# Electroencephalogram Fractral Dimension as a Measure of Depth of Anesthesia

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*Abstract*—**This paper proposes a combined method including adaptive segmentation and Higuchi fractal dimension (HFD) of electroencephalograms (EEG) to monitor depth of anesthesia (DOA). The EEG data was captured in both ICU and operating room and different anesthetic drugs, including propofol and isoflurane were used. Due to the non-stationary nature of EEG signal, adaptive segmentation methods seem to have better results. The HFD of a single channel EEG was computed through adaptive windowing methods consist of adaptive variance and auto correlation function (ACF) based methods. We have compared the results of fixed and adaptive windowing in different methods of calculating HFD in order to estimate DOA. Prediction probability ($P_k$) was used as a measure of correlation between the predictors and BIS index to evaluate our proposed methods. The results show that HFD increases with increasing BIS index. In ICU, all of the methods reveal better performance than in other groups. In both ICU and operating room, the results indicate no obvious superiority in calculating HFD through adaptive segmentation.**

***Keywords- adaptive segmentation; bispectral index; depth of anesthesia; fractal dimension***

## I. INTRODUCTION

An anesthesiologist effort in providing optimal working conditions to surgeons and also in ensuring patient safety is essential in operating room. However awareness during surgery with rate of 1:1000 [1, 2] and over dosing with anesthetic agents are major clinical problems of anesthesia. Subsequently necessity to assessment and monitoring depth of anesthesia (DOA) is obvious. Monitoring DOA based on autonomic responses of patient body such as respiration pattern, blood pressure, body temperature, tearing, sweating and heart rate is a classic method [3], but these responses are affected indirectly by anesthetic agents however, it is known that these agents have significant effects on the EEG waveform.

A large amount of information can be extracted from EEG waveform based on different signal processing methods. Ability of this information to predict DOA depends on the variation of its value in different levels of anesthesia, but in general, the goal is to produce a unit less index that monotonically quantifies DOA.

One of the earliest methods is based on the Fourier transform that determines the power of EEG in different frequency bands [4]. Zikov et al. proposed a wavelet based anesthetic value for central nervous system monitoring ($WAV_{CNS}$) that quantifies the depth of consciousness between awake and isoelectric state [5]. Ferenets et al. analyzed the performance of several new measures based on the regularity of the EEG signal. These measures consist of spectral entropy, approximate entropy, fractal dimension and Lempel-Ziv complexity. Their results show highly sensitive behavior of the mentioned measures on frequency content of signal and the dose of anesthetic agent [6]. Application of neural networks (NN) and selecting proper parameters as NN inputs in estimating DOA is reviewed by Robert et al. Various strategies of choosing the NN model were presented and discussed [7].

According to various mentioned methods, different EEG monitors have been introduced. The Narcotrend™ monitor (Monitor Technik, Bad Bramsted, Germany) that based on pattern recognition of the raw EEG and classifies the EEG into different stages, introduce a dimensionless Narcotrend™ index from 100 (awake) to 0 (electrical silence). The algorithm uses parameters such as amplitude measures, autoregressive modeling, fast Fourier transform (FFT) and spectral parameters [8]. The SEDLine™ EEG monitor that capable of calculating of PSI™ index uses the shift in power between the frontal and occipital areas. The mathematical analysis includes EEG power, frequency and coherence between bilateral brain regions [9]. Datex-Ohmeda™ s/5 entropy Module uses entropy of EEG waves to predict DOA and finally BIS™ (Aspect Medical Systems, Newton, MA) that is the first monitor in the marketplace and has become the benchmark comparator for all other monitors. The BIS™ (Bispectral) index is a unit-less number between 100 (awake) and 0 (isoelectric) and according to producer claim, the BIS index between 40 and 60 is a suitable and safe range for operating purposes.

Fractal dimension is a measure of how 'complicated' a self-similar figure is [10]. In the particular case of curves in a plane, while a topological line is one-dimensional, a fractal curve has a fractal dimension $D$ that is in the range of $1 < D < 2$. The fractal dimension of an object provides insight into how elaborate the process that generated the object might have been, since the larger the dimension the larger the number of degrees of freedom likely has been involved in that process [10].

Calculation of fractal dimension of EEG-signal clearly demonstrates an influence of magnetic field on the brain [11]. In general, the compass fractal dimension represents a measure of the degree of shape complexity or roughness of the curve. Higuchi , Katz , Petrosian C , Petrosian D, Sevcik , zero set, adapted box , compass, and variogram are some methods to calculate fractal dimension of signals. Higuchi's method is the most accurate of the other methods for calculating time series fractal dimension.

The aim of this study is to introduce an efficient method with the application of adaptive segmentation, based on fractal dimension to measure DOA. In section II, the methodology is described. The results are presented in section III. Finally, a detailed discussion and conclusion is provided in section IV.

## II. METHODOLOGY

### A. Patients

After study approval by ethical committee of medical school and obtain written informed consent from all selected (6 male, 2 female, with mean age: 56 year and weight: 68kg) subjects, patient was premedicated by intramuscular morphine 0.1 mg/Kg and promethazine 0.5 mg/kg. All patients were coronary artery bypass graft candidate. After arrival in operating room, electrocardiogram, pulse oxymetry, depth of anesthesia, and invasive blood pressure monitoring was established. The BIS-QUATTRO sensor™ (Aspect Medical Systems, Newton, MA) applied to the forehead of patient before induction of anesthesia. Then 8 patients were anesthetized in a same manner by intravenous thiopental sodium (5mg/Kg), pancuronium Bromide(0.1 mg/Kg), fentanyl (5µg/kg), and lidocaine (1.5 mg/Kg). Anesthesia continued by administration of isoflurane (1 MAC), morphine (0.2 mg/Kg) and $O_2$ (100%) until cardiopulmonary bypass (CPB) beginning. During CPB, patients were anesthetized by propofol under BIS control (40-60) and $O_2$ (80%). Patients were undergone mild hypothermia (31-33°C) during CPB. After coronary bypass grafting and separating from CPB, anesthesia continued by isoflurane (1 MAC) and $O_2$ (100%) administration. After surgery, patients were transported to ICU (Intensive Care Unit) under monitoring. Sedative regimen in ICU until complete recovery and extubation was morphine (2 mg if needed).

### B. Data Acquisition

The EEG signal was collected using a BIS-QUATTRO Sensor™ that composed of self-adhering flexible bands holding four electrodes, applied to the forehead with a frontal-temporal montage.

The used EEG lead was Fpz-At1, and the reference lead was placed at FP1. Sensor was connected to a BIS-XP Monitor and all binary data packets containing raw EEG data wave signals and BIS index were recorded via an RS232 interface on a laptop using a Bi-spectrum analyzer developed with $C^{++}$ Builder by Satoshi Hagihira [12].

The algorithms are presented in this study were tested on this raw EEG signals (A/D-Converted in 128 Hz sampling frequency).

Sensor was attached to patient forehead at beginning of anesthesia and data were collected continuously until he/she awaked at ICU. Therefore, in this study a large number of EEG data with its BIS index for each patient was collected. Some other events such as changes of anesthesia regimen, intubations and applying CPB and transferring to ICU were recorded. Because of short acting time of thiopental sodium (approximately 15-20 sec), this part of EEG data were not analyzed.

### C. Adaptive and fixed segmentation

At first and with regards to other works in this area, fixed window lengths would be applied [6,13]. We evaluated the influence of a 60-seonds epoch lengths.

One of the limitations of short-time analysis lies with the use of a fixed window duration. It would be desirable to adapt the analysis window to changes in the given signal, allowing the window to be as long as possible while the signal remains stationary, and to start a new window at the exact instant when the signal changes its characteristics [14]. In order to perform the described approach, two adaptive windowing methods have been used, adaptive variance detection and ACF (Auto-Correlation Function) distance methods. In both approaches, a reference window is extracted at the beginning of each scan, and the given EEG signal is observed through a moving window. In adaptive variance detection method, a segment boundary is drawn when the variance of the moving window become $m$ times greater or larger than the variance of the reference window. By considering the changes of EEG variance, $m$=10 is chosen for applying the above procedure (We name this method, "Adaptive variance method"). On the other hand, for implementing ACF distance method, let $\phi_R(k)$ be the ACF of the reference window at the beginning of a new segmentation step, where $k$ is the lag or delay. Let $\phi_T(n,k)$ be the ACF of the test and sliding window positioned at time instant $n$. A normalized power distance $d_p(n)$ between ACFs is computed as:

$$d_p(n) = \frac{\left|\sqrt{\phi_T(n,0)} - \sqrt{\phi_R(0)}\right|}{\min\{\sqrt{\phi_T(n,0)}, \sqrt{\phi_R(0)}\}} \qquad (1)$$

The condition where $d_p(n)$ becomes larger than a specific threshold, $Th_P$, is considered to represent a significant change in ACF, and used to mark a segment boundary [14]. Again, due to the variation of $d_p(n)$ values, three different $Th_P$s (25000, 30000, and 35000), are examined for evaluating the described approach and $Th_P = 30000$ is used finally. (We name this method, "ACF method").

*D. Fractal Dimension*

Nonlinear methods that assess signal complexity matter if the signal itself is chaotic or deterministic.

Consider the time series $x(1), x(2),..., x(N)$, where $N$ is the total number of samples. The algorithm constructs $k$ new time series as:

$$X_m(k) = \{x(m), x(m+k), x(m+2k),..., x(m + \lfloor (N-m)/k \rfloor k)\}$$

where $m = 1,2,..., k$ . The length, $L_m(k)$, is calculated as:

$$L_m(k) = \left[ \left( \sum_{i=1}^{\left\lfloor \frac{N-m}{l} \right\rfloor} \left| x(m+ik) - x(m+(i-1)k) \right| \right) . \frac{N-1}{\left\lfloor \frac{N-m}{k} \right\rfloor .k} \right] / k \qquad (2)$$

Higuchi algorithm calculates fractal dimension of a time series directly in the time domain. It is based on a measure of length, $L(k)$ of the curve. An average length is computed for all time series having the same scale $k$, as the mean of the $k$ length $L_m(k)$ for $m = 1,2,3,..., k$. If $L(k)$ scale like, $L(k) \propto k^{-D_f}$, then the curve is said to show fractal dimension $D_f$ [15].

The fractal dimension of EEG signal is calculated via above method while applying adaptive and fixed windowing methods.

*E. Statistical Analysis*

The correlation between BIS index and the extracted sub-parameters was investigated with the model-independent prediction probability ($P_k$). As a nonparametric measure, the $P_K$ is independent of scale units and does not require knowledge of underlying distributions or efforts to linearize or otherwise transform scales. A $P_k$ value of 1 means that the predicting variables always predict the value of the predicted variable (e.g., BIS index) correctly. $P_k$ value of 0.5 means that predictors predict no better than by chance only. The $P_k$ values were calculated on a spreadsheet using the Excel 2003 software program and the PKMACRO written by Warren Smith [16]. In the case of inverse proportionality between indicator and indicated parameters, the actual measured $P_k$ value is 1-$P_k$.

## III. RESULTS

The results presented in this section are categorized in three groups of experiment which contain isoflurane, propofol and ICU. Also, the performance of ACF method, variance method and fixed length windowing is evaluated. First of all the behavior of HFD due to the BIS index changes is examined. The HDF increases while BIS index increase and vice versa. This could be seen from Fig.1 through Fig. 3 in which the Bispectral index is plotted versus HDF in three different groups.

In order to investigate the ability of described windowing methods such as fixed or adaptive in estimating DOA in different groups of drugs, the $P_k$ values are calculated. The results are depicted in Fig.4 through Fig. 6.

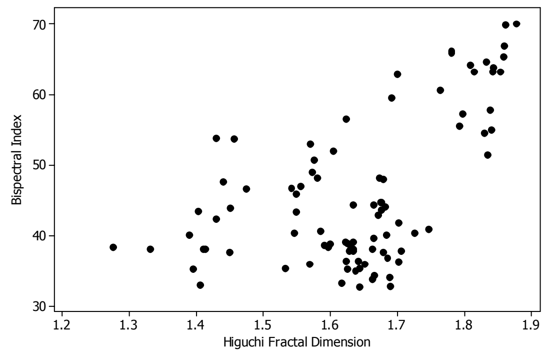


Figure 1. Bispctral Index versus Higuchi Fractal Dimension in ICU using Fixed length windowing

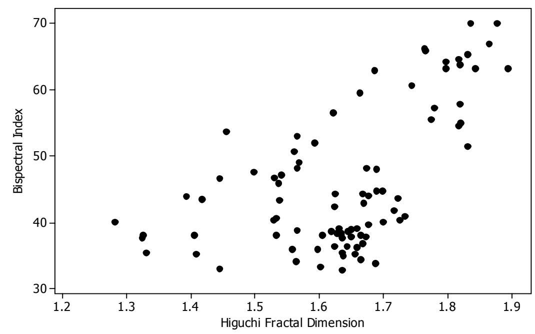


Figure 2. Bispctral Index versus Higuchi Fractal Dimension in ICU using adaptive variance method

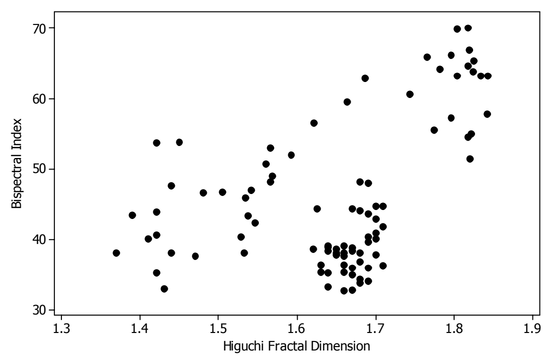

Figure 3. Bispctral Index versus Higuchi Fractal Dimension in ICU using ACF metohd

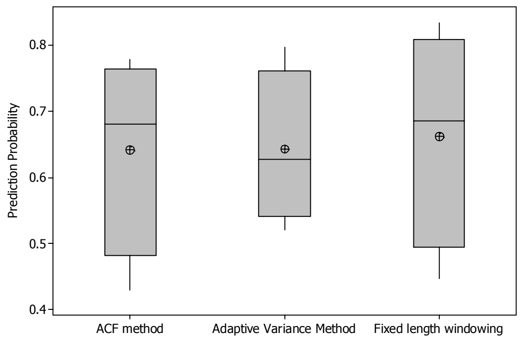


Figure 4. Prediction Probability value for Different methods of windowing in calculation of Higuchi Fractal Dimension in ICU

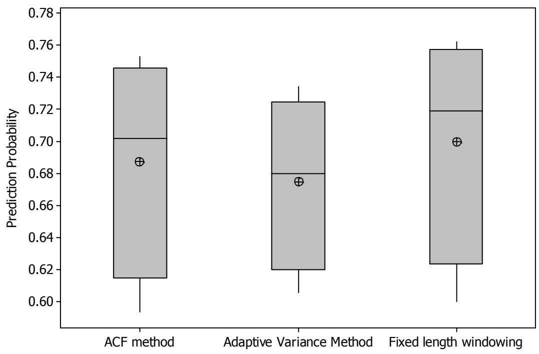


Figure 5. Prediction Probability value for Different methods of windowing in calculation of Higuchi Fractal Dimension in Isoflurane

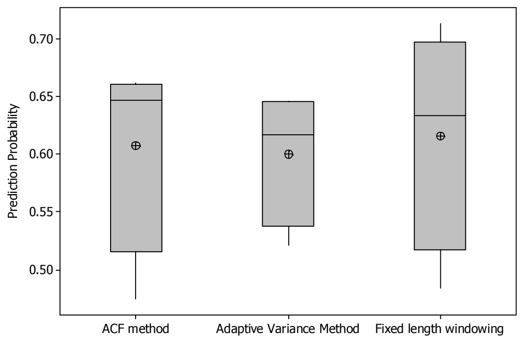


Figure 6. Prediction Probability value for Different methods of windowing in calculation of Higuchi Fractal Dimension in Propofol

Finally, for the comparison of the proposed algorithms in different groups of drugs and via different methods of segmentation, Fig. 7 could help us significantly.

## IV. DISCUSSION AND CONCLUSION

Our results confirm the previous results which claim that HFD decreased with increasing DOA. The reason is to some extent due to the decreasing manner of EEG complexity. According to Fig. 4, Fig. 5, and Fig. 6, there is no sensible and visible difference in different methods of segmentation based on extracted $P_k$ values. The above statement is correct in each

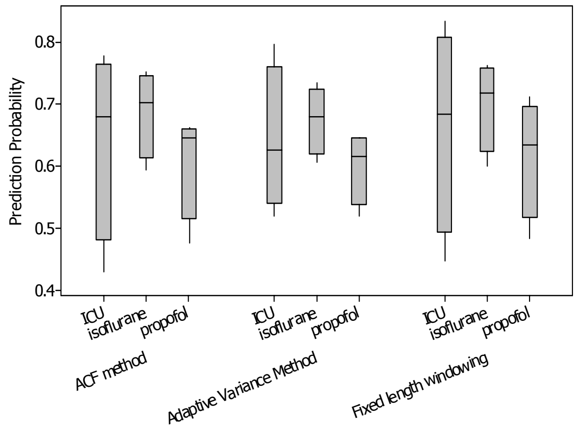


Figure 7. Prediction Probability value for Different methods of windowing in calculation of Higuchi Fractal Dimension in all of the groups

of the methods. There is a slight difference in the ranges of $P_k$ values which could not be observed as a measure of superiority of each of the groups. Consequently, adaptive segmentation is not able in improving the assessment of DOA based on calculation of HFD. On the other hand and in comparison to other methods in this literature HFD is an appropriate method for estimating DOA. This could be guessed out of relatively high $P_k$ values.

Finally, according to Fig. 7, the evaluation of different algorithms in various groups reveals the dominance of results obtained in ICU and the weakness in propofol. So, other methods are required for estimating DOA in the case of propofol anesthesia.


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## REFERENCES


[1] W. H. D. Lui, T. A. S. Thorp, S. G. Graham, and A. R. Aitkenhead, “Incidence of awareness with recall during general anesthesia,” Anaesthesia, vol. 46, pp. 435-437, 1991.

[2] J. G. Jones, “Perception and memory during general anesthesia”, British Journal of Anaesthesia, vol. 73, pp. 31-37, 1994.

[3] R. D. Miller, Miller’s anesthesia, Sixth edition, Elsevier Churchill Livingstone, 2005.

[4] H. S. Traast, and C. J. Kalkman, “Electroencephalographic characteristics of emergence from propofol/sufentanil total intravenous anesthesia,” Anesth Analg, vol. 81, pp. 366-371, 1995.

[5] T. Zikov, S. Bibian, G. A. Dumont, M. Huzmezan, and C. R. Ries, “Quantifying cortical activity during general anesthesia using wavelet analysis,” IEEE Trans. Biomed. Eng., vol. 53, no. 4, pp. 617-632, 2006.

[6] R. Ferenets, T. Lipping, A. Anier, V. Jäntti, S. Melto, and S. Hovilehto, “Comparison of entropy and complexity measures for the assessment of depth of sedation,” IEEE Trans. Biomed. Eng., vol. 53, no. 6, pp. 1067-1077, June 2006.

[7] C. Robert, P. Karasinski, C. D. Arreto, and J. F. Gaudy, “Monitoring anesthesia using neural networks: A survey,” J Clin Monit Comput, vol. 17, pp. 259-267, 2002.

[8] R. Bender, B. Schultz, and U. Grouven, “Classification of EEG signals into general stages of anesthesia in real time using autoregressive models,” Proceeding of the 16th Annual Conference of the Gesellschaft fur Klassifikatione, University of Dortmund, 1992.

[9] D. R. Drover, H. J. *Lemmens* , J. *Harry*, E. T. *Pierce, G. Plourde, G. Loyd, et al.,* “Patient State Index: titration of delivery and recovery from propofol, alfentanil, and nitrous oxide anesthesia” Anesthesiology, vol. 97, pp. 82–89 , 2002.

[10] A. P. Pentland, “Fractal-based description of natural scenes,” IEEE Trans. Patt. Anal. Mach. Intel. PAMI-6(6), pp. 661-674.

[11] W. Klonowski, E. Olejarczyk, and R. Stepien, “Nonlinear dynamics of EEG-signal reveals influence of magneticfield on the brain. Engineering in Medicine and Biology Society,” Proceedings of the 22nd Annual International Conference of the IEEE, vol. 4, pp. 2955-2958, 2000.

[12] S. Hagihira, M. Takashina, T. Mori, T. Mashimo, and I. Yoshiya, “Practical issues in bispectral analysis of electroencephalographic signals,” Anesth Analg, vol. 93(4), pp. 966–970, 2001.

[13] X. S. Zhang and R. J. Roy, “Derived fuzzy knowledge model for estimating the depth of anesthesia,” IEEE Trans. Biomed. Eng., vol. 48, no. 3, pp. 312-323, March 2001.

[14] R. M. Rangayyan, Biomedical Signal Analysis: A Case-Study Approach, NJ: IEEE press, 2001.

[15] T. Higuchi, “Approach to an irregular time series on the basis of the fractal theory,” Physica D, vol. 31, pp. 277-283, 1988.

[16] W. D. Smith, R. C. Dutton, and N. T. Smith, “ Measuring the performance of anesthetic depth indicators,” Anesthesiology, vol. 84, no. 1, pp. 38-51, 1996.