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An intelligence Model Based on Brain Signals for Deep anesthesia and Awake stages classification

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Abstract:

Monitoring The depth of anesthesia (DoA) is One of the current challenges in medicine. An accurate DoA can deliver an adequate amount of anastatic medications that could reduce the risk of consciousness or excessive anesthesia. In this study, an intelligent model classifies deep and awake stages from an electroencephalogram (EEG) signal was used. It consists of two stages that are considered vital in designing the DoA. A hierarchical dispersion entropy (HDE) was applied to de-noised EEG segments. In this study, the EEG signal is decomposed into four experimentally levels. Then DE entropy features are extracted from each band. An LS-SVM classifier is used to classify the extracted features into two anesthetic states. We then compared the results of the Least Squares Support Vector Machines LS-SVM classifier with other types of classifiers such as Multi-class-SVM and k-nearest. We found that the results of our study were the best because the accuracy reached by us was (95.23%) higher than the other two classifiers.

Keywords: Electroencephalogram, Deep Anesthesia, Depth of Anesthesia (DoA), Hierarchical Dispersion Entropy (HDE), Classification,

1. Introduction:

Monitors that measure the depth of anesthesia (DoA) are a relatively new addition to the anesthesia profession. The major goal of monitoring DoA is to keep patients from becoming awake during surgery by indicating anesthetic depth. This process is usually done by analyzing the spontaneous (EEG) [1]. When the patient is anesthetized, the EEG changes in frequency, amplitude, phase connections, and entropy among them [1]. Most commercial monitors rely on these advancements as their technological foundation, while the notion of EEG DoA monitoring is appealing in theory, its effectiveness in lowering anesthetic consciousness is unknown [2]. The basic technology used by DOA monitors to convert brain electrical activity into a measure of conscious level is complicated or even concealed, causing some to assume that their output does not accurately reflect the depth of anesthesia or the underlying EEG. Despite a score on the monitor suggesting appropriate anesthesia, it is conceivable that a patient is awake [3]. Several reasons such as signal deterioration from the input filters or poor electrode contact resulting in an “inappropriate” input to the screen; Noise from nearby muscle activity or electrical equipment resulting in 'wrong' input to the monitor, or a single discrepancy (idiopathic or due to pre-existing brain problems) resulting in minor misclassification despite valid EEG data being delivered to the monitor [4]. In addition, anesthesia and surgical processes, such as hypotension and hypoxia and anesthetic medication selection, might have an unpredictable effect on EEG morphology and result in mistakes [5]. As a result, numerous DoA monitoring approaches based on EEG signals have been developed, including the Patient State Index (PSI), Bispectral Index (BIS), and Cerebral State Index [6]. In 1992 the BIS was created by Aspect Medical Systems, which is the industry standard for DoA monitoring [7]. The BIS values are accepted by anesthesiologists as a reference for providing the proper quantity of anesthetic agents to reduce consciousness and facilitate postoperative recovery [8]. Although the BIS is useful in practice, it does have several limitations. It, for example, does not function with all anesthetic medicines, is not consistent between patients, and is delayed [9]. The BIS and other devices have shown a long-time delay in reflecting a shift in awareness state [10].

2. Related Work:

The BIS and other devices have shown a long-time delay in reflecting a change in a state of consciousness [10]. To address these issues numerous models have been developed to trace the DoA over recent years. For example, Nguyen et al., [11] proposed a modified DMA approach to monitor DoA. In that study, the (BIS) index was used to compare the results. It discovered a close relationship between the proposed model's outcomes and BIS. In identifying the state of consciousness of a patient undergoing anesthesia. Nguyen et al [12] developed a new Bayesian Depth of Anesthesia (BDoA) function that uses Bayesian approaches to measure DoA by assessing five EEG signals to determine awareness and level of anesthesia DoA. The results of the study show, that the new indicator correctly measures the patient's sleeping states compared to the BIS. Shalbaf., et al [13] proposed a model made up of a multiband adjusted entropy index that assesses the level of complexity in EEG data. They reported that a combination of EEG measurement and hemodynamic factors, combined with LDA, could achieve an overall accuracy of 89.4 percent for biomarker categorization under various anesthetic states. Liu et al., [14] developed a new method based on multi-scale entropy, which applies entropy values to several time scales. In their study, Dataset was collected from 26 patients. The results indicated that the new model and the BIS index had a greater correlation compared with others. Jahanseir., et a1[15] used the relative intensity of EEG frequency bands and EEG entropy measurements to provide a new method for detecting the depth of anesthesia states based on (LS-SVM) classifiers. The Dataset was collected from 20 patients in that study. Gu., et al [16] proposed a model that extracts four parameters: flipping entropy, spectral edge frequency 95 percent, Beta Ratio, and

SynchFastSlow, from EEG signal, and then the parameters were used as input into an ANN. This method was tested on 16 patient data sets. BIS and the index had a correlation value of (0.892) during propofol anesthesia. Zhu et al [17]. proposed in their paper a technique for monitoring DOA by using the EEG's sample entropy (SampEn) as a feature vector. The Weighted K-Nearest Neighbor (WKNN) classifier was then used to categorize anesthesia into four categories. The correlation coefficient between the EEG SampEn and (BIS) Index was higher than 0.8. Guo and colleagues., [18] employed the wavelet transform method to analyze EEG data to monitor sedation and then aggregate the characteristics retrieved by the wavelet transform to evaluate sedation depth.

3. Material and Method:

3.1 EEG data:

Ethical approval for use (EEG data during anesthesia), was granted by the University of Southern Queensland Human Research Ethics Committee (No: H09REA029) and Darling Downs Health Services Human Research Ethics Committee (No: TDDHSD HREC 2009/016), Australia. There were 37 individuals in all who participated in this study, including 15 females and 22 men. Table 1 shows the demographic information about the database. Each patient had four electrodes attached to his forehead to capture EEG data. The collected EEG data was transmitted and stored in a desktop computer for analysis. The EEG data acquired included the BIS indicator, EEG signals, monitoring error log, and real-time log. The obtained EEG signals were sampled at a frequency of 128 Hz. Based on previous studies that have used (this dataset) [26], EEG data from Channel 2 was adopted in our experiments.

Table 1: Patients' characteristics

Demography information		Anesthesia type	
Gender (M/F)	12/15	Midazolam (mg)	2-5
Age (years)	22-35	Alfentanil (mg)	500, 750, 1000
Weight	55-150	Propofol (mg)	90-200
		Parecoxib (mg)	40
		Fentany1 (mg)	100-150

3.2 Pre-Processing and EEG Signal De-noising:

Electrode noise, which can be introduced during recording or created by the body itself, can cause noise in the brain signal. These artifacts must be eliminated since they make EEG signal interpretation and further processing difficult and can lead to misdiagnosis [19]. In this study, an improved non-local method (NLM) was adopted to filter EEG signals [19]. The improved NLM method was combined with the wavelet transform (WT) method. The method is carried out in the following steps

First, the raw EEG signals are fed into a WT transform to analyze the aesthetic signals into different levels of Wavelet coefficients. Each signal is decomposed into two parameters (details and coefficients). Every detail is analyzed into new WT coefficients until the input EEG signals are completely decomposed into WT coefficients.

Second, the NLM is applied to the wavelet coefficients generated from the first processing step. The NLM method works on calculates the weighted sum of a patch. The similarity between the points of the own patch and those of its neighbor determines the weight of each point. The noise is filtered out using the weighted sum [27].

Third, silent EEG signals are reconstructed (which is a reverse process) on EEG signals that have been processed from noise, using the wavelet transform (WT) method on them. This step will produce EEG de-noising signals.

4. Methodology

This study developed a robust DoA monitoring model based on hierarchical Dispersion entropy (HDE). Figure 3 describes the proposed methodology for monitoring DoA. The original EEG signals include electrocardiogram (ECG) noise, and EMG (muscle stimulation) noise, generated from devices used in the operating room, such as wire power interference, and poor fixation of EEG electrodes, filtered using an improved Non-Local Mean Method. Next, the EEG De-noise signals are divided into intervals using a sliding window technique. The EEG signal is then decomposed into four levels. HDE is calculated from each EEG segment. The extracted features were tested to identify the strongest features. Using machine learning algorithms, the extracted features were categorized into anesthetized states (Deep anesthesia and Awake stages). Where the reading of the patient's signal (EEG De-noise) is between (100-60), the patient will be classified as in the Awake stages. And if the reading of the patient's signal is between (40-20), the patient will be classified as Deep anesthesia. Table 2 below shows the certified readings of the BIS device. The highest value is 100 and the lowest level is 0. According to the BIS records shown in the table below: -

Table 2 : The Certified Readings of The BIS Device.

Anesthesia States	Awake	Awake-Light	Deep
BIS records	100-80	80-60	40-20

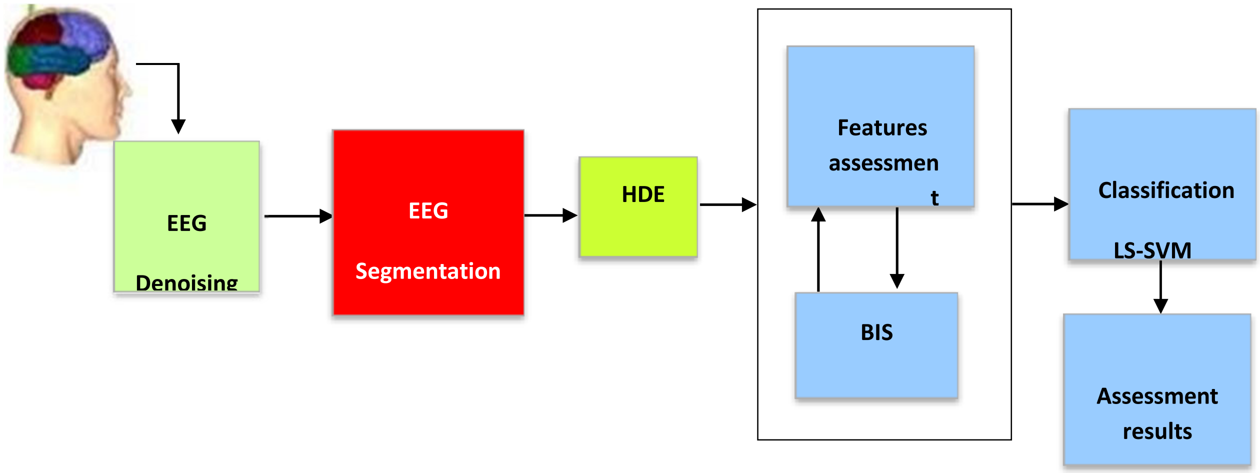

Figure 1. The proposed framework of DoA monitoring

4.1 Segmentation

After the step of filtering the signals from noise and converting them to EEG De-Noise signals, here the signal will be ready for the analysis process for the purpose of benefiting from it according to the study objective in a way that gives better results. The process of analyzing the EEG signal needs to segment the signal into smaller sections with identical statistical characteristics such as amplitude and frequency [20]. In this study, (Sliding Window Technique) was used depending on two basic parameters: window size (set to 56 s), and overlap (set to 55 s). As shown in Figure 2, the result of sliding windows over each other gives (1 second) for each movement equal to 128 data points. We determined the values of the parameters (window size and overlap) above in proportion to the way the BIS device works in recording data points, as it depends on recording data from one minute at a time and interfering with the length of the EEG signal. Below, Figure 2 shows an example segmentation of the EEG De-Noise signal (subject No 4) using the sliding window technique.

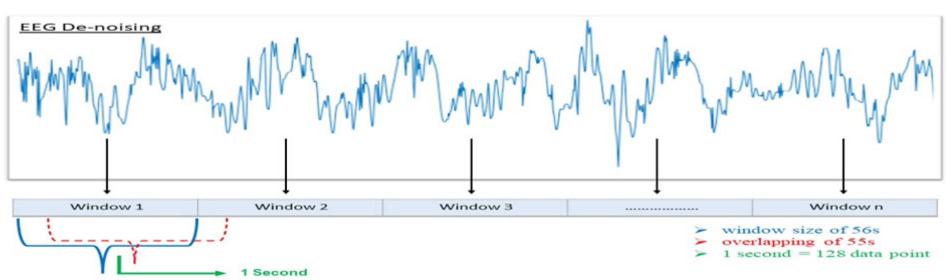

Figure 2. An Example of an EEG Signal Segmented Using the Sliding Window Technique

4.2 The Theory of Hierarchical Dispersion Entropy:

Previous studies have found that multiscale analysis algorithms evaluate only low-frequency signal components [21_23]. As a result, a hierarchical DE (HDE) technique was developed, which combines hierarchical decomposition with DE to better determine the regularity of complex signals and more fully measure the signal content. Figure 5. Show the diagram of the Hierarchical Dispersion Entropy (HDE) algorithm. Suppose we have the following signal for which we will compute HDE s_1 L= (l_1, l_2, ..., $l_{n)}$ of length M (M = 2m, m is a positive integer) The steps will be:

First Step: steps for hierarchical analysis of vibration signals:

1) The mean operator ϵ_0 and a difference operator ϵ_1 are constructed in the following ways:

$$\epsilon_0(L) = \frac{\mathrm{L(2i) + L(2i+1)}}{2} \qquad i = 0,1,2,\dots,2^{m-1}$$

$$\epsilon_1(L) = \frac{\mathrm{L(2i) + L(2i+1)}}{2} \qquad i = 0,1,2,\dots,2^{m-1}$$

where ϵ_0 (L) and ϵ_0 (L) represent L's low- and high-frequency characteristics at scale (2).

L={($\epsilon_0(L)_i + \epsilon_1(L)_i\,, (\epsilon_0(L)_i - \epsilon_1(L)_i\,)\}\,, i = 0,1,2,\dots,2^{m-1}$

2) The following is the matrix formulation of the operators ϵ_i (i = 0 or 1):

$$\epsilon_i = \begin{Bmatrix} \frac{1}{2} & \frac{-1^i}{2} & 0 & 0 & \dots\dots. & 0 & 0 \\ 0 & 0 & \frac{1}{2} & \frac{-1^i}{2} & \dots\dots & 0 & 0 \\ 0 & 0 & 0 & 0 & \dots\dots. & \frac{1}{2} & \frac{-1^i}{2} \end{Bmatrix}$$

3) The aforesaid operators must be used repeatedly in order to accomplish the hierarchical analysis on signal L. Let Q ∈ M, a vector [$ß_1$, $ß_2$,…, $ß_b$]∈{0, 1} may be created to represent the integer D:

$$D = \sum_{i=1}^{Q} ß_i 2^{Q-i}$$

It may be deduced that there is a single vector [$ß_1$, $ß_2$,…, $ß_b$] agree with a given number E.

4) The $L_{k,d}$ component of the hierarchy (where k and d denote the number of layers and nodes, respectively) is expressed as:

$L_{k,D}$= $\epsilon_{ß1}$, $\epsilon_{ß2}$,…, $\epsilon_{ßb}$. L

The second step: is to calculate the dispersion entropy of several hierarchical nodes. To obtain the HDE, the DE of the hierarchical component at node D and layer k is calculated:

$$HDE\ (L,k,D,\ ɱ,\ \check{c},\tau) = DE\ (L_{k,D},\ ɱ,\ \check{c},\tau)$$

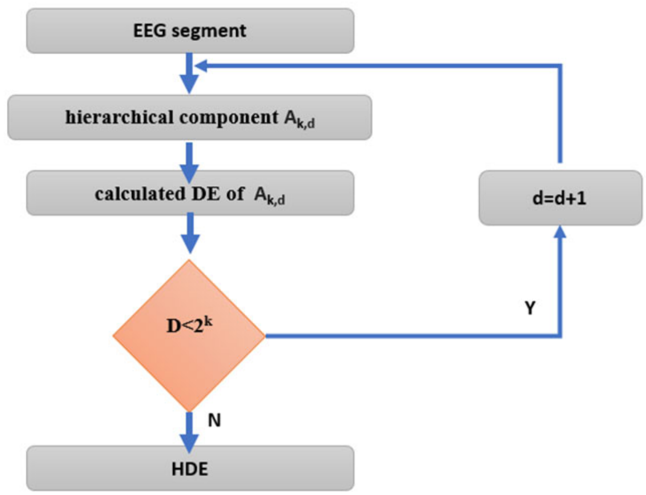

Figure 3. The diagram of a Hierarchical Dispersion Entropy (HDE) algorithm.

4.3 Parameter selection for HDE method:

Four parameters were chosen carefully in this paper to calculate HDE including:

- Embedded dimension n was set to 3, because if n were too large, more data length was needed, according to the study in [24].
- Time delay was selected as t = 1 [2].
- Class number or group number č was set to 5, as it was found that when d was too small, different features were classified as a class, while when it was too large, similar features were identified as different classes [24].
- Hierarchical layers (k), the decomposition value k = 4 is chosen. In our study, the analysis was done in four levels (k=4), because previous studies have shown that when k was too large, the calculation efficiency and sample points involved in each level calculation were reduced, while, when k was too

small the frequency band of the signal was not carefully divided, and the hierarchical components become insufficient [23][24].

4.4 Feature selection

the HDE is calculated by dividing the signals into four levels to capture the desired characteristics in the EEG segment at each level. The HDE at level 2 rose across 22 subjects during anesthesia states, as a result, the DoA is traced using the HDE at level 2. During the tests, it was discovered that the suggested model gave values that were similar to the BIS index.

5. Least Square Support Vector Machine (LS-SVM)

LS-SVM is a statistical tool introduced by Suyken [25] as a modified version of the original SVM and is a set of related supervised learning methods that analyze data and recognize patterns that are used for classification and regression analysis. It has been widely used in the fields of image classification, and EEG signals. The LS-SVM was used to predict BIS values, and the values of γ and σ were experimentally set. The best performance for the proposed method for determining anesthetic states was achieved when $\gamma = 1$ and $\sigma = 1$.

6. Experimental Results

In this section, the main results are discussed using some statistical measures: root means square error (RMSE), accuracy, sensitivity, and specificity. EEG data from two EEG channels (channel 1 and channel 2) were tested separately, and our findings showed that Ch2 gave satisfactory results. We used all the data from EEG recordings except one for the training. The proposed model was then examined by verifying its performance on the one EEG recording which was left out. This process was repeated until every EEG recording was treated. The statistical feature that we used in this study is (max, min, and standard deviation) to analyze the EEG De-noise signals. Then we applied HDE to EEG De-noise signals to form a vector of features and the signals were analyzed into 4 levels, each level tested separately. The LS-SVM was used as a classifier to define the deep anesthesia and Awake stages. To ensure that our results are accurate, the results of the filter used in our study were compared with other classifiers such as SVM and k-nearest.

7. Performance Evaluation

- The performance of the proposed model was evaluated for each level separately. Our results showed that level 2 gave more accurate results so that the performance of the proposed model was close to BIS. Table 3 shows the results obtained. We can notice that level 2 gave high accuracy compared with other levels 1, 3, and 4. We also note that the highest accuracy was at level 2, while level 3 recorded the lowest accuracy rate.

Table 3

The performance of the proposed model

Level of Decomposition	RMSE			Classification			
	Std	Min	Max	Accuracy	Sensitivity	Specificity	AUROC
1	2.821	4.672	17.342	87%	87%	89.2%	87.3%
2	2.324	4.365	15.234	96.5%	97.54%	96.45%	95.23%
3	2.932	4.830	17.892	85%	82.1%	86.1%	86.3%
4	2.821	4.672	17.342	87%	87%	89.2%	87.3%

In this section, the proposed model is evaluated using different machine learning algorithms. Extracted HDE features were fed to (LS-SVM, k-nearest, and Multi-class-SVM) and compared using accuracy, sensitivity, and specificity. Table 4 shows the results of the comparisons. Based on the obtained results, the proposed method achieved better results with LS-SVM than other classifiers. One can see that the best accuracy is 96.5% by LS-SVM. Moreover, the sensitivity and specificity with the same classifier are 97.54% and 96.45%, respectively. The second highest accuracy, sensitivity, and specificity were scored 93.5%, 91%, and 92.2%, respectively, using a Multi-class-SVM classifier, while the k-closest scored a lower accuracy rate. From these results, it was clear that the LS SVM was the best classifier for anesthetic states in the EEG signals.

Table 4

The Performance of LS-SVM and Compared with Other Classifiers

Classifier	RMSE			Classification			
	Std	Min	max	Accuracy	Sensitivity	Specificity	AUROC
Multi-class-SVM	2.310	4.500	15.342	93.5%	91%	92.2%	93.1%
LS-SVM	2.324	4.365	15.234	96.5%	97.54%	96.45%	95.23%
k-nearest	3.932	5.830	18.892	79%	78.1%	77.4.1%	75.4%

- A comparison with previous studies was conducted. Table 5 reports the comparison results. Liu et al., [27] recorded an accuracy of 93.5 %. Short-time Fourier transforms coupled with a deep convolutional neural network CNN model were applied to EEG signals to predict the DoA. The BIS values were used as an index to assess the proposed model. Comparing with our results, it can be noticed that the obtained accuracy by our model was around 2 % higher than Liu et al., [48].

Chowdhury et al., [8] adopted an image-based deep convolutional neural networks approach to predict the DoA. Average accuracy of 86% was obtained in that study. Chowdhury et al., [8] recorded less accuracy than our method.

Table 5

Comparisons among the proposed model with previous studies

Authors	Approach	Signal	Accuracy
Liu et al., [27]	short-time Fourier transform coupled with a deep convolutional neural network	EEG	93%
Diykh et al., [26]	Complex network-based spectrum technique	EEG	86%
Chowdhury et al., [8]	Image-based deep convolutional neural network model	ECG and PPG signals	86%
Shalbaf et al., [13]	multiband adjusted entropy index that assesses the level of complexity	EEG	89.4%
The proposed model	HDE	EEG	95%

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