Anesthesia assessment based on ICA permutation entropy analysis of two-channel EEG signals

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Abstract. Inaccurate assessment may lead to inaccurate levels of dosage given to the patients that may lead to intraoperative awareness that is caused by under dosage during surgery or prolonged recovery in patients that is caused by over dosage after the surgery is done. Previous research and evidence show that assessing anesthetic levels with the help of electroencephalography (EEG) signals gives an overall better aspect of the patient's anesthetic state. This paper presents a new method to assess the depth of anesthesia (DoA) using Independent Component Analysis (ICA) and permutation entropy analysis. ICA is performed on two-channel EEG to reduce the noise then Wavelet and permutation entropy are applied on these channels to extract the features. A linear regression model was used to build the new DoA index using the selected features. The new index designed by proposed methods performs well under low signal quality and it was overall consistent in most of the cases where Bispectral index (BIS) may fail to provide any valid value.

Keywords: Depth of anesthesia, Electroencephalograph, Independent Component analysis, Permutation entropy.

1 Introduction

Anesthesia is a drug that is used on patients during a medical operation such as surgery to reduce the pain and discomfort that patients may face during surgery. The anesthesia depth (DoA) is reflected in the change of partial pressure of anesthetics in the brain [1]. It is important to obtain accurate DoA assessment results since inaccurate assessment may lead to inaccurate levels of dosage given to the patients that may lead to intraoperative awareness that is caused by under dosage during surgery or prolonged recovery in patients that is caused by over dosage after the surgery is done [2, 3]. Previous research and evidence show that assessing anesthetic levels with the help of electroencephalography (EEG) signals gives an overall better aspect of the patient's anesthetic state. Bispectral index (BIS) is the widely used monitor today in hospitals but it has a couple of issues such as failing to give accurate levels of anesthesia when the signal quality is low and providing inaccurate assessment for certain patients with medical issues [4]. The existing algorithms that are present today that try to solve the problems from the bispectral index usually suffer from problems when used in real-time such as time delay and inaccurate data filtering techniques.

One of the problems with the EEG data is there are a lot of corrupt signals or a mix up of signals so interpreting the output and proceeding to the next stage of the process is very difficult. So, one solution to this problem can be blind source separation and the official algorithm to solve this is independent component analysis (ICA). One of the papers that were researched [5] combines both the technique Blind source separation (BSS) and ICA and gives a very decent output where the ECG artifacts are removed from the EEG. Ansell and Hossain introduce a technique that combines ICA and Wavelet to preprocess the EEG data before going to feature extraction [6].

For an accurate and reliable depth of anesthesia assessment, intensive research has been conducted, and various algorithms were developed. The latest methods includes Entropy [7], Detrended moving-average (DMA) [8], Isomap-based estimation [9], Empirical-mode decomposition (EMD) [3], and Bayesian [10]. Nguyen-Ky developed a new technique to rectify the problems of BIS by developing a wavelet-based depth of anesthesia (WDoA) with a help of discrete wavelet transform(DWT) and power spectral density function (PSD) [1]. On comparing the readings of the BIS to real-time, it was found that there was a slight time lag from the BIS monitor. Although the outcome of the paper solves a time lag problem, it doesn't address some serious issues that are possessed by BIS such as missing readings where the BIS fails to give any valid output and handling the situation in low signals which can be done with a help of signal quality index. The focus of this paper aims to solve those issues and develop a good algorithm that assesses the accurate level of anesthesia for most patients and it also aims to perform well when the signal quality is less.

2 Methods

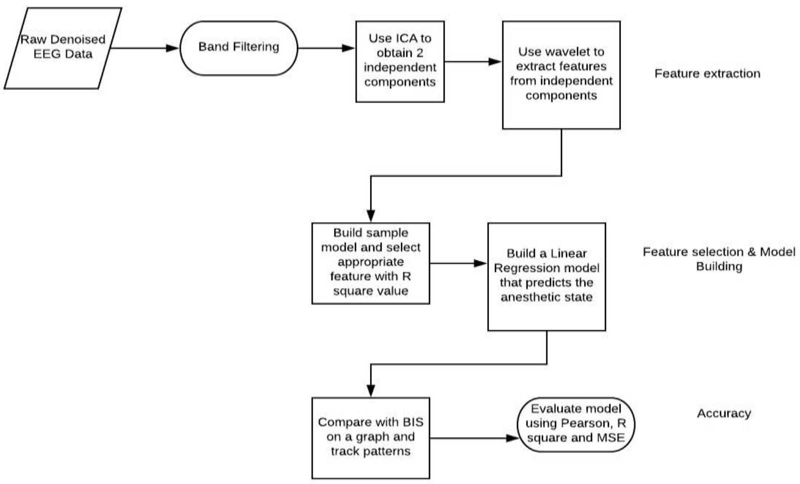


Fig. 1. Flow chart

The proposed methods are applied as the flow chart in Fig.1. Initially, the denoised EEG data is passed through a bandpass filter where frequencies that fall within the specified range are taken and the remaining signal is rejected and reconstructed using the signal that falls within the range.
The band filtered signals are then passed through ICA algorithm where it tries to separate both the sources since both the channels may have data that may have been corrupted with noise and consists of artifacts since this is very normal with EEG data.
The independent channels are then taken to the next step where wavelet transformation is applied to the signals at level 5. This process is called feature extraction where a single channel is split up into 10 channels where adding up the extracted channels will produce the original channel. Wavelet transformation produces one approximation (a1) and one detail (d1) at each level and in this process 10 features are produced ranging from a1 to a5 and d1 to d5. Wavelet is done to control the oscillations that may occur in real-time data. Once the features are extracted, permutation entropy is performed on these features with a window size of 55 seconds since the input should match the dimensions of the BIS and usually, BIS recordings are done at every interval of 55 seconds.

The PE is calculated using the following algorithm [11]. Define the EEG signal [$x(i)$,i=1,2,...] into a m-dimension space $X[x(i),x(i+L),...,x(i+(m-1)L)]$ firstly, m is the number of dimension，L is the time delay. Secondly, sort the EEG series in the m dimension space in increasing sequence:

$$[x(i+(j_1-1)L)\leq x(i+(j_2-1)L)\leq..\leq x(i+(j_m-1)L)] \quad (1)$$

j_1, j_2, ..., and j_m show the new order of the series. For a m-dimension space, there are total $m!$ orders. Each $X[x(i),x(i+L),...,x(i+(m-1)L)]$ reflects one of these ‘$m!$’orders. Assume the probabilities of each order are P_1, P_2,..., P_K respectively. According to the Shannon Entropy, the permutation entropy $PE(m)$ is calculated as follows:

$$PE(m)= -\sum_{j=1}^{K} P_j \ln P_j \quad (2)$$

To build the machine learning model, we can use all the 10 features generated that may lead to a robust model but the complexity of the model increases resulting in technical difficulties such as time delay. So, a process called as feature selection is applied where a sample machine learning model is built giving only one feature as an input and the R square is calculated for all the 10 features and the 2 most appropriate features that exhibited high R square value were selected to build the final model. The selected features were then given as input to the supervised Linear Regression Machine learning model where the label data was the BIS. The DoA index that was built in this process was plotted against the BIS index to check how well the proposed index was built compared to the BIS. The following equation is used to calculate the proposed index after the Linear regression model is built.

$$\text{New Index} = k(1) + k(2) * x1 + k(3) * x2 \tag{3}$$

Where k is derived from the factor b that is generated from the regress inbuilt function from the Matlab. The regress function is used for the linear regression model where factor b is generated which is a component used to calculate the proposed index. The factors x1 and x2 represent the input features that are fed into the model.

The model then calculates the proposed anesthetic state of a patient based on the inputs and the final model is then plotted against the BIS.

Finally, the proposed model is evaluated using Pearson Co-efficient, R square and root mean square error. The proposed model is also plotted against the BIS with the signal quality indicator so that it gives an overall visualization of the performance of both the proposed model and the BIS at low signal quality conditions.

3 Results

3.1 Data pre-processing by ICA

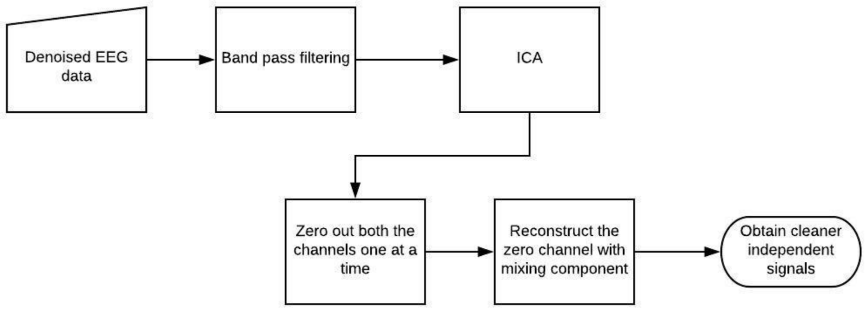
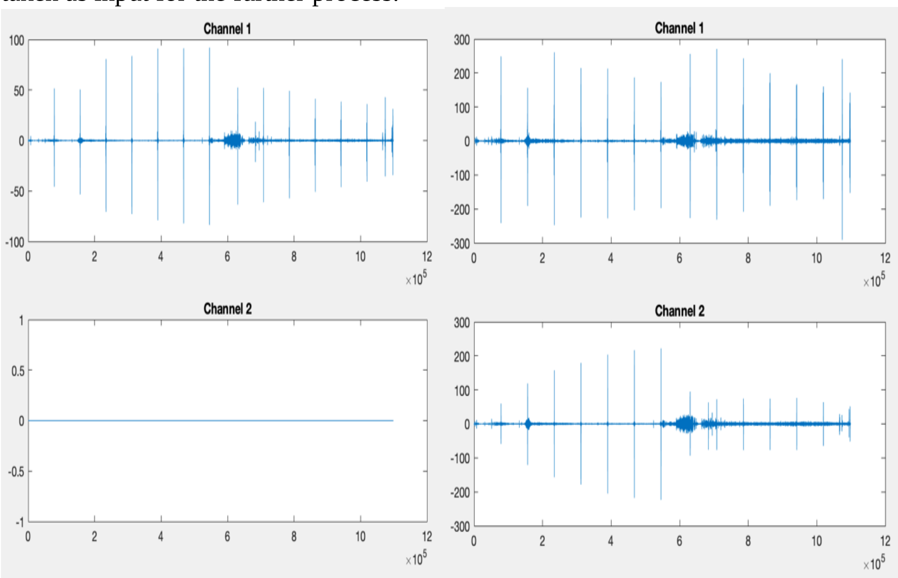


Fig. 2. Flow chart of Data pre-processing

The data sets that were used for this paper is time-series EEG signal. The sampling rate is 128 so the time series EEG data includes 128 readings for each minute. The data were obtained from 12 Adult Patients at the Toowoomba St Vincent's Hospital (7 used for training, 4 used for testing, 1 used for signal quality).

The two-channel raw EEG data were obtained through Quatro electrodes of BIS monitors which were placed diagonally on the forehead with electrode No. 1 at the centre of the forehead, electrode No. 4 directly above the eyebrow, No. 2 between No. 1 and No. 4, No. 3 on the temple, between the corner of the eye and hairline [12]. The EEG data pre-processing are processed in the flow chart as Fig.2. The original denoised EEG data is passed onto the bandpass filter to reduce noise [13]. Bandpass filtering (BPF) takes the signal input and process the signals that fall within a frequency range (21.5Hz-30Hz) and rejects the remaining signal. The overall length of the signal is maintained by reconstructing the rejected parts with the help of the data that is present which falls under the frequency range. The resulting signal is a much more versatile signal with less noise. This process is done for both channels.

Independent component analysis is then performed on these band filtered signals to reduce noise and dependencies that may have occurred while extracting the signal from the brain. The algorithm takes both the signals as input and tries to separate each signal that is independent of each other and then channel 1 is replaced with zero and it is reconstructed using the mixing component that was originally used to separate the signals. The same process is repeated for channel 2 and the reconstructed signals are taken as input for the further process.



(a) (b)

Fig. 3 Data pre-processing results (a) output after the ICA process (b) output after reconstructing

Fig. 3(a) is the output after the ICA process where channel 1 is the output from ICA algorithm and channel 2 is also the output from the ICA algorithm but the values were replaced with zero. On looking at the signal of channel 1 closely compared to the original signal, the signal is smoother overall and the frequency range has reduced and the overall noise of the signal is reduced.

Fig. 3(b) is the output after reconstructing the signal using the mixing component where channel 2 was obtained by mixing channel 1 and the mixing component that was originally used to separate the signals. The resulting output is a robust signal that has the same length and frequency range as the original signal and is also free from noise and corruption and artifacts sharing with the other signal. The same process is repeated for channel 1 where it is replaced with zero and reconstructed with the other channel. The output of these independent channels is then used for the next phase.

3.2 Feature extraction and Feature selection

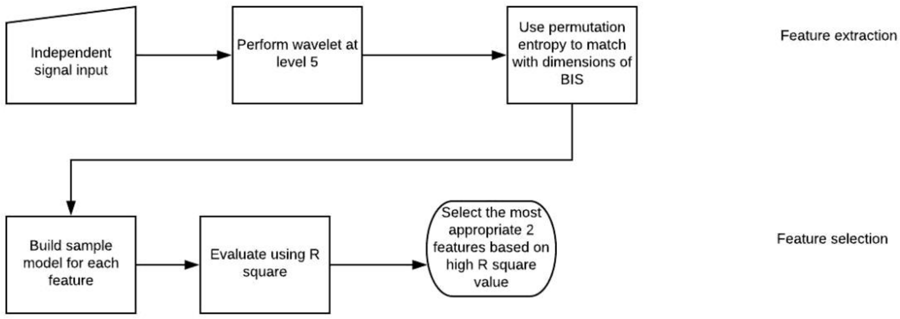


Fig. 4. Flow chart of Feature extraction and Feature selection

The feature extraction and feature selection are processed in the flow chart as Fig.4. The independent signals are then taken as input for this feature extraction process where a technique called wavelet is applied to these signals. The level of the wavelet that was used for this process was at 5 so the resulting set would have 10 features for each channel where 5 features are for the approximations and 5 features are for the details. It was found that db16 and sym8 wavelet were the most appropriate wavelet for EEG data. Once the features are extracted, permutation entropy is performed on these features with a window size of 55 since the input should match the dimensions of the BIS and usually BIS recordings are done at every interval of 55 seconds but there are 128 readings for a single minute for the EEG data.

A sample model is then built on these extracted features where all the features were given as an input individually and 11 models were built and compared against the BIS and evaluated using R square value. The two Features that exhibited high R square value was selected as the final features that would be fed as an input to the machine learning model.

Take Patient 4 for example, the R square values are calculated by 11 signals which include the original signal, its a1 to a5 and its d1 to d5. The highest R square value is represented by the features a1 and d2. So, at the end of this step, it was decided that db16 wavelet transformation on Channel 1 with the features of a1 and d2 is the most appropriate features.

3.3 Model building and evaluation

The model building and evaluation are processed in the flow chart as Fig.5. Once the appropriate features a1 and d2 that exhibited high correlation with the BIS were selected, a linear regression model as equation (4) was built on these features and the label input for the supervised machine learning model is the BIS readings.

$$\text{New Index} = 2074.81 - 2248.69 * PEa1 + 1097.91 * PEd2 \tag{4}$$

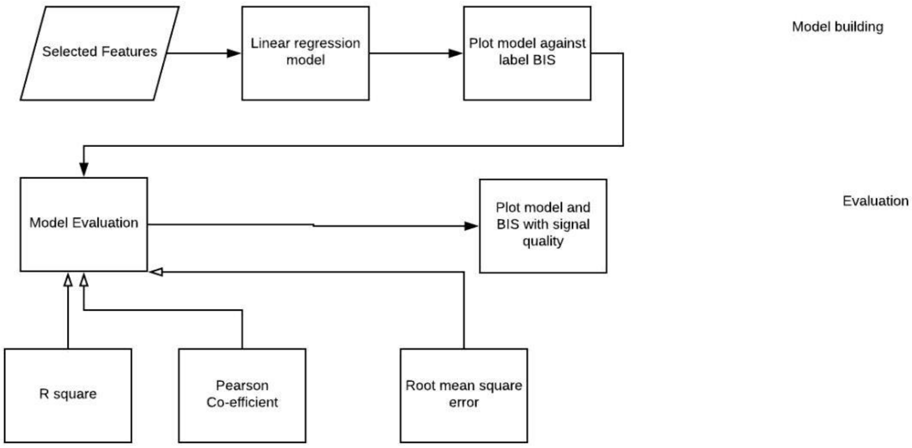
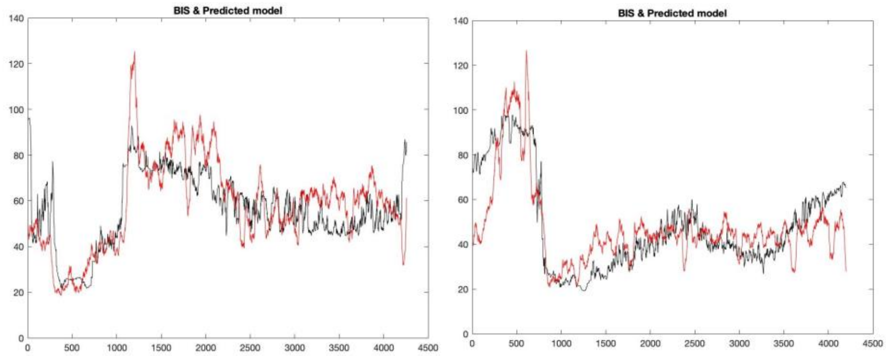


Fig. 5. Model building and evaluation



(a) (b)

Fig. 6. Sample results of testing data, BIS (black) Predicted model (red) (a) patient 3 (b) patient 7

For combined training data of seven patients, the Pearson Co-efficient between the new index and BIS is 0.7308. Fig. 6 shows the proposed model plotted against the BIS for the testing set of patients. The same feature extraction methods (a1 and d2) that were selected from the training set (patients 1, 2, 4 5, 6, 8, 9) were applied on the testing set (patients 3,7,10 and 11).

Take testing set patient 3 and patient 7 for example. The black plot shows the label values BIS and the red plot shows the new proposed index. From Fig. 6, it is clear that the proposed index gives a more stable value overall and holds well against the BIS. After plotting the BIS and Proposed index, the model is formally evaluated using R square, Root mean square error and Pearson Co-efficient. For the data set provided for this paper, the label BIS have a range of 0 to 130 and the RMS values for the observed values are shown below for all the training and testing sets that were used. For patient 3, the R square is 0.5324, Pearson Co-efficient is 0.7261 and MSE is 191.9214. For patient 7, the R square is 0.6311, Pearson Co-efficient is 0.7938 and

MSE is 166.1439. For patient 10, the R square is 0.5602, Pearson Co-efficient is 0.7956 and MSE is 119.4157. For patient 11, the R square is 0.6603, Pearson Co-efficient is 0.7324 and MSE is 176.0294.

One more evaluation factor is taken into consideration where the proposed index is plotted against the BIS and the signal quality is taken into consideration now. This plot tells if the model performs well in low signal conditions where the BIS fails to provide any valid value.

The Fig. 7 shows the proposed model plotted against the BIS with the signal indicator for the patient 12. The blue line represents the signal indicator while the black line represents the BIS and the red line represents the proposed index. On looking closely at the second figure where the first figure was zoomed in to the situation where the quality of the signal drops it is found out that when the signal quality drops below 40 initially, the BIS tends to exhibit invalid or fuzzy values. A couple of factors may come into play for this behavior since BIS tends to start calculating the anesthetic level of patients after a certain amount of time but because the signal was a little low initially BIS flattens out and fail to provide any value. Meanwhile, the proposed model holds well in most signal conditions and gives an even and a smooth curve which tells us that the assessment of the patient's anesthetic state is quite stable.

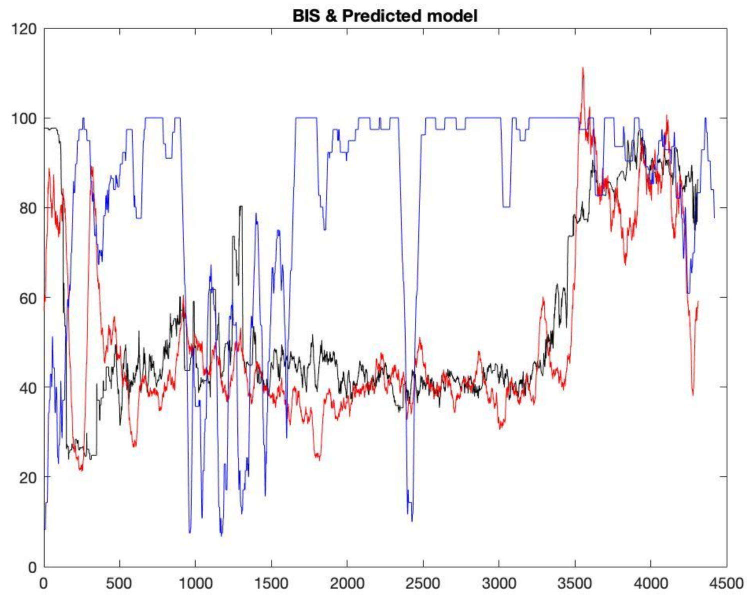


Fig. 7. Sample results of testing data patient 12, BIS (black) Predicted model (red) SQI (blue)

4 Discussion

Because the feature PEa1 and PEd2 show a good linear relation with BIS, the linear regression is selected for creating the final index. Besides, comparing with other machine learning algorithms such as neural network, support vector machine and K-nearest neighbor algorithm, the computation complexity of a linear model is the lowest. Therefore, the predicted model based on the line model can reduce the time delay to some extent which is also a big challenge for real-time DoA assessment. Further work can be done by using different machine learning algorithms to improve the performance of the final index and using more patients' data for training to enhance the robustness of the predicted model.

5 Conclusion

In this paper, initially the denoised patient's data was taken and BPF was applied to the data to obtain a cleaner data that falls under the required range of frequency and frequencies that didn't fall in the range were removed and the overall length of the signal was still maintained because the remaining part of the signal was reconstructed using the signal that fell under the frequency range. ICA was then applied to the filtered signal and the aim was to remove the artifacts and dependencies both the signals may possess and both the channels were replaced with zero one at a time and reconstructed using the mixing component. The independent channels were then transformed using wavelet transformation where it was found that sym8 and db16 were the most appropriate types of wavelets for EEG data and db16 exhibited the highest R square value. By using the feature selection method, it was found that the channel 1 db16 output with the features of a1 and d2 was the most appropriate features that would help in assessing the accurate level of anesthesia. The features were fed as an input to the linear regression machine learning model with the label variable BIS and the output which was the proposed index was plotted against the BIS. It was found out that the proposed index holds well overall against the BIS and in certain cases performs better than the BIS which was validated in the high Pearson Co-efficient score and root mean square value which was consistent among all the patients that were used for training and testing. Finally, the proposed model was plotted against the BIS in low signal quality conditions and it was found out that when the signal quality is low initially, BIS provides invalid output and exhibits fuzzy and unreliable values due to its method of assessing anesthesia and thus it can be concluded that the proposed model is better than BIS.

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