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A wavelet-based estimating depth of anesthesia

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ABSTRACT

In this paper, an efficient method for quantifying the depth of anesthesia using underlying content of electroencephalogram (EEG) signal is presented. This method could be as an alternative instead of other clinical criteria such as pain reflex, auditory evoked potential, bispectral index scale (BIS) or amount of burst suppression. The proposed method is based on analysis of a single-channel EEG signal of patients during anesthesia, using wavelet transform. In order to use wavelet information, entropy is selected as the statistical tool. The obtained results suggest our method called Wavelet Coefficient Energy Entropy (WCEE) as a quantitative index for depth of anesthesia. To validate the introduced index, WCEE is applied to EEG signals of 22 people during the surgery and their determined indices are compared to BIS index, which is now a reference in anesthesia monitoring. The comparison results reveal a high correlation between WCEE index and BIS index during different anesthesia states. Moreover, WCEE values could precisely classify different anesthesia states with less computational burden than BIS index.

1. Introduction

The main task of anesthesiologist is ensure patient healthy and comfort during general anesthesia, and preparing patient's conditions for surgery. In this way, anesthesiologist employs different kinds of drugs such as muscle relaxing drugs, breathing regulators, pain killers and tranquilizers. Injecting a certain volume of anesthetic agents during a surgery has been a challenging issue among anesthesiologists (Orser, 2008). One of the main problems is over-sedated, which is due to use of a high volume of the anesthetic agents like isoflurane that finally leads to comma. On the other hand, applying a low volume of such a drug, maintains the patient's state near to the consciousness (Muncaster et al., 2003; Shao-hua et al., 2009).

Anesthesiologists control the depth of anesthesia using clinical symptoms such as blood pressure, heart beat, body movements, oxygen saturation level (SPO_2) and breathing. In the short-time surgeries such as cesarean, the mentioned monitoring tools can properly monitor the depth of anesthesia but in long-period operations such as brain, backbone and orthopedic surgeries, the traditional indicators like level of SPO_2 cannot reveal the pain level, which may lead to awaken a patient during these painful surgeries.

To monitor the depth of anesthesia in the long-time painful surgeries, features of electroencephalogram (EEG) have been successfully employed (Sebel et al., 2004). EEG signals can be affected by anesthetic agents like pain killers or tranquilizers, since these drugs try to block the pain receptors that cause to deteriorate the whole integration of neurons activity (Sebel et al., 2004). Thus, the EEG patterns are not only dependent to different levels of anesthesia, but they are also drug-dependent. To overcome these drawbacks, it has been shown that there exist stable EEG features, which are independent to the anesthetic agents (John, 2001). Hence, these experiments confirm that, the EEG can provide a reliable basis for deriving a measurement of hypnosis (Stanski, 1994).

In general, there are several EEG-based approaches to determining depth of anesthesia. Analyzing the auditory evoked potential (AEP) is used to measure excitability of a patient according to his/her response to the audio stimulus (Jensen et al., 1996; Litvan et al., 2002). In another approach, modern anesthetic depth monitors just use the frontal EEG signal (one channel) to extract the bispectral index scale (BIS) (Rampil, 1998), which decreases monotonically with increasing anesthetic dosage. BIS index consists of three different algorithms, which are computed separately. The resulting values are combined with different weights to construct BIS index. Nevertheless, BIS index has some shortcomings; BIS value is highly sensitive to low EEG amplitude (Sigl and Chamoun, 1994), and also BIS index response to different anesthetic drugs with various doses is not quick due to BIS-XP monitor delay for calculation (10 s). Using BIS-XP monitoring reduces anesthetic drug usage up to 20% (Rosow and Manberg, 2001), and also reduces intra-operative awareness during anesthesia up to 80% (Myles et al., 2004). Therefore, using this index has some

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benefits such as reduction of the anesthetic drug usage, soon recovery, etc. BIS index is a patented algorithm with noticeable attention from researcher; therefore, there have been many efforts to extract an efficient index that behave similar to this index (Rampil, 1998).

The third EEG-based approach is Narcotrend index (Monitor Technik, Bad Bramstedt), which has been proposed to analyze sleep stages. This method uses Kugler's classification and denomination scheme to classify EEG patterns into different classes (Kugler, 1981). The Narcotrend exhibits stepwise changes during increasing or decreasing hypnotic depth. The Narcotrend is based on multivariate algorithm, and also seems to perform better during emergence than BIS index (Schmidt et al., 2003).

Through the last three decades, a lot of research has been performed to develop an efficient time–frequency representation of signal (Garrett et al., 2003). In this way, several time–frequency techniques are designed that each of them is suitable for a specific signal characterization (Garrett et al., 2003; van Steenis et al., 2005; Flandrin, 1999). Generally speaking, linear time–frequency transforms such as short time Fourier transform (STFT), wavelet transform (WT), packet wavelet and multi-wavelet transform can reveal the frequency content of a signal, in different scales in term of intensity while non-linear time–frequency transforms such as Wigner–Ville, Choi–Williams and smoothed pseudo-Wigner–Ville distributions reflect the energy distribution of a signal in the time–frequency domain, which suffer from producing of unwanted cross terms (Hlawatsch and Boudreaux-Bartels, 1992). In the following paragraph, some of these applications are introduced.

EEG signals behave more irregular when state of the brain is changed; consequently, it seems that fractal dimension can be an informative index for this signal (Song et al., 2006; Sabeti et al., 2011; Weiss et al., 2009). The main weaknesses of fractal-based methods is that, EEG signals have non-uniform and complex fluctuations even in a certain state that lead to determine different fractal dimension values for a certain brain state (Ma et al., 2006). Therefore, fractal dimension methods cannot describe these signals very well (Ma et al., 2006). In addition, multifractal was introduced to measure the irregularity of a signal in different time scales (Ivanov et al., 1999). This technique was also employed in modeling the energy cascading process in turbulent flows (Ivanov et al., 1999; Meneveau and Sreenivasan, 1991). Moreover, as an application of using the chaos theory in analyzing time series, detrended fluctuation analysis (DFA) was introduced (Peng et al., 1995; Gifani et al., 2007; Nguyen-Ky et al., 2010) as a method to determine the statistical self-affinity and self-similarity of a non-stationary signal. It is useful to detect a long-range correlation in a long signal, like EEG signal during anesthesia. However, DFA avoid detecting long-range correlation of artifacts (Peng et al., 1995; Gifani et al., 2007; Nguyen-Ky et al., 2010).

As another effective feature, wavelet is one of well-known tools in signal processing (Blanco et al., 1998; Zoubek et al., 2007). In this paper, the performance of wavelet is enhanced by adding some pre-processing and post-processing methods. We can summarize the contribution of this paper in two main parts:

1- We have proposed a normalization operator for each frame separately, to decrease the effect of EEG amplitude in the time–frequency plane.
2- We introduce a new method in the wavelet domain to determine the anesthetic depth, which is comparable to BIS index.

In this research, we investigate the performance of the most successful indices and compare their ability with the proposed quantitative method referred to as Wavelet Coefficient Energy Entropy (WCEE). This method extracts information from single channel EEG signal to estimate depth of anesthesia. The WCEE exploits wavelet decomposition, and uses entropy to analysis wavelet information. This novel index can give a faster feedback compare to BIS index that is very important for anesthesiologists.

The rest of this paper is organized as follows: In Section 2, data acquisition and some of the previous works are reviewed. The new method and its implementation details are discussed in Section 3. In Section 4, experimental results are presented. Section 5 represents some discussions and finally Section 6 concludes the paper.

2. Materials and methods

2.1. Data acquisition

In this study, 22 subjects were participated all of whom used the isoflurane anesthetic drug but their surgery and duration of their anesthesia were different. Patients' age ranged from 35 to 65 years (mean=48.36, SD=25.93), and in weight from 43 to 87 kg (mean=70.56, SD=14.02). Before using any drug, the patients were asked to lay down and being relaxed for a few minutes. Then, anesthetic drugs were used till the time that patients drove in the suitable anesthetic depth for surgery. All the patients were used 2–4 mg/kg midazolam and 300 mg pentanal. The anesthesia was induced with 10–13 mg/kg sufentanil. The muscle relaxant used in this study was atracurium (30–45 mg/kg in the induction phase). The main drug that drove the patients into anesthesia was isoflurane (90–130 cc).

Meanwhile, BIS index was determined in successive ten second intervals simultaneous to recording the raw EEG signal. To record EEG signal, BIS-XP (Aspect Medical System Inc.) instrument was used and the recording was perform from one channel with 128 Hz sampling frequency. The positions of EEG electrodes in BIS-XP monitor were as follow: the first electrode was placed between corner of eye and hairline, the second one was directly above eyebrow and the third one was approximately 2 in above bridge of nose. Data was transferred to a portable computer by RS232 interface using software (BSA software v.3.16). The raw EEG data along with the indices determined by BSA including the depth of anesthesia index, SEF90, Burst Suppression Ratio (BSR), Beta ratio, bispectral ratio, power spectrum and Signal Quality Index (SQI) were stored for later analysis. The exact time and dosage of all drug infusions were also noted.

To the best of our knowledge, BIS index is based on bispectral analysis, which can represent the coupling of EEG frequencies and gives a dimensionless value in the range 0–100, which points to deep anesthetic level up to consciousness (Sigl and Chamoun, 1994). BIS value between 40 and 60 is sufficient range for general anesthesia while BIS value in the interval of 60–80 reveals moderate or light anesthesia. During the maintenance of anesthesia if BIS index was higher than 60 or anesthesiologist assessments were showing lightness of anesthesia, atracurium was induced.

All patients were operated in Namazi hospital, which is the training center of Shiraz University of Medical Sciences. EEG samples during anesthesia are shown in Fig. 1, in which EEG signal in the higher anesthetic depth contains more regular rhythms in comparison with the awaked state. In this study, for a function that would adequately estimate the anesthetic depth, 4 different sets corresponding to 4 different anesthetic states were recorded as shown in Fig. 1, for representative samples. The data set contain awake, light anesthesia, moderate anesthesia and deep anesthesia, which are listed as follows:

1) *Awaked state*: 170 min recorded from 5 healthy adult subjects who were awaked or lightly sedated. Subjects were asked to keep their eyes close and relax while recording the EEG signal.
2) *Light anesthesia*: 200 min recorded from 5 subjects.