electroencephalogram analysis with ensemble empirical mode decomposition during the induction of general anesthesia

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## Abstract

*Background.* Ensemble empirical mode decomposition (EEMD) was proposed for decomposing electroencephalography (EEG) signals into intrinsic mode functions (IMFs), which obtain instantaneous frequency data and work well with data that are nonstationary and nonlinear. Hilbert–Huang Transformation (HHT) was used in this study to convert IMFs into spectrograms, which are useful for observation. We recorded EEG signals through a bispectral index (BIS) monitor for EEMD analysis, and calculated the energy change after HHT. *Methods.* A total of 19 patients who had received general anesthesia were included. The EEG signals were recorded by physiological monitor with BIS electrode strip and saved in a portal computer. The frequency changes of the IMF spectrograms were compared during the induction period, and the raw data energy changes were quantified with moving window standard deviation every 10 s. *Results.* The second IMF, with an initial spectrum of approximately 10–30 Hz, was focused between 10 and 15 Hz after the patient was anesthetized. All patients presented with decreased frequency and bandwidth focusing in the second IMF and indicated energy gathering. *Conclusions.* We found energy gathering in IMF2 after patient was anesthetized. The results suggest that examining IMFs rather than EEG signals was more useful for determining the particular bandwidth changes in which synchronization phenomena occur. With this method, it is easily to observe the separate energy changes of IMFs within the EEG signals.

## Introduction

In contemporary surgical procedures, accurate and noninvasive monitoring of the depth of anesthesia (DOA) [1] is indispensable. The bispectral index (BIS) is one example of a system for monitoring the DOA. When a patient arrives in an operating room, anesthesiologists aim to prepare the patient for surgery quickly and safely. However, whole brain electroencephalography (EEG) is an invasive medical technique for monitoring and recording the electrical activity of brain; in addition, EEG probe placement is time consuming and can delay the operation start time. Moreover, EEG is complicated and unfriendly interpreted, and the raw data cannot be observed during anaesthetization of the patient. The BIS is a practical alternative that provides real-time clinical information during surgery with an special self-prepping electrode strip that is easily attached to patient's forehead [2].

Many researchers have measured the physiological signals that represent physical changes during anesthesia, especially EEG signals. Some studies have used fast Fourier transform (FFT) which continues to be applied, for spectral analysis of EEG signals in the frequency domain [3, 4]. The disadvantage of FFT is that it has difficulty managing physical signals, which are modulated by the autonomic nervous system and multiple other factors; furthermore, physical signals are both nonlinear and nonstationary and produce broad frequencies. One study applied a bandpass filter to decompose EEG signals and used wavelet analysis and sample entropy to examine EEG messages [5]. Subsequently, D'Avanzoa and Sparacinoady similarly applied a wavelet-based methodology to extract quantitative time-frequency parameters from EEG signals [6].

In 2005, Huang suggested that synchronization was the primary mechanism for dynamic integration of the neuronal activity necessary to produce coherent cognitive acts [7]. Specifically, Huang proposed decomposing nonstationary and nonlinear signals into intrinsic mode functions (IMFs) through ensemble empirical mode decomposition (EEMD) [7]. An IMF is defined as a simple oscillatory function that has the same number of extrema and zero crossings and whose local mean is zero [8]. Because the empirical mode decomposition algorithm substantially depends on the extrema crossing of the input signal, extracted IMFs can have mode mixing problems because the input signals are noisy. Therefore, Wu *et al* proposed a noise-reducing EMD algorithm, which they called ensemble-EMD, a more robust model for examining practical and real-time signals [9]. EEMD is also a self-adaptive, data-driven separation method that can decompose nonlinear and nonstationary signals, including most biological and physiological signals, into several IMFs with an intrinsic time scale. Wu *et al* proposed that IMFs may be used to detect the frequency changes during which synchronization phenomena occur. Therefore, Hilbert–Huang Transform (HHT) was developed to convert IMFs into spectrograms that are more useful for observation.

The increases in frontal EEG power and power focusing to lower frequencies during anesthesia induction have been defined as synchronization processes [10]. For example, Brown noted that during the induction of propofol, the median frequency decreased from 23.1 to 12.0 Hz and the bandwidth decreased from 17.4 to 9.1 Hz [11]. Furthermore, as patients entered the loss of conscious stage, energy traveled from the occipital lobe to the frontal lobe. He used the term 'traveling peak' in order the explain the symptom that energy gathering while patient loss of consciousness. Spatially coherent frontal alpha oscillations during unconsciousness may explain how the design of the BIS monitor can detect the DOA from frontal EEG.

In the present study, we recorded frontal EEG signals during the induction period of patients under general anesthesia. We then applied EEMD to decompose the original signals into multiple IMFs, and compared the HHT results with those of FFT. Finally, a moving window of the instantaneous standard deviation (SD) of the IMFs and the original EEG signals was proposed as the partial 'energy' of a signal.

# Method

## Ethics statement

The Institutional Review Board of National Taiwan University Hospital approved the present study. All the participants provided informed consent for BIS data analysis.

## Clinical approach

In total, 19 patients between the ages of 20 and 40 years who had a low anesthetic risk (i.e., American Society of Anesthesiologists physical status classification I or II) and required total intravenous general anesthesia were recruited. Each patient was received in an operating room, and all standard monitors, including a pulse oximetry, electrocardiogram, BIS monitor, and blood pressure monitor, were set up and began recording physiological and physical signals prior to anesthesia induction. After 1 min of monitoring, an anesthesiologist began target-controlled infusion induction with 10 mg $ml^{-1}$ of propofol. Once the patients were fully anesthetized (indicated by loss of consciousness [LOC], loss of verbal response, and loss of eyelid response), anticholinergics and alfentanyl (0.272 mg) were added. The demographic data of each patient were collected, and the signals recordings from BIS monitors were analyzed. EEG waveforms were collected through the BIS monitor (Aspect Medical System's XP platform, a specific electrode strip which mainly frontal electrodes).

## Analysis approach

*Ensemble empirical mode decomposition*

For obtaining an input signal $S(t)$, the EEMD algorithm represents the summation of IMFs and a residual signal $r(t)$ as follows:

$$S(t) = \sum_k \mathrm{imf}_k(t) + r(t).$$

First, a bandpass filter was used to remove the major frequencies of instrument noises. However, we could not assume that all the other noise (such as observation noise) had been removed from the original EEG signal; thus, the EEMD was used to decompose and denoise the signal. There are two parameters in the EEMD: One is the SD of the noise (also known as the power of noise), the other is the ensemble number of noise. Because we did not have clean EEG signals, estimating the power of noise was difficult; thus, variously powered white noise was added. For all the experiments in this study, the SD of white noise was set to 0.1 and the ensemble number was 500.

*Hilbert–Huang transform of IMFs*

Because most IMFs have a time-varying frequency and amplitude, Huang *et al* used the Hilbert spectrum to analyze the frequency and amplitude properties of each IMF. For the specific IMF component (which was the focus of this study) the corresponding Hilbert transformation $g(t)$ was computed as

$$g(t) = \frac{1}{\pi}\text{p.v.}\int_{-\infty}^{+\infty}\frac{f(\tau)}{t-\tau}\mathrm{d}\tau,$$

where p.v. denotes the Cauchy principal value. With the Hilbert Transform $g(t)$, we can have an analytic signal, $z(t)$, as

$$z(t) = f(t) + \mathrm{i}g(t) = a(t)\mathrm{e}^{\mathrm{i}\theta(t)},$$

where $a(t) = \sqrt{f^2(t) + g^2(t)}$ and $\theta(t) = \arctan\left(\frac{g(t)}{f(t)}\right)$ correspond to the amplitude and frequency parts of the IMF $f(t)$, respectively. Then, we can analyze the properties of IMF $f(t)$ via analyzing its amplitude part $a(t)$ and frequency part $\theta(t)$.

*Fast Fourier transform*

An FFT algorithm converts a signal from its original domain (often time or space) into a representation in the frequency domain [12], according to the definition of discrete Fourier transform (DFT), which is the most crucial discrete transform and is used to perform Fourier analysis in many practical applications [13].

According to the definition of DFT, a sequence of $N$ complex numbers ($x_0$, $x_1$, …$x_{N-1}$) is transformed into an $N$-periodic sequence of complex numbers as follows:

$$X_k \stackrel{\text{def}}{=} \sum_{n=0}^{N-1} x_n \cdot \mathrm{e}^{-2\pi \mathrm{i}kn/N}, \quad k \in \mathbb{Z}, \tag{1}$$

where $Z$ is the set of integer numbers.

Using Euler's formula, the DFT formulae can be converted to the trigonometric form used in engineering and computer science:

*Fourier transform*

$$X_k = \sum_{n=0}^{N-1} x_n \cdot \left(\cos\left(-2\pi k\frac{n}{N}\right) + i\,\sin\left(-2\pi k\frac{n}{N}\right)\right), \quad k \in \mathbb{Z} \tag{2}$$

Because of periodicity, the customary domain of $k$ is computed as (0, $N$—1) when the DFT is implemented through the FFT algorithm, and the left and right halves of an FFT output sequence are swapped. Thus far, the commonly used FFT of the Cooley–Tukey algorithm is used to divide the transform into two pieces of size $N/2$ at each step, and is therefore limited to power-of-two sizes to reduce the steps of calculation.

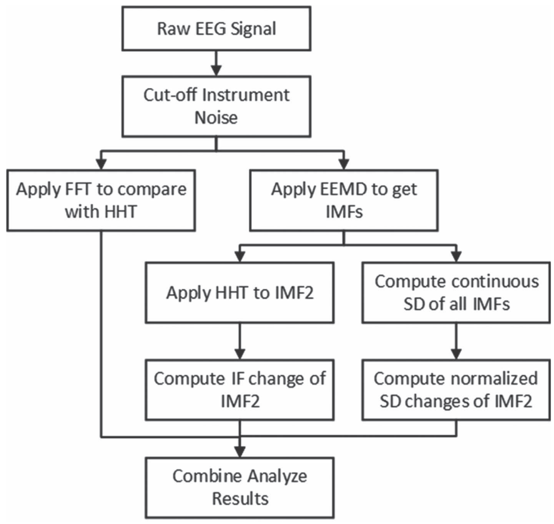
*Computing standard deviation of original EEG and IMFs*

After computing the Hilbert spectrum of the IMFs, we compared the instantaneous SD of the IMFs with the original EEG signal. Notably, the SD can be used to quantify the 'energy' of a signal partially. Here, to examine the 'energy' change of the IMFs over time, a sliding window technique, with a moving window size of 10 and 3 s intervals, was applied to derive the time variation SD$(t)$ of a signal $S(t)$, which can be defined as

$$\mathrm{SD}(t) = \sqrt{\frac{1}{N}\sum_{\tau=-N/2}^{N/2}(S(t+\tau) - \overline{S_N(t)})^2}, \tag{3}$$

where $\overline{S_N(t)}$ denotes the mean of $S(t)$ in the window $\left[t - \frac{N}{2},\ t + \frac{N}{2}\right]$.

Finally, the baseline data (T1), loss of consciousness (T2), postremifentanil injection (T3), and presurgical incision (T4) were compared with repeated measures of one-way ANOVA.




Flowchart: Processing steps of this experiment.

After a raw data was input, our overall analysis processes consisted of the following steps:

(1) Remove the instrument noise by using a bandpass filter (cut-off frequency = 42 Hz);

(2.1) Apply the standard FFT to the denoised EEG signal used as a standard comparison index with HHT;

(2.2) Apply EEMD to the denoised EEG signal and acquire the IMFs;

(3.1) Apply HHT to IMF2;

(3.2) Compute the instantaneous frequency (IF) change of IMF2;

(4.1) Compute the continuous SD of all the IMFs to analyze their energy change;

(4.2) Use a normalized SD change (which is computed as the SD percentage change of IMF2/EEG) to quantize the energy change of IMF2;

(5) Combine the analysis results with those of the FFT from step (2.1), the IF change in step (4.1), and the energy change in step (4.2) to draw the final conclusion.

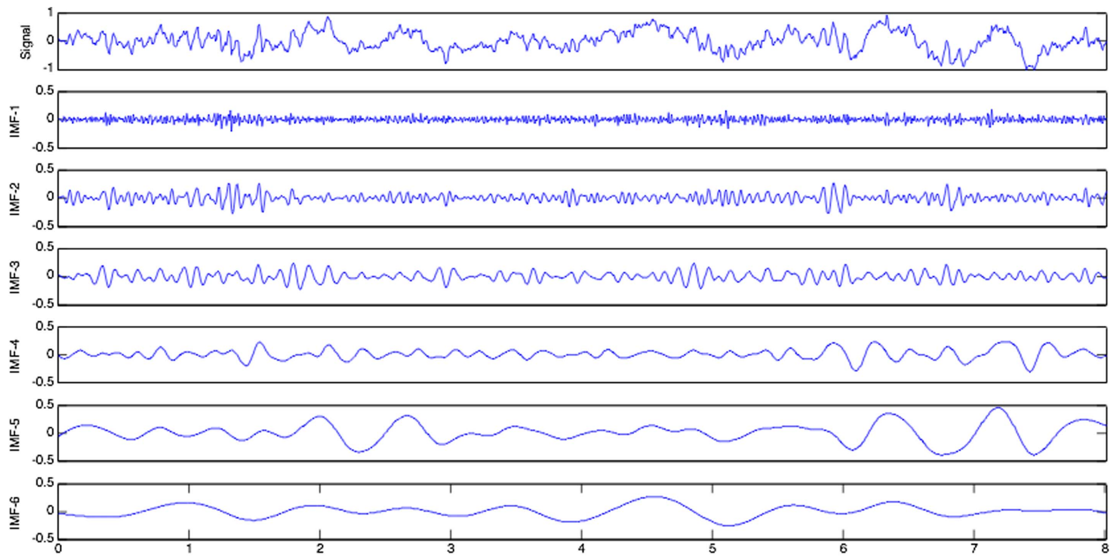



**Figure 1.** (a) Separate oscillations decomposed by EEMD from the original EEG waveform. The mean frequencies of IMF- 1, 2, 3, 4, 5, and 6 are 36, 25, 12, 5, 2, and 1 Hz, respectively. (b) Frequency bands of IMFs 1–6.

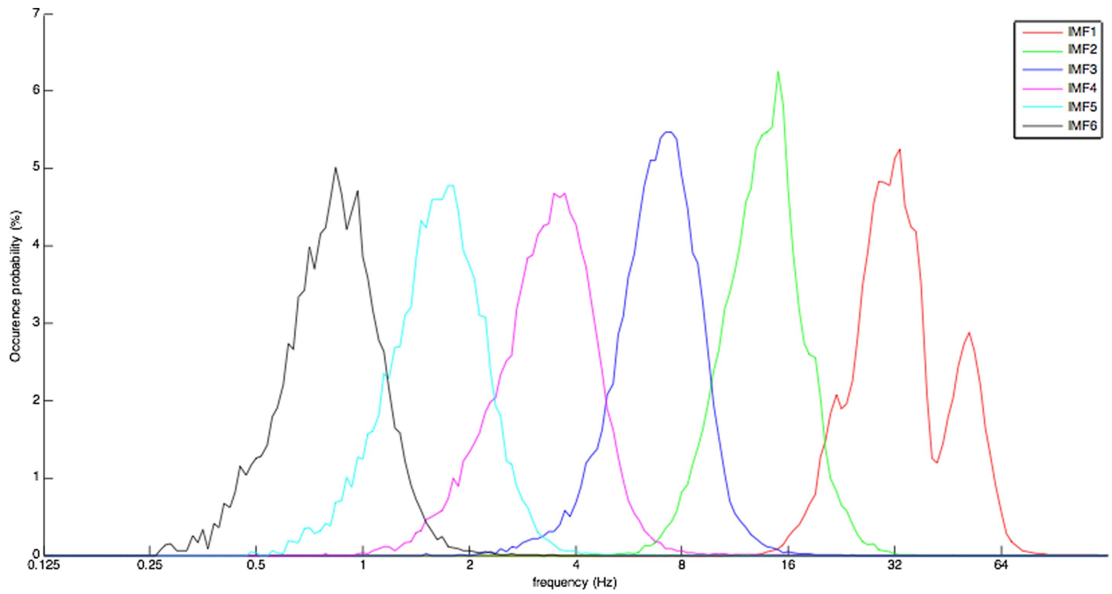



**Figure 1.** (Continued.)

## Results

Using EEMD, we decomposed the raw BIS signals into 20 IMFs to separate the BIS data completely. The 10-s signals of the first six IMFs are depicted in figure 1(a), with mean frequencies of 36.5, 20.5, 11.4, 5.5, 2.3, and 1.0 Hz, respectively. Notably, the second IMF indicates the frequency of the beta oscillations, with an average of 16 Hz, whereas the third IMF indicates the frequency of the alpha oscillations, with an average of 8 Hz (figure 1(b)).

We also compared the frequency width of the change of the IMF spectrograms and determined that the second IMF, with an initial spectrum of approximately 10–30 Hz, was centralized to 10–15 Hz after the patient was anesthetized (i.e., reached LOC) (figure 2(a)). Compared with the FFT results, the frequency centralization was more easily observed from the spectrogram after performing HHT on IMF-2 (figure 2, lower image).

Figure 3 illustrates the moving window SDs of the raw data and other IMFs that represent the quantifiable energy changes. In particular, the energy of IMF2 increased after the patients were anesthetized. We quantified the energy as a percentage of the original data (IMF-2/EEG) and compared the percentage before and after LOC. The average energy before induction of IMF-2 was 15%, which substantially increased to 50% after the patients were anesthetized (Table 1). All cases indicated that the patients had

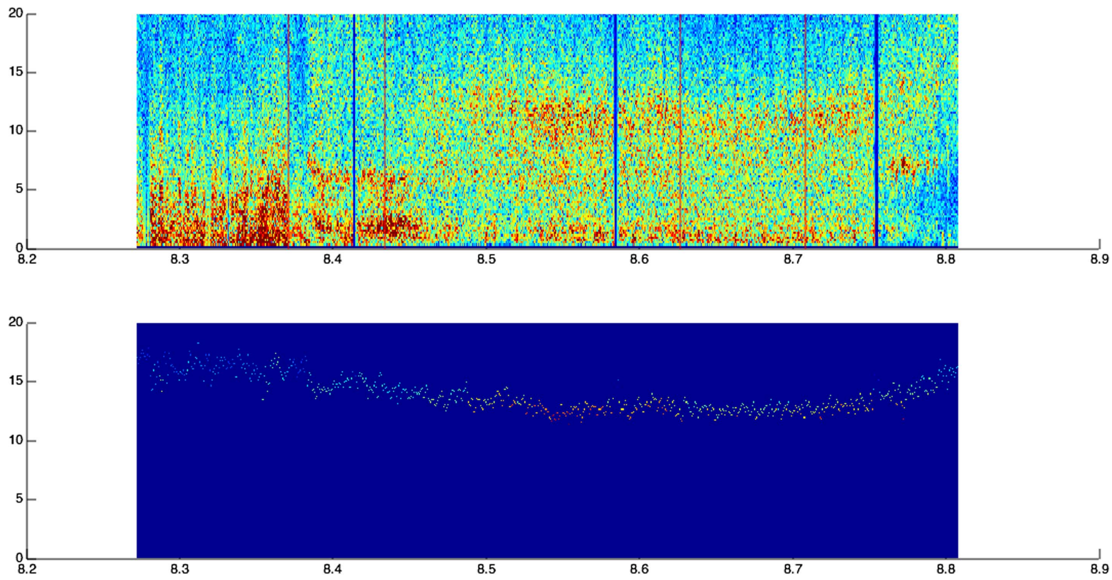



**Figure 2.** Time-frequency spectrogram of the second IMF during the induction stage. By (a) FFT (b) HHT of IMF-2.

**Table 1.** Original data of the energy change percentage during the anesthesia induction period.

| IMF2 /EEG (%) | Baseline (T1) | Loss of consciousness (T2) | After alfentanil injection 3 min (T3) | Before incision (T4) |
|---|---|---|---|---|
| 1 | 11.66 | 30.01 | 58.97 | 60.56 |
| 2 | 9.90 | 36.50 | 50.46 | 50.85 |
| 3 | 12.20 | 15.49 | 46.53 | 50.48 |
| 4 | 29.93 | 22.11 | 34.70 | 41.69 |
| 5 | 24.22 | 21.82 | 60.88 | 43.30 |
| 6 | 12.04 | 18.70 | 36.70 | 33.54 |
| 7 | 22.80 | 29.34 | 55.47 | 50.49 |
| 8 | 10.72 | 38.71 | 58.58 | 55.13 |
| 9 | 11.18 | 34.79 | 62.89 | 67.69 |
| 10 | 10.36 | 23.33 | 59.76 | 60.80 |
| 11 | 15.94 | 17.32 | 38.50 | 48.71 |
| 12 | 11.41 | 29.28 | 55.86 | 45.78 |
| 13 | 12.19 | 15.61 | 50.81 | 27.35 |
| 14 | 19.72 | 34.36 | 47.97 | 45.21 |
| 15 | 13.50 | 29.70 | 55.92 | 52.73 |
| 16 | 22.57 | 32.07 | 52.80 | 57.01 |
| 17 | 13.73 | 31.32 | 57.55 | 49.77 |
| 18 | 17.90 | 22.95 | 58.48 | 55.48 |
| 19 | 13.23 | 38.54 | 62.59 | 61.61 |
| Average | 15.54 | 27.47 | 52.92 | 50.43 |

bandwidth focusing and energy gathering within the second IMF ($P < 0.01$) (Table 2).

## Discussion

As anesthesiologists, we used several single electrode monitors in the operating rooms instead of whole EEG monitoring to determine the DOA, because they are especially applicable for preventing perioperative awareness in high-risk patients. Previously, we had used these monitors during surgery; however, we now know that frontal EEGs represent most of the consciousness changes during anesthetization, because alpha power is concentrated in the frontal channels following patient LOC. It is thus appropriate to use frontal EEG analysis for perioperative neurophysiology research.

As we observed the raw EEG waveforms in this study, the stage when patients became fully anesthetized was indistinguishable. The multiple oscillations with various amplitude and frequency changes during induction obscured our observation. However, EEMD enabled satisfactory decomposition that transformed the frontal EEG waveforms to several IMFs while still preserving the physiological and physical characteristics (figure 1). Although it was clear that the total energy observed in the EEGs had decreased after the patients were anaesthetized, EEMD decomposed the complexity of the information.

In particular, the second IMF revealed a narrowed frequency bandwidth following LOC, indicating that the frontal EEG was similar to the median frequency change noted by the whole EEG monitor (figure 2). In short, our method decomposed frontal EEG efficiently during the induction period, suggesting that synchronization occurs in the second IMF after anesthetization. Furthermore, our results demonstrate that frontal EEGs also have distinct characteristics that represent the most obvious changes during the induction period, even though EMD disperses energies to other IMFs and thus limits the significance of IMF-2.

We then calculated the time-window SD figure to determine the energy change in IMFs (figure 3). Because EEMD decomposed EEGs as multiple oscillations, the energy might have decomposed to various modes, thus obscuring the power distribution. Observing the IMF-2 separately, we noted that the SD

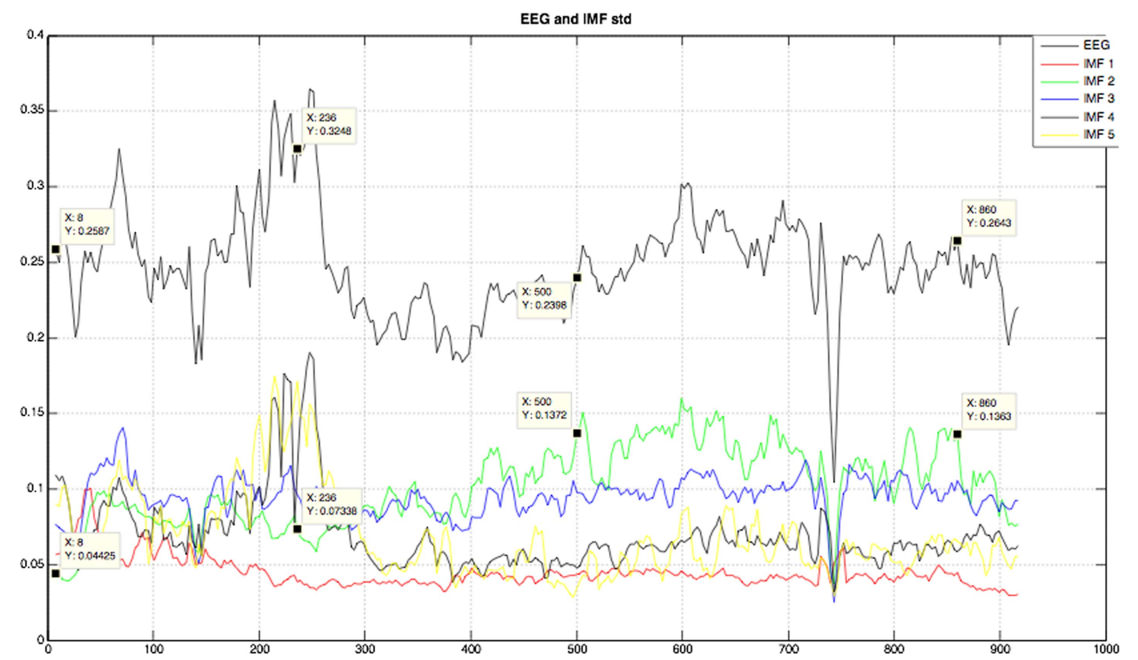



**Figure 3.** Moving window SD of the raw data and other IMFs, representing energy change.

**Table 2.** Results of repeated ANOVA measurement.

| Descriptive Statistics | | | |
|---|---|---|---|
| | Mean | Std. Deviation | *N* |
| VAR00001 | 15.537 | 5.7162 | 19 |
| VAR00002 | 27.471 | 7.6303 | 19 |
| VAR00003 | 52.917 | 8.5863 | 19 |
| VAR00004 | 50.431 | 9.7947 | 19 |

**Multivariate Tests**[7]

| Effect | | Value | *F* | Hypothesis df | Error df | Sig. |
|---|---|---|---|---|---|---|
| Time | Pillai's Trace | .943 | 88.748[8] | 3.000 | 16.000 | .000 |
| | Wilks' Lambda | .057 | 88.748[8] | 3.000 | 16.000 | .000 |
| | Hotelling's Trace | 16.640 | 88.748[8] | 3.000 | 16.000 | .000 |
| | Roy's Largest Root | 16.640 | 88.748[8] | 3.000 | 16.000 | .000 |

[7] Design: Intercept, Within subjects design: time.
[8] Exact statistic.

changed promptly following the loss of verbal response in the patients. Of all the IMFs, IMF-2 was not the major component (comprising only 15%); although the EEG does not focus on middle frequency oscillation, it still changes the most after LOC. The SDs elevated as the patients reached LOC, and energy was concentrated to 50%. This phenomenon was significantly consistent ($P < 0.001$) among the 12 cases in this study (figure 4).

Notably, signal quality can be improved. The initial data from this study remain inconclusive because of interference from the patients' blinking, shaking, and moving their foreheads. We specifically provided no anxiolytics or premedication before the propofol induction because we wanted to record baseline responses. For future research, we suggest improving signal quality by decreasing signal noise and limiting surrounding interferences.

## Conclusion

The results suggest that IMFs may be used to determine the particular frequency bandwidths in which synchronization phenomena occur. In contrast to other analysis methods, HHT is a more practical approach to using clinical data because the instantaneous frequency analysis enables examining the non-stationary characteristics of clinical data.

Because anesthesiologists continually use various tools to analyze EEG data, we propose applying the HHT technique for decomposing EEG and quantifying the real-time frequency chance and energy change. The results suggest that examining IMFs rather than EEG signals was more useful for determining the particular bandwidth changes in which synchronization phenomena occur. With this method, it is easily to observe the separate energy changes of IMFs within the EEG signals.

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