Comparison Study of Seizure Detection Using Stationary and Nonstationary Methods

Ying Li, Yue-Loong Hsin, and Wentai Liu

***Abstract*— We present an accurate seizure detection algorithm, and make a detailed comparison of two frequency analysis methods: a widely used stationary method –Fast Fourier Transform (FFT) and a relatively new nonstationary method – Hilbert-Huang Transform (HHT). Two public databases and one our own database were tested. The results show that our algorithm has very high accuracy compared with the state-of-the-art. More interestingly, it shows that the nonstationary method HHT offers better performance than the stationary method FFT in seizure detection. Therefore we propose that we should pay attention to the nonstationarity of EEG signal, since the "stationary assumption" may introduce some inaccuracy.**

I. INTRODUCTION

Epilepsy is one of the most common neurological diseases, affecting over 3 million people in U.S. and 50 million (~1%) people worldwide. Electro-Encephalography (EEG) can display clear abnormalities when a seizure begins, thus is very suitable for seizure detection. Conventionally, the detection of seizure is achieved by visual scanning of EEG recordings by an experienced neurophysiologist. However, this method has the drawbacks of time-consuming and subjective. Hence, many algorithms have been developed to detect seizure automatically since 1970s. A seizure detection algorithm usually consists of three stages: 1) frequency/time analysis; 2) feature extraction; 3) classification.

Frequency/time analysis is the first stage of seizure detection algorithm, whose accuracy will directly influence the following two stages. Currently, many researchers use Fast Fourier Transform (FFT), which assumes that the signal is stationary. However, EEG signal itself is nonstationary even within a short window, thus the stationary assumption may introduce inaccuracy. To verify this, we compared the performance of FFT and a nonstationary method "Hilbert-Huang Transform (HHT)" in seizure detection.

After frequency/time analysis, some features can be extracted to characterize the signal. The features vary from time domain features (such as minimum, maximum, mean, variance, energy, entropy, etc.) [1][2], frequency domain features (such as energy, dominant frequency, weighted frequency, etc.) [3][4], to features from cross correlation [5], PCA [6], ICA [3], etc. Here we used the power in different frequency bands and the total power as our features. Although Oweis et al. [4] also used HHT for frequency analysis, but it turns out that our features are more effective and achieve much higher accuracy.

After feature extraction, the features will form two classes (seizure or non-seizure) in the feature space. The goal of the classification stage is to classify the testing signal to the seizure or non-seizure class. Some commonly used classifiers include K-nearest neighbor (KNN) [7], artificial neural networks (ANN) [8], support vector machines (SVM) [1][5], etc. In our algorithm, we chose the KNN classifier, which is usually used as benchmark of various classifiers.

Combined all of the above three stages, we developed our own seizure detection algorithm, which is explained in detail in Part II. The testing results are shown in Part III and a brief conclusion is drawn in Part IV.

II. MATERIALS AND METHODS

In this part, we will give a detailed explanation of the Hilbert-Huang Transform as well as the three stages of our algorithm. Fig. 1 shows the flow chart of our algorithm.

A. Hilbert-Huang Transform

Hilbert-Huang Transform (HHT) is a powerful tool in dealing with nonlinear and nonstationary signal. It mainly involves two steps: Empirical Mode Decomposition and Hilbert Transform. [9]

1) Empirical Mode Decomposition (EMD)

The purpose of EMD is to decompose the signal into some intrinsic mode functions (IMFs) that can be handled by Hilbert Transform.

An IMF represents a simple oscillatory mode that is more general and data-adaptive than the harmonic function: it can have a variable amplitude and frequency as functions of time. That's why HHT can deal with nonstationary signals. IMF is defined with two requirements: 1) 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 the local maxima and the envelope defined by the local minima is zero. Fig. 2 shows the IMFs of a seizure signal from our database.

In the end, the original signal can be expressed as the sum of the IMFs. Let $x(t)$ represent the original signal, c_j represent

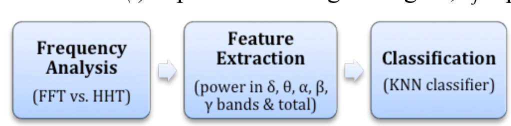

Figure 1. Flow chart of the three stages of our algorithm.

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Y. Li and W. Liu are with the Biomimetic Research Laboratory (BRL) in the Bioengineering Department at University of California, Los Angeles, CA 90095 USA. e-mail: yingli.ucla@gmail.com.

Y. L. Hsin is with Neurology Department, Chung Shan Medical University, Taichung, Taiwan.

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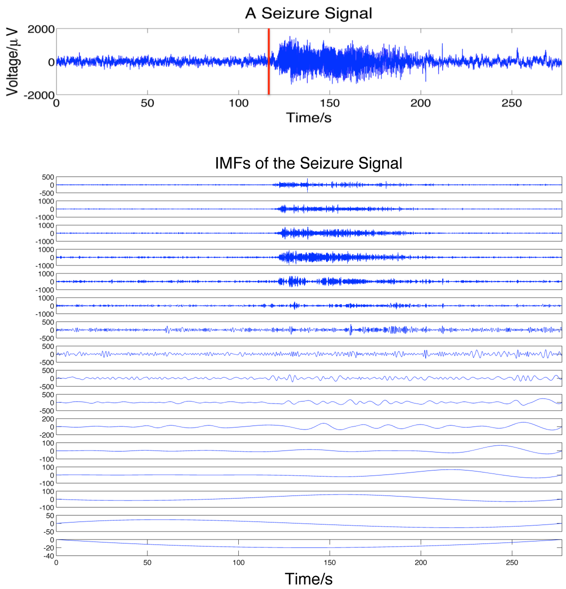

Figure 2. (Top) A seizure signal from our database (red line is the seizure onset); (Bottom) all of the IMFs of the signal.

the IMFs and r_n the residue, then we have

$$x(t) = \sum_{j=1}^{n} c_j(t) + r_n(t). \tag{1}$$

2) Hilbert Transform (HT)

After we decompose the original signal into several IMFs, there's no difficulty to apply the Hilbert transform to each IMF component. Hilbert transform is defined as:

$$y(t) = \mathrm{H}[x(t)] = \frac{1}{\pi} \mathrm{PV} \int_{-\infty}^{\infty} \frac{x(\tau)}{t-\tau} d\tau. \tag{2}$$

Here "PV" indicates the principal value of the singular integral. Now, we can calculate the instantaneous amplitude *a(t)*, phase *θ(t)* and frequency *w(t)* as follows:

$$a(t) = \sqrt{x^2 + y^2}, \quad \theta(t) = \arctan(\frac{y}{x}) \quad \text{and} \quad w(t) = \frac{d\theta}{dt}. \tag{3}$$

In the end, the original signal can be expressed as the real part in the following form:

$$x(t) = \Re\left\{ \sum_{j=1}^{n} a_j(t) \exp\left[i \int w_j(t) dt \right] \right\}. \tag{4}$$

B. Frequency Analysis

Fig. 3 compares the FFT and HHT frequency spectrum of the signal shown in Fig. 2 (top), from which we can have two observations: 1) the resolution of HHT spectrum is better than FFT; 2) FFT has a wider frequency distribution, while HHT stresses on lower frequencies.

The reason why HHT can give a more accurate frequency analysis than FFT is as follows: in FFT, the frequency is derived by convolution, thus there will be a trade-off between time resolution and frequency resolution; while in HHT, the frequency is derived by differentiation, hence it is not limited by the uncertainty principle and can provide both high time resolution and high frequency resolution at the same time.

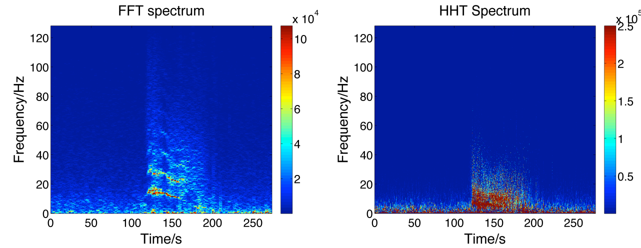

Figure 3. Frequency spectrum of FFT (left) and HHT(right).

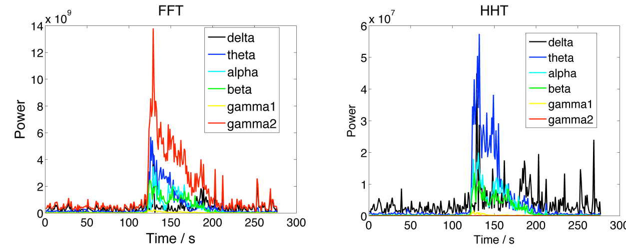

Figure 4. Power change of different frequency bands during a seizure. (Left) FFT; (Right) HHT.

C. Feature Extraction

After frequency analysis, a total of 7 features were extracted: power in delta (0.5–4Hz), theta (4–8Hz), alpha (8–13Hz), beta (13–30Hz), gamma1 (30–60Hz), gamma2 (>=60Hz) frequency band & total power.

To calculate the power of a certain frequency band using HHT, we first calculated the energy of each IMF within a small moving window, then summed all of them together and divided by time to get the total power. The energy of each IMF can be calculated as follows: 1) find the time points when the instantaneous frequency located within the frequency band; 2) sum the square of the instantaneous amplitude corresponding to these time points.

Fig. 4 shows the power change of different frequency bands of the signal in Fig. 2 (top). From the figure we can see a dramatic increase of power in some frequency bands when seizure starts. That's why our proposed features are very effective. Moreover, we can see the difference between FFT and HHT again: HHT stresses on lower frequencies.

D. Classification

In this step, the data is separated into training set and testing set. The training set is labeled (seizure or non-seizure class), and the task of the classifier is to predict labels of the testing set. Here we use KNN as our classifier, whose idea is intuitive: it classifies unlabeled examples based on their similarity with examples in the training set.

For example, Fig. 5 shows 2 dimensions of the feature space, from where we can clearly see two classes: seizure (red) and non-seizure signal (blue). Our goal is to find a class label for the unknown testing example *x* (green). Assume we use *k*=5 neighbors. After searching for the 5 closest neighbors of *x*, we find that all of them belong to the seizure class, so *x* is assigned to the seizure class.

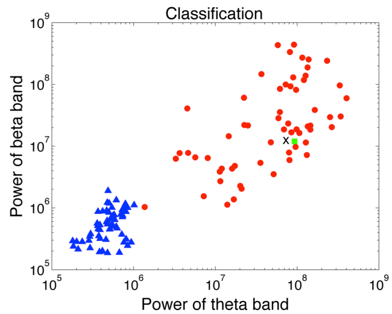

Figure 5. KNN classification. 2 dimensions of the feature space (log-scale) are shown. x is predicted as "seizure" by the KNN classifier.

III. Results and Discussion

Three databases were tested here: 1) Bonn database; 2) Freiburg database; 3) Tzu Chi Medical Center database.

A. *Result of Bonn database*

Bonn database is available online [10], which was recorded by the University of Bonn. There are totally five datasets (denoted A-E) each containing 100 single-channel EEG segments of 23.6 s. The sampling rate is 173.61Hz, and the ADC has the spectral bandwidth 0.5~85 Hz. In our study, we use 3 sets of them: A (recorded from healthy volunteers relaxed in an awake state with eyes open); D (recorded within the epileptogenic zones); E (recorded during seizure activities). Fig. 6 shows some examples from these 3 datasets. Here we formed two classification problems: 1) classify set A (healthy) and E (ictal); 2) classify set D (interictal) and E (ictal). We separated all of the sets into 50%-50%: half for training, and half for testing.

1) A & E classification problem

Table I shows that our algorithm achieves 100% accuracy for both FFT and HHT, which is a good result compared with other recent algorithms (Table II). In addition, the features and classifier of our algorithm are relatively simple compared to others. For example, Polat et al. [6] also achieved 100% using FFT, but they used more than 100 features.

2) D & E classification problem

D&E problem is more difficult than A&E, since the waveform difference between D&E is not as distinct as that of A&E (Fig. 6). Table III shows the results of using different window lengths. We can see that the accuracy is also very high, and HHT performs better than FFT in all cases.

B. *Result of Freiburg database*

Freiburg database is available online by request [11]. This database contains intracranial EEG recordings from 21 patients at the Epilepsy Center of the University Hospital of Freiburg. There are in total 87 seizures, 509h of interictal and 73h of preictal or ictal data. For each patient, six channels are available, of which 3 focal and 3 extrafocal electrodes. The data were acquired using a Neurofile NT digital video EEG system with 256 Hz sampling rate, and a 16 bit ADC. Before using this database, we firstly filtered the data by a 50Hz notch filter to remove the line noise.

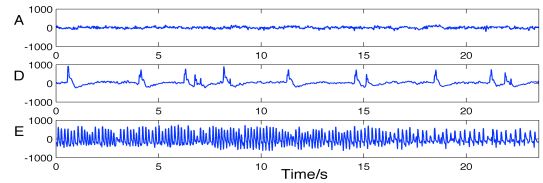

Figure 6. Signals of dataset A, D and E from Bonn database.

We tested all the 21 patients (87 seizures and 509 h interictal signals) in the Freiburg database. A window length of 4s was used, since there are many short seizures (<5s) in this database. Our classification criteria are: for ictal signal, as long as one window is classified as "seizure", we'll say that a seizure is detected; for interictal signal, if one window is classified as "seizure", then we will report a false alarm.

To guarantee the reliability of our algorithm, we used 21-fold cross validation: use 20 patients for training and one for testing, then repeat this procedure for 21 times. Since there isn't enough ictal data for training, we used a window with 80% overlap to generate more training examples. Also, since the interictal signals are very long and they are more than enough for training, thus we randomly picked up 200 windows from each signal. Using FFT, we obtained a sensitivity 89.66% and specificity 93.26%; for HHT, the results are better: the sensitivity is 93.10% and specificity is 95.17% (Table IV). Also, for some special cases, for example patient 12, FFT gives a very bad specificity (62.98%), but HHT still gives a high specificity (90.64%).

Table IV compares some algorithms using Freiburg database. The performance of our algorithm is significantly better than others. It seems that the result of Raghunathan et al. [15] is also good, but they only tested 5 patients, which are relatively easy cases.

C. *Result of Tzu Chi Medical Center Database*

This database was recorded by our collaborator Dr. Yue-Loong Hsin at Hualein Tzu Chi Medical Center, Taiwan. A total of 33 ictal recordings are available from 13 patients. The sampling rate is 256Hz, and the channel number varies from 5 to 52. Fig. 2 (top) is a representative ictal recording from this database.

When testing this database, we used the ictal and interictal signals from Freiburg database for training. We expect that the signal power between different databases will be different since they use different electrodes for recording. Therefore, we normalized the power in different frequency bands by the total power. The result shows that all of the seizures were detected (100% sensitivity), which have been verified by experienced epileptologists.

D. *Compare the Performance of FFT and HHT*

All of the above testing results show that HHT outperforms FFT in seizure detection (except when both of them achieve 100% accuracy).

It is usually assumed that the signal can be regarded as "stationary" when the window is short. But our results show

TABLE I. RESULT OF THE A&E CLASSIFICATION PROBLEM

Window	*Method*	*Sensitivity*	*Specificity*	*Accuracy*
4096 (23.6s)	FFT	100	100	100
	HHT	100	100	100
2048 (11.8s)	FFT	100	100	100
	HHT	100	100	100
1024 (5.9s)	FFT	100	100	100
	HHT	100	100	100

TABLE II. ALGORITHMS USING BONN DATABASE (A&E)

Authors	*Methods*	*Accu*
Subasi (2007) [12]	Discrete wavelet transform (DWT), mixture of expert model	95
Polat et al. (2008) [6]	Principal Component Analysis and FFT, Artificial immune recognition system	100
Chandaka et al.(2009) [5]	Cross-correlation, LS-Support vector machine	95.95
Oweis et al. (2011) [4]	MEMD or EMD, weighted frequency, t-testing/Euclidean clustering	80% or 94%
Our work	Fast Fourier Transform or Hilbert-Huang Transform, K-nearest neighbor classifer	100

TABLE III. RESULT OF THE D&E CLASSIFICATION PROBLEM

Window	*Method*	*Sensitivity*	*Specificity*	*Accuracy*
4096 (23.6s)	FFT	94.00	92.00	93.00
	HHT	96.00	94.00	95.00
2048 (11.8s)	FFT	95.00	93.00	94.00
	HHT	95.00	94.00	94.50
1024 (5.9s)	FFT	94.00	94.50	94.25
	HHT	98.00	94.50	96.25

TABLE IV. ALGORITHMS USING FREIBURG DATABASE

Authors	*# of patients*	*Sensitivity*	*Specificity*
Schad et al. (2008) [13]	6 patients	38%-77%	-
Aarabi et al. (2009) [8]	21 patients	68.9%	97.8%
Orosco et al. (2011) [14]	21 patients	41.4%	79.3%
		69.4	69.2%
Raghunathan et al. (2011) [15]	5 patients	87.5%	99.82%
Our work (FFT)	21 patients	89.66%	93.26%
Our work (HHT)	21 patients	93.10%	95.17%

that even the window is only 4s, HHT still has advantage over FFT. Therefore we conclude that the "stationary assumption" can introduce some inaccuracy, and propose that we should pay attention to the "nonstationarity" of the EEG signal. On the other hand, we should also notice that HHT takes longer time for computation. Hence, our suggestion is using HHT when higher accuracy is required, and using FFT when less computation is required.

IV. CONCLUSION

We developed a highly accurate seizure detection algorithm whose performance is very competitive among the current algorithms. The features and classifier in our algorithm are simple but very effective, therefore is very suitable for hardware implementation. Most importantly, we conducted a detailed comparison of the stationary method FFT and nonstationary method HHT in seizure detection, and found that HHT offers better performance for difficult cases in aspect of both sensitivity and specificity. To the best of our knowledge, this is the first to compare stationary methods and nonstationary methods in seizure detection. Tradeoff of accuracy and computation power suggests to use FFT when less computation is required and use HHT if higher accuracy is needed.

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