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Complex networks approach for depth of anesthesia assessment

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ABSTRACT

Despite numerous attempts to develop a reliable depth of anesthesia (DoA) index to avoid patients' intraoperative awareness during surgery, designing an accurate DoA index is a grand challenge in anesthesia research. In this paper, an attempt is made to design a new DoA index. We applied a statistical model and spectral graph wavelet transform (SGWT) to monitor the DoA. The de-noised electroencephalography (EEG) signals are partitioned into segments using a window technique. The window size is determined empirically, then each EEG segment is divided into sub-blocks to make the signal quasi stationary. 10 statistical characteristics are extracted from each sub-block. As a result, a vector of statistical characteristics is pulled out from each segment. Each vector of the features is then mapped as a weighted graph and spectral graph wavelet transform is performed. The total energy of wavelet coefficients at different scales is tested. The energy of wavelet coefficients at scale 3 is selected to form a $\mathbf{SGWT_{DoA}}$ function. The $\mathbf{SGWT_{DoA}}$ is evaluated using an anesthesia EEG recordings and the bispectral (BIS) from 22 subjects. The Bland-Altman, regression, Q-Q plot and Pearson correlation are used to verify the agreement between the $\mathbf{SGWT_{DoA}}$ and the BIS. The experimental results demonstrate that the $\mathbf{SGWT_{DoA}}$ has the ability to estimate the DoA accurately. The $\mathbf{SGWT_{DoA}}$ is also compared and tested with the BIS in the case of poor signal quality. Our findings show that, the $\mathbf{SGWT_{DoA}}$ can reflect the transition from unconsciousness to consciousness efficiently even for a poor signal while the BIS fails to display the DoA values on the monitor.

1. Introduction

Awareness during general anesthesia is an ongoing challenge as its consequences on patients and some juristically issues for anesthesiologists are critical [7,20,22]. Awareness happens when a patient is supposed to be anesthetized under anesthesia medications but his or her brain is active. As a result, after surgery the patient could endure severe psychological problems, such as nightmares, anxiety and depression [17,16,23].

Delivering a sufficient amount of anesthesia agents to patients helps anesthesiologists to avoid awareness during surgery, reduce costs associated with anesthesia medications consumption, maintain hemodynamic constancy and keep the recovery period short. The majority of the methods and devices that assess the DoA are based on clinical signs, such as heart rate, blood pressure and sweating could not estimate the DoA precisely, and are not reliable [9,17,26,28,29,30,31]. Using some types of anesthetic agents, such as a muscle relaxant can make the interpretation of those signs difficult [13,14]. However, clinical research and individual studies showed that there were no abnormalities in those signs for some patients who suffered awareness during general anesthesia [2,7,9,21].

Different human and animal research demonstrated that the electrical brain activities significantly correlated with the DoA during surgery. Consequently, most of the recent research have been turned their attention to developing and finding noninvasive ways of monitoring the DoA based on EEG signals [6,12,39,43,45].

Up to now, several clinical systems for monitoring the DoA were reported and developed in which the EEG signals were mainly used as an input for designing a DoA index [26,39]. One of the popular DoA index widely used for monitoring the DoA is the bispectral index (BIS). The BIS processes EEG data based on the frequency components of EEG signals [38]. The values of the BIS index are between 0 and 100, and are displayed on the BIS monitor. According to several clinical studies, up to now the BIS index reflects the patient's anesthetic states during surgery [38], which can help anesthesiologists to deliver appropriate amounts of anesthesia medications to patients [35]. However, it has received some criticisms, such as being delayed, not robust with different anesthesia medications [29], and not accurate across patients.

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Some alternatives to the BIS index, however, are being contemplated.

Most of the developed methods of monitoring the DoA or diagnosing different health issues were based on the analysis of EEG signals in frequency domain [14,16,17], time domain [48], or time and frequency domain [48]. EEG signals analysis based on graph domain (both terms of graphs and networks will be used interchangeably in this paper) has also been attracting a great deal of attention as different modern studies have shown the strength of using networks concept in the data analysis and classification [3,40,46,47].

Recently, a new structure for analysing signal/data through graphs, which is known as graph signal processing (GSP), has been developed [1,9,10,32,39,41,47]. The GSP is a powerful tool to analyse data in machine learning [1,6]. The most popular transformation technique in GSP is spectral graph wavelet (SGWT) which was introduced by Hammond et al. [10]. It allows the extension of the classical multiscale transform to an irregular domain [19,10,1,15]. The SGWT was used by Pham et al. [30] to recognize texture features of satellite images, by Drew et al. [5] to study the air traffic behaviour, by Smalter et al. [39] to design a chemical predicative model, and by Malek et al. [19] to classify the colour images.

We were motivated by the promising results from applying spectral graph wavelet and statistical approaches to analyse stationary and non-stationary behaviors of signals. In this paper, we sought to estimate the DoA based on the SGWT and a statistical model using EEG signals. A window technique is employed to divide de-noised EEG signals into segments. Each EEG segment is partitioned into k sub-blocks. Ten statistical characteristics are then extracted from each sub-block. A vector of the statistical features is pulled out and mapped into a weighted graph. An average energy of the wavelet coefficients and scale coefficients is obtained from each graph and used as the key characteristics for estimating the DoA. Our findings show that the energies of the wavelet coefficients vary consistently with the BIS values. As a result, a new function of the DoA ($SGWT_{DoA}$) is then designed. The proposed index is assessed using anesthetic EEG recordings and the BIS values from 22 subjects. The Bland-Altman, regression, and Pearson correlation are employed to verify the agreement between the $SGWT_{DoA}$ and the BIS. The obtained results demonstrate the ability of the new index to estimate the DoA state. The $SGWT_{DoA}$ is also compared and tested with the BIS in the case of poor signal quality. The findings from this research show that the $SGWT_{DoA}$ can reflect the transition from unconsciousness to consciousness accurately in the case of a poor signal while the BIS fails to show the value on the BIS monitor.

The remainder of the paper is arranged as follows. Section 2 presents a brief review about the current techniques of the DoA estimating. Section 3 depicts the datasets used in this paper. Section 4 reviews the key concept of spectral graph wavelet. Section 5 describes the proposed method. Section 6 presents the experimental results and simulations. Section 7 shows a case study of evaluating a poor signal quality signal case by the proposed method. Finally the conclusions of the study are drawn in Section 8.

2. Related work

Various techniques have been reported to estimate the DoA based on EEG recordings. The leading task of those methods was to design an accurate index to monitor the DoA. In this section, we review some of recent methods in which DoA indexes were developed.

Nguyen-Ky et al. [24] proposed a method to assess the DoA based on a Bayesian method. The maximum posterior probability (MPP) was used to examine the distribution of the EEG signal. A DoA function was designed using the MPP. That study was reported that the values of the MPP changed correspondingly with the change of the anesthetic depth. Tupaika et al. [44] applied a symbolic dynamics analysis method to monitor the DoA. An EEG signal was filtered and then separated into segments. Each segment was transferred into a sequence of three symbols with an overlapping of two symbols. As a result 64 different patterns of symbols were obtained. The Shannon entropy and Rényi entropy of those patterns were calculated and used to identify the different anesthetic states from EEG signals.

Jospin et al. [12] utilized detrended fluctuation analysis (DFA) to examine the EEG fluctuations for monitoring the anesthetic depth. 17 subjects were involved in that study. The behaviors of four slopes of the DFA were used as the indexes, and tested in two different EEG segment lengths: 30 s and 15 s. Palendeng et al. [28] suggested a DoA index based on a stationary wavelet transform (SWT). The EEG signals were analysed second by second using a window technique. The amplitude and instantaneous phases were obtained from every EEG segment and recursively computed through the whole EEG signal after applying the SWT.

Mousavi et al. [20] utilized a complex wavelet transformation to estimate the DoA. The behaviors of EEG signals in Alpha and Beta bands were studied. Each of those bands was also decomposed into 5 sub-bands and the modulation of signal (MS) was then calculated separately. The entropy of the MS was obtained and used as the key value to derive a DoA index. Zoughi et al. [49] considered the entropy of wavelet coefficients as a feature to estimate the DoA. An EEG signal was decomposed into different levels using discrete wavelet transform. The entropy at each scale was calculated and used to design a DoA index. 22 subjects were involved in that study. Liu et al. [18] traced the changes of the DoA using a multiscale entropy (MSE). 25 subjects were involved in that study. The MSE was used to analyse the complexity of EEG signals. The MSE and independent entropy combined with an artificial neural network were used together in designing a DoA index.

Kalinichenko et al. [13] made an attempt to monitor the DoA based on frequency domain, and a single channel EEG signal was used. A combination of several indexes was designed and tested. The approximate entropy, power spectrum density and signal randomness analysis were utilized in the DoA derivation and a statistical approach was employed to compare those methods. Shalbaf et al. [35] applied a permutation entropy and a frequency measure called Delta-Index for estimating the DoA. Those features were pulled out from each EEG segment to formulate a DoA index. The designed index was tested using a combination of statistical measures.

Nguyen-Ky et al. [25] also estimated the DoA based on a wavelet transform. The EEG signal was decomposed into different levels to extract the desired frequencies. As a result, six bands: θ-band, α-band, β-band, δ-band, γ-band and Electromyography (EMG), were extracted, and then an eigenvector of wavelet coefficients was considered. An index was designed based on the statistical characteristics of the extracted features and was then compared with the BIS index. Although, the existing studies achieved promising results compared with the BIS monitor, there are a surge of needs to improve the existing methods, especially in terms of accuracy and complexity time. This paper is to assess the depth of anesthesia (DoA) using graph domain and statistical features. More details about the proposed method is presented in Section 5.

3. Experimental data

The data used in this paper were collected from 37 adult subjects. The ethics approval was obtained from 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).

The demographics information of all the participants who involved in this study are explained in Table 1. Four adhesive forehead Quatro electrodes were applied to each subject. The EEG data were recorded through those electrodes. For the off line analysis, the captured data were transferred to a personal computer. The exported EEG data file contained the real time log, EEG data, the BIS index and the monitor error logs (critical events and any monitor errors). The EEG data were sampled at frequency of 128 Hz. The data were converted from ASCII