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CHAOS-MODIFIED DETRENDED MOVING AVERAGE METHODOLOGY FOR MONITORING THE DEPTH OF ANAESTHESIA

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Abstract*—This paper proposes a new method to monitor the depth of anaesthesia (DoA) based on the EEG signal. This approach firstly uses discrete wavelet transform (DWT) to to remove the spikes and the low frequency noise from raw EEG signals. After de-noising the EEG signals, the modified Hurst parameter is proposed with two new indices (CDoA and CsDoA), to estimate the anaesthesia states of the patients. To reduce the fluctuation of the new DoA index, a combination of Modified Chaos and Modifying Detrended Moving Average is used (MC-DMA). Analyses of variance (ANOVA) for C-MDMA and BIS distributions are presented The results indicate that the C-MDMA distributions at each anaesthesia state level are significantly different and the C-MDMA can distinguish five depths of anaesthesia. Compared with BIS trends, MC-DMA trend is close to BIS trend covering the whole scale from 100 to 0 with a full recording time.

Index Terms— **Electroencephalogram (EEG), Chaos method, Modified Detrended average method, Depth of anaesthesia (DoA).**

I. INTRODUCTION

Anaesthesia is the term given to the loss of feeling or sensation. This is a method of decreasing sensitivity to pain in a patient while surgery is being performed. Anaesthesia may be accomplished without the loss of consciousness, or with partial or total loss of consciousness. There are two kinds of anaesthesia: general anaesthesia, which affects the entire body and causes a loss of consciousness, and local anaesthesia which is accomplished using drugs that temporarily block the sensation of pain in a certain area of the body while the patient remains awake. This study is only concerned with general anaesthesia.

Pharmacological methods are used for preparation of medical procedures. Drugs can be administered by injection into muscle or under the skin with a needle, intravenously (by needle into a vein), or with a gas mask for inhalation. Creams, gels, liquids can directly be applied onto the area being treated. The administration and monitoring of anaesthesia require both knowledge and practice. Vital signs and other monitoring parameters are assessed continuously throughout the procedure. There are many reasons underlying an increased risk of underdose and overdose in surgery which could include inadequate drug dosing, poor monitoring, failure to refill the anaesthetic machine's vaporizers, insufficient training, unfamiliarity with techniques used, machine misuse and malfunction. Monitoring the depth of anaesthesia will help anesthesiologists to adjust the anaesthetic under administration, and to prevent the incidence of awareness and anaesthetic overdose during surgery. DoA monitor systems provide anaesthesia professionals with an additional method to assess anaesthetic effects and patient responses during surgery. A robust measurement of depth of anaesthesia will benefit patients in recovery time and help anaesthetists in primary anaesthetic use (Yentis, 2009; Taylor, 1993; Kelley).

A number of methods have been developed over the years to determine depth of anaesthesia such as clinical signs (systolic blood pressure, heart rate, sweating and tears), the minimum alveolar concentration (MAC), lower esophageal contractility (LOC), and isolated forearm technique. However, all these methods could not achieve the desired accuracy of anaesthetic depth. Clinical signs may vary over a wide range depending on disease, drugs and surgical technique. Heart rate, blood pressure, lacrimation, sweat and ocular signs are not valuable in predicting response to a noxious stimulus [1]. Individual patients have variability and various factors, such as the degree of stimulation and pain induced by surgery and the use of concomitant analgesic drugs. It is impossible to gain a constant level of consciousness through pre-calculating the exact dose of anaesthetics.

Many methods are devised and implemented for purpose of monitoring the depth of anaesthesia based on EEG signals. The Cerebral State Index (CSI) monitoring was not consistent with the clinical observations in the different stages of depth anaesthesia [2]. Narcotrend did not adequately detect the transition between awareness and unconsciousness in surgical patients [3]. The most popular Bispectrum (BIS) index has also received some criticisms, such as being redundant [4], not responsive to some anesthetic agents such as ketamine and nitrous oxide [5], and not robust across patients [6]. In addition, the BIS monitor is unable to give an accurate estimate of the patient's hypnotic state in case of poor signal quality [7]. Time delay between "awake", "general anaesthesia", and "deep anaesthesia" was presented in [8]. Recently, a new method detected DoA levels based on a time-domain signal processing combined with multi-layer perceptron [9]. An adaptive time-frequency analysis method based on ensemble empirical-model decomposition was used to analyses EEG signal for estimating the DoA [10]. The spectral features of EEG signal were proposed in [11] for separating the anesthetic effects. The Isomap-based estimation is used to assess neurophysiological changes during

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anaesthesia [12]. The Hurst exponent and wavelet transform was applied in multiscale rescaled range analysis (MRRA) algorithm to measure of anesthetic drug effects on brain activity [13].

In this paper, we propose a new method for monitoring the DoA using modified Chaos method. This approach firstly uses discrete wavelet transform (DWT) to de-noise EEG signals. After de-noising the EEG signals, the modified Hurst parameters are used to estimate the anaesthesia states of patients. To assess DoA with accuracy, a combination of Chaos and MDMA methods (*MC-DMA*) is applied. *MC-DMA* and BIS indices are compared through the whole scale from 100 to 0 with full recording time on 50 patients. The new *MC-MDMA* index reflected the clinical state of our small series of patients accurately.

This paper is organized as follows. Data acquisition is introduced in Section II. Section III presents chaos method, modified the Hurst parameters, and two new indices *CDoA* and *CsDoA*. A combination of Chaos and MDMA methods is applied for monitoring the DoA is presented in Section IV. The statistic results are provided in Section V. Finally, conclusions are drawn in Section VI.

II. DATA ACQUISITION

The study was approved by the University of Southern Queensland Human Research Ethics Committee (No: H09REA029) and the Toowoomba and Darling Downs Health Service District Human Research Ethics Committee (No: TDDHSD HREC 2009/016). In this study, 50 adult patients are involved. All patients underwent general anaesthesia induced with clinically appropriate doses of conventional pharmaceuticals including midazolam; alfentanil; fentanyl and propofol. Intravenous morphine, clonidine, parecoxib and paracetamol were used as indicated for post-operative analgesia. The airway was supported by endotracheal intubation or by laryngeal mask airway insertion as indicated clinically. Anaesthesia was maintained with desflurane or sevoflurane in combination with air or nitrous oxide. Skeletal muscle paralysis was variable but always reversed with neostigmine and atropine or glycopyrrolate. The timestamps from the BIS monitor recording for all intravenous dosing and significant intra-operative events were recorded by the attending anesthetist. Patient demographic characteristics and mean drug doses (when used) are presented in Table 1. Loss of consciousness (LOC) was clinically assessed by lack of response to verbal and tactile stimulus. Loss of the lash reflex was used in case of doubt.

In this study, all patients were maintained with volatile anaesthesia agents (always supplemented with intravenous opiates and sometimes supplemented with intravenous anti-inflammatories and clonidine). No patients underwent exclusively intravenous anaesthesia maintenance.

We made pre- and intra-operative use of the proprietary BIS VISTA^{TM} monitor (BIS VISTA Version 3.00, Algorithm Version BIS 4.1, Aspect Medical Systems). Raw EEG data were obtained using the four adhesive forehead sensors used clinically for BIS monitoring. Data were exported to a USB drive and transferred to a portable computer for off-line analysis. Processed BIS index was presented in a file with updates every second whilst raw EEG data was presented as a binary file documenting two channels of unfiltered signals. Each EEG sample was a 16-bit signed integer in units of 0.05μV. Data were sampled at 128 times per second for each channel [7].

Table 1: Patient demographics and intraoperative drug usage.

	Mean ± SD or Number
Age (yr)	59 ± 16
Weight (kg)	98 ± 32
Gender (F/M)	30/25
Midazolam (mg)	4 ± 1
Alfentanil (μg)	850 ± 150
Propofol (mg)	170 ± 60
Parecoxib (mg)	40
Fentanyl (μg)	135 ± 35

III. METHODOLOGY

A. Preprocessing

The EEG signals are mainly affected by eye blinks, electrocardiograms (ECGs), and electrooccluograms (EOG). An attempt is made to remove ECG patterns, but it is not always successful because recognition requires a detectable repetitive waveform. If any ECG is detected (as a glitch) but not removed, then that epoch of data is considered unusable in BIS. Electromyographic (EMG) is not considered as an artefact, but if the EMG is large enough to trigger some of the other artefact detectors, it will cause the Signal Quality Indicator (SQI) to decrease [7]. A wavelet-based de-noising algorithm is used to remove the spikes and the low frequency noise from raw EEG signals in [14].

B. Hurst exponent in Chaos method to estimate the depth of anaesthesia

Chaos analysis of EEG signals has been reported by many researchers in recent years [15-20]. A chaotic system is characterized by 'unpredictability', which simply means that one cannot predict how a system will behave in the future on the basis of a series of observations along time. From various experiments, it has been well established that neuronal activity and EEG recordings show many characteristics of chaotic behavior. In other words, the electrical rhythms of the brain show signs of chaos.

The dynamics of brain electrical activity were presented by Rapp *et al*. [21-22]. In their study, they estimated the correlation dimension of the human EEG signals and event-related brain potentials. Dafilis *et al*. discussed the evidence for the existence of chaos in a theory of brain electrical activity and provided unique depictions of the dynamics of brain chaotic model [23]. The periodic evolution of brain states through sequences of attractors was studied by Freeman [24]. The Lyapunov exponents estimate the mean exponential

convergence of nearby trajectories of the attractor [25-26]. The Hurst exponent is directly related to the "fractal dimension", which gives a measure of the roughness of a surface, and has been used to measure the roughness of coastlines. For example, the relationship between the fractal dimension (*D*) and the Hurst exponent (*H*) is $D = 2 - H$. Hurst exponent can distinguish fractal from random time series, or find the long memory cycles. The values of the Hurst Exponent range between 0 and 1. Sum of the accumulated deviation from the mean of the time series x_i having length *L* is:

$$Y(i) = \sum_{i=1}^{L} [x_i - \langle x \rangle], \qquad i = 1,..., L \tag{2a}$$

where <*x*> is the average of the time series, that is

$$\langle x \rangle = \frac{1}{L} \sum_{i=1}^{L} x_i \tag{2b}$$

The range *R*(*i*) is the difference between the maximum and the minimum of *Y(i)*, over the length *L*:

$$R(i) = \max_{1 \le i \le L}(Y(i)) - \min_{1 \le i \le L}(Y(i)) \cdot \tag{3}$$

Standard deviation over the length *L* is:

$$S(i) = \sqrt{\frac{1}{L} \sum_{i=1}^{L} (x_i - \langle x \rangle)^2} \tag{4}$$

The rescaled range is calculated by dividing the range *R* by the standard deviation:

$$R / S = \frac{R(i)}{S(i)} \tag{5}$$

The Hurst exponent is estimated by calculating the average rescaled range over multiple regions of the data. Call the average (mean) of a data set *x* is *E*[*x*], the expected value of *R/S* is calculated over a set of regions. It converges on the Hurst exponent power function as:

$$E\left[\frac{R(i)}{S(i)}\right] = Ci^H \tag{6}$$

The constant *C* influences the value of *H*.
Hurst exponent (*H*) is computed by:

$$H(i) = \frac{\log(R / S)}{\log(i)} \tag{7}$$

Fig. 1 shows *R/S* trends of a patient for five states of anaesthesia: very deep anaesthesia (R/S_1), deep anaesthesia (R/S_2), moderate anaesthesia (R/S_3), light anaesthesia (R/S_4) and awake (R/S_5). In this figure, four different states of anaesthesia can be identified. With the same value *log*(*i*), we have $R/S_1 < R/S_2 < R/S_4 < R/S_5$. However, R/S_3 of the moderate anaesthesia has the highest value. Therefore, it is difficult to distinguish the change of patient's state in real time and also difficult for setting a DoA index from R/S trends.

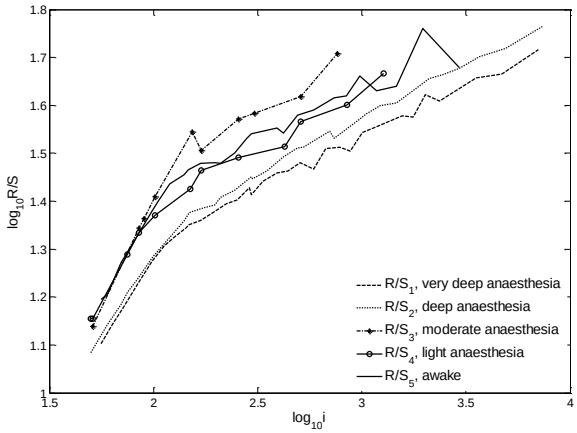

Fig. 1: R/S trends for five states of anaesthesia: awake, light anaesthesia, moderate anaesthesia, deep anaesthesia and very deep anaesthesia.

C. Modified Hurst exponent to estimate the depth of anaesthesia

Figure 2 presents *R*(*i*), *S*(*L*) and *H(i)* of the EEG signal of patient 3, respectively.

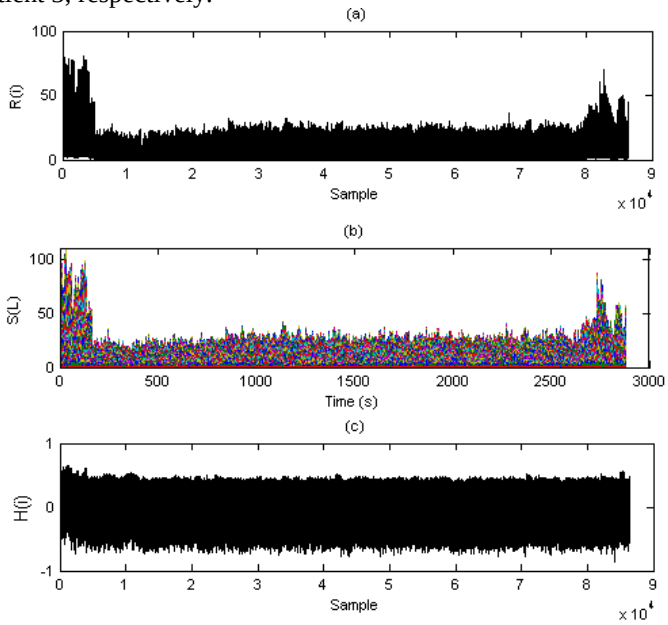

Fig. 2:
(a) *R*(*i*) is the difference between the maximum and the minimum of value *Y(i)*, over the length *L* = 2881 and window length *m* = 30, the sample = *L* x m = 2881 x 30 = 86430.
(b) *S*(*L*) is the standard deviation over the length (*L*=2881) of the signal.
(c) The Hurst exponent *H*(*i*) is estimated by calculating the average rescaled range over multiple regions of the data. The length *L* = 2881 and window length *m* = 30. The sample = *L* x m = 2881 x 30 = 86430.

Patient 3 was a 55 year old, 87 kg, male. Surgery was undertaken from 10:10:58 pm to 10:55:30 pm. Drug administration consisted of midazolam (4 mg) as a sedative drug at 10:10:58 pm. At 10:11:20 pm, alfentanil (1000 μg) was used as strong pain relief given only once during the

operation. Propofol (160 mg) at 10:12:29 pm was the main drug used to induce sleep. The patient fell asleep within 30 seconds of injection, eyes closed, and the effect wore off in about 3 minutes. At 10:12:46 pm, desflurane and nitrous oxide (N_2O) were started. Desflurane is a gaseous anaesthesic agent, breathed continuously during anaesthesia to keep a patient asleep. N_2O is a gaseous anaesthesic agent, breathed continuously for short-acting pain relief. Parecoxib (40 mg) was used at 10:19:24 pm for moderate pain relief.

The maximum values of $S(L)$ and $R(i)$ in this figure have the relationship with the change of DoA of patient 3. When the patient's state have changed from consciousness to unconsciousness, maximum values of $S(L)$ and $R(i)$ reduced from 100 to 22, corresponding to BIS values reducing from 97 to 20. During the deep anaesthesia time, maximum values of $S(L)$ and $R(i)$ have values between 20 and 30. When the patient's state have changed from unconsciousness to consciousness, maximum values of $S(L)$ and $R(i)$ increase from 20 to 80 in Figs. 2(a) and 2(b).

However, the Hurst exponent $H(i)$ in Fig. 2(c) does not show the relationship with the clinical state of patient 3. $H(i)$ could not directly reflect the patient's clinical states from awake to deep anaesthesia and vice versa. Therefore, a modification from Hurst parameters is proposed for monitoring the DoA. We set:

$$mSS = \frac{\max(S) + mean(S)}{2} \tag{8}$$

$$mS = \max(mSS) \tag{9}$$

$$mR = \max(R) \tag{10}$$

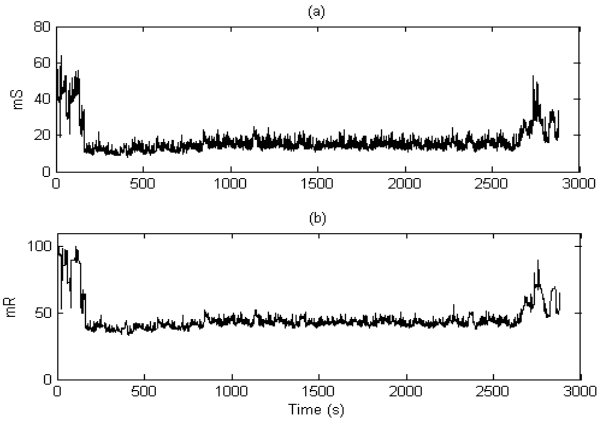

Fig. 3: (a) *mS* is the maximum values of $S(L)$ when the patient's states have changed from consciousness to unconsciousness, *mS* values decreased from 60 to 10. During the deep anaesthesia time, *mS* values fluctuate from 10 to 20. In emergence time, when the patient's states have changed from unconsciousness to consciousness, *mS* values increased from 10 to 50.
(b) *mR* is the maximum values of $R(i)$. When the patient's states have changed from consciousness to unconsciousness, *mR* decreased from 100 to 40. During the deep anaesthesia time, *mR* fluctuated from 35 to 45. In emergence time, when the patient's states have changed from unconsciousness to consciousness, *mR* increased from 40 to 90.

Fig. 3 represents the diagrams of *mS* and *mR*, respectively. In this figure, when the patient's states have changed from consciousness to unconsciousness, *mS* decreased from 60 to 10 in Fig. 3(a) and *mR* decreased from 100 to 40 in Fig. 3(b). During the deep anaesthesia time, *mS* fluctuate from 10 to 20, and *mR* fluctuates from 35 to 45. In emergence time, when the patient's states changed from unconsciousness to consciousness, *mS* increased from 10 to 50 and *mR* increased from 40 to 90. However, during deep anaesthesia, *mS* and *mR* fluctuate widely in the range of 10 and 40, respectably. To reduce this fluctuation, *mS* and *mR* are divided for H_S values. Define *CDoA* and *CsDoA* be the DoA indices, we have:

$$CDoA = k_{mR} mR + V_{OFFSET}^{mR}$$
$$CsDoA = k_{mS} mS + V_{OFFSET}^{mS} \tag{11}$$

k_{mR}, k_{mS}, V_{OFFSET}^{mR}, and V_{OFFSET}^{mS} are the values calculated in the offline analysis. Empirically, values like $k_1=1$, $k_2=2$, $V_{OFFSET}^{mR}=5$, and $V_{OFFSET}^{mS}=20$ produced the best results. These constant values are merely estimates of a unit of measure, to fix the *CDoA* and *CsDoA* values in the range of 0-100.

In order to estimate the results on anaesthesia states of the patients, *CDoA* and *CsDoA* trends were compared with BIS trends, covering the whole scale from 100 to 0 with a full recording time. The *CDoA* and *CsDoA* trends are close to BIS trend in the whole time range in Fig. 4 and Fig. 5.

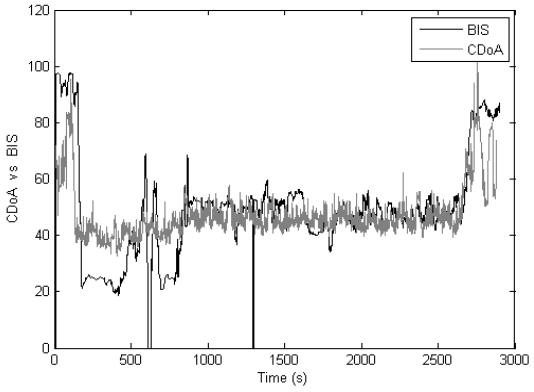

Fig. 4: *CDoA* trend are compared with BIS trend. When the patient's states changed from consciousness to unconsciousness, *CDoA* values decreased from 100 to 40. During the deep anaesthesia time, *CDoA* values fluctuate from 45 to 50. In emergence time, when the patient's states have changed from unconsciousness to consciousness, *CDoA* values increased from 40 to 100.

When the patient's states changed from consciousness to unconsciousness, *CDoA* values decreased from 100 to 40 and *CsDoA* values decreased from 90 to 30. During the deep anaesthesia time, *CDoA* values fluctuate from 45 to 50, and *CsDoA* values fluctuate from 35 to 45. In emergence time, when the patient's states have changed from unconsciousness to consciousness, *CDoA* values increased from 40 to 100 and *CsDoA* values increased from 35 to 110. Comparing with BIS trends, covering the whole scale from 100 to 0 with a full recording time, *CDoA* and *CsDoA* trends are close to BIS trend in this time range. Therefore, *CDoA* and *CsDoA* can be used to monitor the depth of anaesthesia.

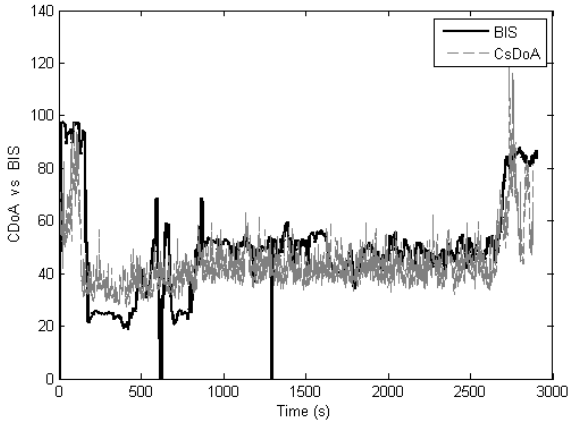

Fig. 5: *CsDoA* trend are compared with BIS trend. When the patient's states changed from consciousness to unconsciousness, *CsDoA* values decreased from 90 to 30. During the deep anaesthesia time, *CsDoA* values fluctuate from 35 to 45. In emergence time, when the patient's states have changed from unconsciousness to consciousness, *CsDoA* values increased from 35 to 110.

IV. Combination of Chaos and Modified Detrended Moving Average (MDMA) methods

In order to reduce the fluctuation of *CDoA*, a combination of Chaos and Modified Detrended Moving Average (MDMA) methods [27] is applied for 57 patients. Detrended Moving Average method studies the scaling properties of time series [23-24]. The scaling property is obtained by using a moving average function. Modified Detrended Moving Average (MDMA) method [28-29] for monitoring the DoA was presented in our previous paper [27]. A brief description of MDMA method is presented below:

The first step of the MDMA method is to detect trends in data by employing a moving average. The moving average assigns equal weight to each data point in a window of size *s*. The output R_i of Chaos method is the input of MDMA. For a window of size *s*, the simple backward moving average is defined as:

$$\hat{Y}_s(i) = \frac{1}{s}\sum_{k=0}^{s-1} Y(i-k), \tag{12}$$

where *Y(i)* is the integrated signal defined in:

$$Y(i) = \sum_{k=1}^{i}[R_k - \langle R\rangle], \qquad i = 1,...,L, \tag{13}$$

with R_i sample length *L*, and the average of the time series <*R*> is:

$$\langle R\rangle = \frac{1}{L}\sum_{k=1}^{L} R_k \ . \tag{14}$$

Here, the average of the signal data points within the window refers to the last data point covered by the window.

In the second step**,** we de-trended the signal by subtracting the trend $\hat{Y}_s$ from the integrated profile *Y(i)*:

$$C_s(i) = Y(i) - \hat{Y}_s(i). \tag{15}$$

For the backward moving average, we then calculated the fluctuation for a window of size *s* as

$$F_M^2(s) = \frac{1}{(L_s - s)}\sum_{i=3}^{L_s} C_s(i)^2[(v-1)s + i], \tag{16}$$

where $L_s = [L/s]$, $v = 1,..., 2L_s$ and $C_s(i)$ is as in (16).

Finally, we averaged all the v^{th} segments and took the square root to obtain the fluctuation function as follows:

$$F_{MDMA}(s) = \left[\frac{E_m}{L}\sum_{s=3}^{L} F_M^2(s)\right]^{\frac{1}{2}}, \tag{17}$$

where E_m is the wavelet entropy which is presented in [27] as the gain parameter .

In the combined Chaos and *MDMA* method, the MDMA is chosen as a feature function. The output signal (R_i) of Chaos method is the input signals of the MDMA method. A new index for monitoring DoA is proposed as:

$$\text{C-MDMA} = K_{\min}^{Modify} \min(\ln F_{MDMA}) \tag{18}$$

with $K_{\alpha}^{Modify} = 250$ and $K_{\min}^{Modify} = 5$ as the gain parameters. These constant values are merely estimates of a unit of measure, to fix the *C-MDMA* value in the range of 0-100.
The diagram for this combination is shown in Fig. 6 as:

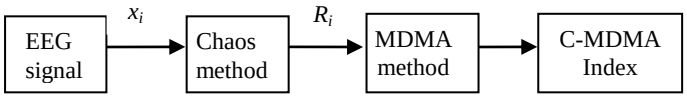

Fig. 6: The diagram of *C-MDMA* method.

The *C-MDMA* trend is compared with BIS trend again. Fig. 7 shows the results of *C-MDMA* trend and BIS trend of a patient in the 2809 second recording time. In this figure, the *C-MDMA* trend is closed to BIS trend in this time range. The fluctuation of *C-MDMA* trend is lower than that of *CDoA* and *CsDoA* in Figs. 4 and 5.

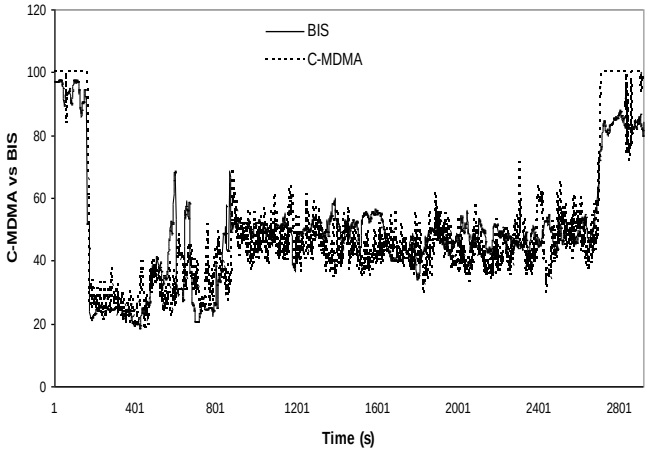

Fig. 7: A comparison between *C-MDMA* trend and BIS trend.

V. STATISTIC RESULT

The BIS index is used to compare with the new index C-MDMA. BIS value is scaled between 0 and 100 to correlate with clinical states of a patient. There are five states of anaesthesia. Very deep anaesthesia and deep anaesthesia states have the BIS values from 0 to 40, moderate anaesthesia state from 40 to 60, light anaesthesia state from 60 to 80 and awake state from 80 to 100. If a BIS value is lower than 60, a patient has an extremely low probability of consciousness. The BIS value higher than 70 may have a greater probability of consciousness and potential for recall [30].

A comparison of *C-MDMA* and BIS index for 57 patients undergoing general anaesthesia is presented in Fig. 8. Five data groups of *C-MDMA* and BIS are used in this comparison, corresponding to five states of anaesthesia with BIS index ranges form 0-20, 20-40, 40-60, 60-80, and 80-100. The boxes illustrate the 25th to the 75th percentiles of the distribution of *C-MDMA* at each plane of anaesthesia as "defined" by the BIS level on the Y-axis whilst the whiskers illustrate the range for each distribution [26].

Analyses of variance (ANOVA) for C-MDMA and BIS distributions are presented in Fig. 8. In this figure, "Source" is the source of the variability; "SS" is the Sum of Squares for each source; "*df"* is the degrees of freedom associated with each source; "MS" is the Mean Squares (*MS*) for each source, which is the ratio *SS/df; "F"* is the F statistic, which is the ratio of the *MS*'s; the *p*-value is derived from the specified cumulative distribution function (*cdf*) of *F*. In this figure, the p-value of 0 indicates that differences between the five states of anaesthesia are very significant. Analysis of variance results in Fig. 8 and Fig. 9 indicates that the *C-MDMA* distributions at each anaesthesia state level are significantly different (p=0). The *C-MDMA* can distinguish five depths of anaesthesia in our sample.

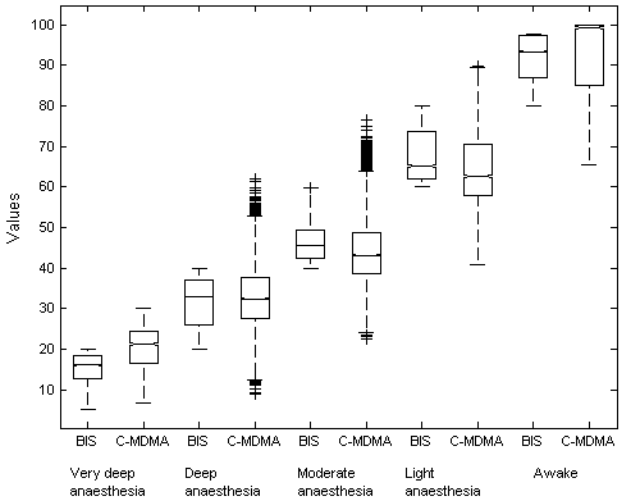

Fig. 8: The *C-MDMA* distributions of 57 patients are presented by the box plot in a different anaesthesia state level.

ANOVA Table

Source	SS	df	MS	F	Prob>F
Groups	6.62524e+007	9	7361376.64	187500.26	0
Error	1.01637e+007	258878	39.2606		
Total	7.64161e+007	258887			

Fig. 9: ANOVA Table for *C-MDMA* and BIS distributions.

VI. DISSCUSION

The BIS index is a good monitor but in some cases BIS index could not display the correct values on the screen. There is a case where BIS goes wrong while C-MDMA seems to be reliable as shown in Fig. 10. In the period from second 473 to second 609, BIS trend drops to value from 10 to 2.1 when the C-MDMA only is in the range of 25 to 28. Fig. 10(a) shows the trends of C-MDMA and BIS.

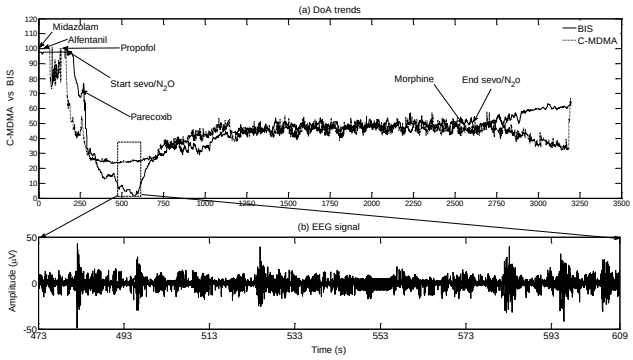

Fig. 10: (a) C-MDMA and BIS trends for a patient. (b) EEG signal in a period from 473 to 609 seconds when the BIS values drop from 10 to 2.1.

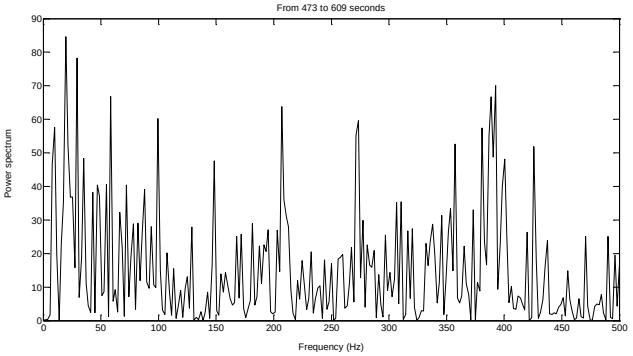

Fig. 11: Power spectrum of EEG signal during the time from 473 to 609 seconds.

The timing of all intravenous dosing and significant intraoperative events was recorded and presented in this figure. Patient 37 was a 26 year old, 101 kg, male. Surgery was undertaken from 10:15:06 am to 11:08:22 am. Drug administration consisted of midazolam 5 mg at 10:17:40 am. At 10:17:45 am, alfentanil 1000 μg was used. Propofol 200 mg at 10:18:40 am was the main drug used to induce sleep. At 10:18:45 am, sevoflurane and nitrous oxide (N2O) were started. Parecoxib 40 mg was used at 10:19:40 am for moderate pain relief. Fig. 10(b) shows the EEG signal in the period from 473 to 609 seconds. During this period, there is no burst suppression EEG pattern in the long time. Another result from power spectrum is considered in Fig. 11. The fast Fourier

transform (FFT) analysis shows EEG power spectrum having high amplitude in the frequency spectrums 0-500 Hz. Therefore, it is impossible for the BIS to have such a low value in the period from 473 to 609 seconds. In contrast, C-MDMA trend is responsive and its movement seems similar to the changes in the clinical state of the patients.

Another case of poor signal quality is presented in Fig. 12 during general anaesthesia. In this case, the BIS value was dropped and could not display the DoA values on the screen. The Signal Quality Indicator (SQI) is a measure of the signal quality for the EEG channel source in the BIS monitor. When the SQI value is lower than 15, the BIS value and BIS trend will not be displayed on the screen [7]. However, the proposed C-MDMA index can compute and display the DoA value at times when the invalid BIS value did not display, as shown in Fig. 12. Compared with the BIS index in this case, during the periods of poor signal quality, the results of C-MDMA method correlates with clinical observations.

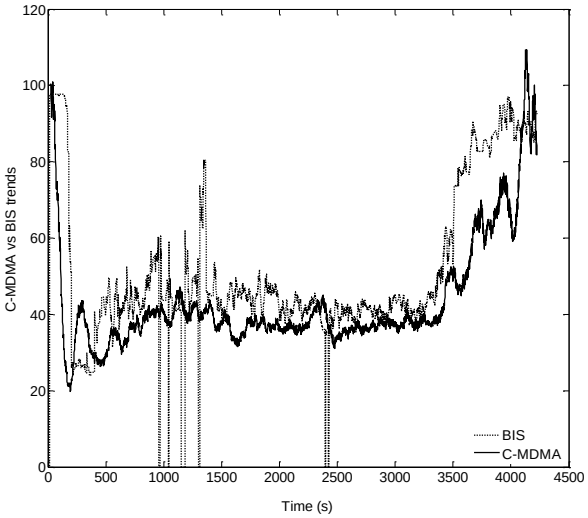

Fig. 12: A comparison between C-MDMA and BIS trends in the case of poor signal quality.

VII. CONCLUSION

This paper proposes a new approach to monitor the depth of anaesthesia using modified Chaos method. The Hurst exponent is estimated by calculating the average rescaled range over multiple regions of the data; and the relationship between the maximum values of $S(L)$ (see (3)) and $R(i)$ (see (4)) and the clinical states of Patient is identified. To estimate the results on anaesthesia states of the patients, *CDoA and CsDoA* indices are proposed and their trends are compared with BIS trends. The simulation result shown that *CDoA* and *CsDoA* trends are close to BIS trend in the whole time range.

To improve the Chaos method for monitoring the DoA, a combination of Chaos and Modified Detrended Moving Average methods is applied. In this new method (*C-MDMA*), the output R_i of Chaos method is the input of MDMA. The *C-MDMA* and the BIS indices are compared through the whole scale range from 100 to 0 with full recording time on 57 patients. We find that *C-MDMA* can reflect the transition from consciousness to unconsciousness with the induction of anaesthesia and from unconsciousness to consciousness during emergence from anaesthesia in nearer to real time.

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