# A Cepstral Analysis based Method for Quantifying the Depth of Anesthesia from Human EEG

Tae-Ho Kim, Young-Gyu Yoon, Jinu Uhm, Dae-Woong Jeong, Seung Zhoo Yoon and Sang-Hyun Park

Abstract— In this paper, a cepstral analysis based approach to measuring the depth of anesthesia (DoA) is presented. Cepstral analysis is a signal processing technique widely used especially for speech recognition in order to extract speech information regardless of vocal cord characteristics. The resulting index for the DoA is called index based on cepstral analysis (ICep). The Fisher criterion is engaged to evaluate the performance of indices. All analyses are based on a single-channel electroencephalogram (EEG) of 10 human subjects. To validate the proposed technique, ICep is compared with bispectral index (BIS), which is the most commonly used method to estimate the level of consciousness via EEG during general anesthesia. The results show that ICep has high correlation with BIS, and is outstanding in terms of the Fisher criterion and offers faster tracking than BIS in the transition from consciousness to unconsciousness.

### I. INTRODUCTION

Anesthesia is a state of loss of consciousness, loss of skeletal muscle activity, and loss of feeling pain due to an anesthetic agent during surgery. It is important to control the dosage of the agent because if the dosage is not managed properly to maintain anesthesia, it could cause many problems, such as intraoperative awareness or coma [1], [2]. Therefore, the DoA should be monitored during surgery in order to dose the proper amount of anesthetic agent.

Historically, the DoA has been measured by using the pulse rate, blood pressure, skin conductance, and various kinds of biological factors. Recently, EEG based techniques to monitor the DoA have started to be widely used in surgery as a reference to determine the state of the patient. Many methods for monitoring the DoA have been developed and commercialized such as the BIS monitor from Aspect Medical Systems [3], the Entropy monitor from Datex Ohmeda [4], and the NeuroSENSE monitor from NeuroWave Systems [5]. Among these, BIS is currently one of the most popular monitors in hospitals. Although BIS is considered a reference to discriminate the state of the patient, some negative claims about BIS have been reported [6]-[8], so the demands on this gold standard for monitoring the DoA are getting higher.

\*Resreach supported by KAIST Institute.

In this paper, cepstral analysis is engaged to measure the DoA. Cepstral analysis is a well-known method of homomorphic signal processing, especially used for speech recognition; this method can extract speech information regardless of vocal cord characteristics. Generally, the convolution of two signals in the time domain is exactly equal to their multiplication in the frequency domain. After taking the Fourier transform, this analysis converts the convolution in the time domain to addition in the quefrency domain by taking the log and the Fourier transform again. This process can be simply expressed with the following equation; the detailed description is in Section II-A.

$$x_1 * x_2 \xrightarrow{\text{FT}} x_1' \times x_2' \xrightarrow{\log, \text{FT}} x_1'' + x_2''$$
 (1)

where FT stands for the Fourier transform, \* is the convolution, and both  $x_1$  and  $x_2$  are anonymous signals.  $x'_1 = FT(x_1), x''_1 = FT(\log(x'_1)).$ 

We hope that we will be able to derive the index related to the DoA regardless of the information unrelated to the DoA by using cepstral analysis. The EEG signal generated from the brain contains anesthetic status information and a lot of information unrelated to the anesthetic status. Therefore, the key for characterizing the signal is to determine the most related components from the EEG. In Section II, the motivation and derivation of ICep are described. In Section III, detailed methods for data acquisition and preprocessing are depicted. The results and conclusion are given in Section IV and in Section V, respectively.

#### II. METHODS

The most fundamental thing to ask for when we attempt to quantify the DoA is which part of the EEG is related with the DoA. There exist some restriction on the feature vector to make it appropriate for quantifying the DoA as follows.

- The feature vector should be more sensitive to the DoA than to other biological factors
- The feature vector should rely on stochastic properties of the EEG rather than exact realization of the EEG.

Let f be a feature function that maps an observed EEG segment  $\vec{x}$  to a feature vector,  $\vec{f}$ .

$$f: \vec{x} \to f(\vec{x}) = \vec{f} \tag{2}$$

Two data sets are defined as follows; these sets are extracted from the clinical results in order to derive an index for the DoA. The detailed clinical environment for obtaining the EEG data is explained in Section III-A.

T.-H. Kim is with the department of electrical engineering, Korea Advanced Institute of Science and Technology (KAIST), Daejeon, Korea. Y.-G. Yoon is with the department of electrical engineering and computer science, Massachusetts Institute of Technology (MIT), Cambridge, USA. D.-W. Jeong is with the department of bio and brain engineering, KAIST, Daejeon, Korea. Seung Zhoo Yoon is with the Department of Anesthesiology and Pain Medicine, College of Medicine, Korea University, Seoul, Korea. S.-H. Park and J. Uhm are with the KAIST Institute for IT convergence, Daejeon, Korea (e-mail: ktho22@kaist.ac.kr).

- X<sub>AW</sub> (the awakening state): 57 epochs recorded from 1 awakening healthy adult. Subjects were asked to keep their eyes shut and not to move their bodies. The length of each epoch is 16s.
- X<sub>AN</sub> (the anesthetic state): 8,000 epochs recorded from 6 subjects in the anesthetic state. The length of each epoch is also 16s.

By applying the feature function to each epoch, the averaged feature vectors  $\overrightarrow{f_{AN}}$  and  $\overrightarrow{f_{AW}}$  that represent the two states are obtained. For an observed EEG segment  $\vec{x}$  to be tested, the feature function is applied to obtain a feature vector, and then compared with  $\overrightarrow{f_{AN}}$  and  $\overrightarrow{f_{AW}}$ . One intuitive way to estimate the DoA from these feature vectors can be shown in the following figure.



Figure 1. Feature vectors from an observed EEG segment, the anesthetic state, and the awakening state are depicted as  $\vec{f}$ ,  $\vec{f_{AN}}$ , and  $\vec{f_{AW}}$ , respectively. The DoA is calculated with the inner product between distances of feature vectors.

In this approach, the DoA would be large if the observed feature vector  $\vec{f}$  is close to  $\vec{f}_{AW}$  and vice versa. Since the state of a subject, whether that subject is in the awakening state or the anesthetic state, should be clearly discriminated by monitoring the DoA, the Fisher criterion is engaged to evaluate the discrimination performance of the feature functions. We define our goal as the determination of a feature function that maximizes the Fisher score. The definition of the Fisher criterion is as follows [9]:

Fisher score = 
$$\frac{\left|MEAN(\overline{f_{AW}}) - MEAN(\overline{f_{AN}})\right|^{2}}{Var(\overline{f_{AW}}) + Var(\overline{f_{AN}})}$$
(3)

## A. Cepstral Analysis

Many clinical studies have shown that the EEG spectrum is highly related to the DoA [10]. These results give an inspiration, the idea that the power spectral density (PSD) of the EEG signal itself can be used as a feature vector. However, using the spectrum itself as a feature vector may have some limitations. For instance, with the following definition of the distance between two arbitrary spectra P1( $\omega$ ) and P2( $\omega$ ), the exact shape or the exact value of the spectra at each corresponding frequency may significantly differ, while exhibiting very similar spectral responses, as shown in Fig. 2.



Figure 2.  $P1(\omega)$  (solid line) and  $P2(\omega)$  (dashed line) are presented.  $P1(\omega)$  and  $P2(\omega)$  exhibit similar spectral responses in (a) but not in (b); however, the actual distance between  $P1(\omega)$  and  $P2(\omega)$  is larger in (a) than in (b).

Distance = 
$$\sqrt{(\int_{\omega=0}^{\pi} |P1(\omega) - P2(\omega)|^2 d\omega)}$$
 (4)

In order to compare the overall shape of the spectrum rather than the exact value of the spectrum at each corresponding frequency, a filter bank and cepstrum are employed in this work. A filter bank is an array of band-pass filters that separates an input signal into a set of coefficients. Each filter carries subband frequency information of the input signal. By employing triangular filters with some frequency overlapping, these devices can be considered as band pass filters. Each coefficient is calculated from the particular frequency subband, so it allows a slight shift of spectrum as shown in Fig. 3. As presented in the following equation, cepstral analysis contains log. The mathematical definition of cepstrum is given as follows:

$$Cepstrum = |DCT\{\log\{|FT\{Epoch\}^2\}\}|^2$$
(5)

where DCT stands for discrete cosine transform.



Figure 3. Each filter is a triangular window in the frequency domain. Given spectrum is filtered with each filter; scale coefficients are obtained.

Whereas the main property of cepstrum is that the convolution of two signals can be expressed as the addition of their cepstra, it can be also interpreted as regarding a log-spectrum as a time-domain signal and taking its Fourier transform. Therefore, the low quefrency component in cepstrum includes information about the overall shape of the spectrum; the high quefrency component in the cepstrum includes information about the detailed fluctuation in the spectrum.

The overall procedure for the calculation of ICep is in Fig. 4. After taking the Short-time Fourier transform (STFT) on

pre-processed EEG (detailed description on preprocessing is in Section III-B), the filter bank is wrapped on each epoch. By taking log and DCT, cepstal coefficients are obtained. In order to determine which quefrency most reflects the DoA, the Fisher score is calculated after extracting the feature vector with different quefrencies. The maximum Fisher score of 60.43 is achieved when the second cepstral coefficient is employed for the feature vector, as shown in Fig. 5.



Figure 4 The flow diagram shows the overall processes to derive ICep. Feature vectors are extracted from training EEG set and testing EEG set. ICep is acquired by evulating feature vectors, and performing post processing.



Figure 5. The Fisher score of ICep is calculated when a feature vector is derived by different cepstral coefficient numbers. The Fisher score is maximized when the second coefficient is employed.

#### III. DATA ACQUISITION AND PREPROCESSING

### A. Data acquisition

The study was approved by the Korea University Hospital Institutional Review Board (No.MD11004-001). We collected raw EEG data from 10 adult patients. The patients underwent general anesthesia conducted by senior anesthetists at Korea University Hospital. In all cases, propofol was used for induction; nimbex or rocuronium was used for muscle relaxant. Maintenance of anesthesia was sustained by a mixed gas composed of oxygen, fresh air or nitrous oxide, and anesthetic vapor (sevoflurane or desflurane). Detailed records of anesthetic cases are described in Table 1. Raw EEG signals were acquired at a sampling rate of 128S/s using a BIS-VISTA monitor with standard BIS sensors. The BIS Monitor provides processed variables such as Electromyogram (EMG), BIS, spectral edge frequency (SEF), and impedance information. All variables were stored on a computer for offline analysis.

TABLE I. PATIENTS' CLINICAL RECORDS

No	Age	Sex	W. (Kg)	Premed. (mg)	Induction (mg)	Maintenance
1	36	М	31.8	Mob. 0.2 IM Midaz. 2 IM	Prop. 120	*Des. (1 MAC) + Remif. 0.05–0.1
2	44	М	76	Mob. 0.2 IM Midaz. 2 IM	Prop. 150	*Des. (1 MAC) + Remif. 0.05–0.1
3	54	F	65.6	Mob. 0.2 IM Midaz. 2 IM	Prop. 120	$O_2+N_2O+Des.$ (1.3MAC)
4	37	F	60	Mob. 0.2 IM Midaz. 2 IM	Prop. 120	*Des. (1 MAC) + Remif. 0.05–0.1
5	29	М	71.7	Mob. 0.2 IM Midaz. 2 IM	Prop. 150	$O_2+N_2O+Des.$ (1.3MAC)
6	13	М	51	Atro. 0.4 IM	Prop. 100	*Des. (1 MAC) + Remif. 0.05–0.1
7	36	F	52	Mob. 0.2 IM Midaz. 2 IM	Prop. 120	*Des. (1 MAC) + Remif. 0.05–0.1
8	20	F	60.1	Mob. 0.2 IM Midaz. 2 IM	Prop. 120	*Des. (1 MAC) + Remif. 0.05–0.1
9	18	М	67	Mob. 0.2 IV	Prop. 120	*Des. (1 MAC) + Remif. 0.05–0.1
10	13	М	41	Atro. 0.4 IM	Prop. 80	*Des. (1 MAC) + Remif. 0.05–0.1

W.: Weight; Mob.: Mobinul; Midaz.: Midazolam; Prop.: Propofol; Atro.: Atropine; Des.: Desflurance; Remif.: Remifentanil; \*: O<sub>2</sub> + Air was injected also

## B. Preprocessing

All analyses and simulations were performed on MATLAB R2011b. In order to enhance the signal integrity while minimizing the signal distortion in a desired frequency band, once raw EEG is obtained from the BIS VISTA monitor, a FIR low-pass filter is designed to have linear phase response and a zero at 60Hz. Low frequency artifacts due to breathing were removed by the wavelet denoising technique [11]. Then, the STFT is performed on the denoised signal. The length of each epoch is 16s with 14s overlapping with adjacent epochs. Segmented epoch was filtered by a high pass filter with the 3dB frequency of 29.6Hz. The filtered epoch was normalized with the RMS value of the unfiltered epoch.

## IV. RESULTS

Since BIS is the most widely used method in anesthetic cases, the results are mainly composed of comparisons between BIS and ICep. As is well known, the length of the moving average is 15-30s for BIS; we used 10s length of the moving average for ICep. In the time domain, the upper 0.05% of EEG signals in terms of magnitude are classified as invalid signals. The ICep, calculated from invalid components, is replaced with the previous index. Finally, ICep is truncated within [0,100].

The correlation coefficient in steady state between BIS and ICep is 0.9782, as shown in Fig. 6. Note that ICep has lower values than BIS in the anesthetic state, and has higher values in the awakening state. Furthermore, as shown in Table 2, ICep shows higher performance than BIS for the Fisher score. This implies that ICep outperforms BIS at discriminating between the anesthetic state and the awakening state. In Fig. 7, the early parts of the time courses of BIS and ICep are plotted together. Let time delay be the delay between BIS and ICep when the DoA is 80. Time delay between the ICep and BIS is observed. ICep precedes BIS by  $53.6s \pm 8.2s$  (Mean  $\pm$  STD) for the transition from the awakening state to the anesthetic state. Some cases that show invalid values are excluded. The whole set of time courses of the DoA is shown in Fig. 8. Note that the

signal quality for the first part of time course sent from the BIS VISTA monitor is poor, so ICep shows invalid values, as BIS does. Both ICep and BIS change along with surgical events such as injection of propofol or awakening of the subjects.



Figure 6. Correlation of the anesthetic state and the awakening state between ICep and BIS for 10 patients.



Figure 7. The early parts of time courses of BIS and ICep are plotted together. When the index of ICep is 80 set as 0s, BIS shows a  $53.6s \pm 8.2s$  (MEAN ± STD) delay.



Figure 8. Time courses of BIS and ICep are plotted together. For the first three minutes, invalid signal is observed. The DoA trend of ICep is similar to that of BIS.

TABLE II. FISHER SCORE OF DIS AND ICEP	TABLE II.	FISHER SCORE OF	BIS AND ICEP
--	-----------	-----------------	--------------

Method	Fisher Score
ICep	60.43
BIS	47.11

## V. CONCLUSIONS

In this paper, to assess the DoA, we proposed an ICep method based on cepstral analysis. This approach at first engages filter banks. After taking filter banks, cepstrum is obtained; we used the 2nd coefficient of cepstrum as a feature vector. ICep is calculated based on the inner product of the distances between the feature vectors of the training data sets and that of the testing data sets. By comparison to BIS, we verified that ICep can reflect the DoA from consciousness to unconsciousness and vice versa ( $r^2$ =0.9782). Moreover, ICep can more clearly distinguish between the awakening state and the anesthetic state, and it can also show a lower time delay than that of BIS. Although ICep still depends on training data sets and signal quality, it is certain that ICep is an appropriate method for quantifying the DoA.

## **ACKNOWLEDGMENTS**

This work was supported by the Ministry of Knowledge Economy under grant number 10035137-2010-01. The authors of this paper would like to thank the staff of the Korea University Hospital, for their clinical knowledge and expertise in anesthesia.

#### References

- A. Vakkuri, "Spectral entropy monitoring is associated with reduced propofol use and faster emergence in propofol-nitrous oxide-alfentanil anesthesia," *Anesthesiology*, vol. 103, pp. 274-9, 2005.
- [2] S. Sebel, "the incidence of awareness during anesthesia: A multicenter United States study," *Anesth. Analgesia*, vol. 99, pp. 833-839, 2004.
- [3] J. C. Sigl and N. G. Chamoun, "An Introduction to Bispectral Analysis for the Electroencephalogram," *Journal of Clinical Monitoring and Computing*, vol. 10, pp. 392–404, 1994.
  [4] B. Bein, "Entropy," *Best Practice and Research Clinical Anaesthes*-
- [4] B. Bein, "Entropy," Best Practice and Research Clinical Anaesthesiolgy, vol. 20, pp. 101–109, Mar. 2006.
- [5] T. Zikov et al., "Quantifying cortical activity during general anesthesia using wavelet analysis," IEEE Trans. Biomed. Eng., vol. 53, pp. 617– 632, Apr. 2006.
- [6] S. Pilge, R. Zanner, G. Schneider, M. K. J. Blum, and E. F. Kochs, "Time delay of index calculation: Analysis of cerebral state, bispectral, and narcotrend indices," *Anesthesiology*, vol. 104, pp. 488–494, 2006.
- [7] J. D. Hall and G. G. Lockwood, "Bispectral index: Comparison of two montages," *Br. J. Anaesth.*, vol. 80, pp. 342–344, 1998.
- [8] G. Barr *et al.*, "Nitrous oxide does not alter bispectral index: study with nitrous oxide as a sole agent and as an adjunct to i.v. anesthesia," *Br J. Anaesth.*, vol. 82, pp. 827-830, 1999.
- [9] C. M. Bishop, *Pattern Recognition and Machine Learning*, Springer, 2006, pp. 188.
- [10] Freye E, Levy JV., "Cerebral monitoring in the operating room and the intensive care unit: an introductory for the clinician and a guide for the novice wanting to open a window to the brain. Part I: The electroencephalogram," *J Clin Monit Comput*, vol. 19, pp. 1–76, 2005.
- [11] T. Zikov et al., "A wavelet based de-noising technique for ocular artifact correction of the electroencephalogram," in Proceedings of the 24th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, vol. 1, pp. 98-105, 2002.