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EEG BASED AUTOMATED DETECTION OF ANESTHETIC LEVELS USING A RECURRENT ARTIFICIAL NEURAL NETWORK

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Abstract – **Continuous monitoring of the anesthetic drug dosage administered during a surgery is very important to avoid the patient's interoperative awareness due to inadequate levels of anesthesia. The traditional methods of assessing the anesthetic depth levels which are based on the qualitative physical signs such as heart rate, blood pressure, pupil size, sweating, etc are not very accurate as these autonomic responses may differ from patient to patient depending on the type of surgery and the anesthetic drug administered. Further it is also possible that these autonomic activities may get attenuated due to premedication. For these reasons, Electroencephalogram (EEG) based methods of anesthetic level detection have been gaining prominence in recent years. This paper discusses an automated detection of anesthetic levels based on EEG signals by using a special type of recurrent neural network known as Elman network. A frequency domain feature, namely, normalized spectral entropy is used to characterize the anesthetic levels. Experimental results show that Elman network is capable of detecting the three different anesthetic levels (low, medium, and high) with an overall accuracy rate of 99.6% which is better than the results reported earlier.**

Keywords - **Depth of anesthesia, EEG, Elman network, intravenous anesthetic agents, recurrent artificial neural network, propofol.**

I. INTRODUCTION

The appropriate dose range of the anesthetic drug used during the surgery is very important in order to avoid the patient's interoperative awareness due to inadequate levels of anesthesia. The patient's interoperative awareness can lead to untoward physiological consequences [1]. In order to minimize such incidences, anesthesiologists need a reliable system to monitor the anesthetic levels. The traditional method of assessing the anesthetic depth involves autonomic responses such as blood pressure, lacrimation, facial grimacing, pupil size, sweating, and movement. But these autonomic responses are attenuated after the introduction of the neuromuscular blocking agents as these responses largely depend on the skeletal muscle activity [2].This has paved the way for the development of a more reliable anesthetic depth monitoring system that is independent of muscle reflexes.

Electroencephalogram (EEG) signal generated from within the central nervous system is not affected by the neuromuscular blockers and has been shown to be an effective indicator of anesthetic depth as it provides a graded change in the frequency domain characteristics associated with increased anesthetic concentrations [3].

Artificial neural network (ANN) based detection of anesthetic levels have been proposed by several researchers. The method proposed by Watt et al. [4] uses a three layered feed forward neural network to categorize the spectral signatures associated with EEG recorded at three distinct levels of anesthesia. The overall accuracy rate obtained in this case is 77%. The method proposed by Krikic et al. [5] uses two features, namely, spectral entropy and embedded eigen-spectrum with a radial basis pattern classifier. The overall accuracy rate obtained in this case is in the range of $98 \pm 0.2\%$.

This paper discusses an automated detection of anesthetic levels using a special type of recurrent neural network known as Elman network (EN). It is a two-layered back propagation neural network with a feedback connection from the output of the hidden layer to its input. In our approach we make use of a frequency domain feature called normalized spectral entropy (NSE) [6] to characterize the EEG data obtained from three different anesthetic levels. It is found from the experiments that an overall detection accuracy rate as high as 99.6% can be obtained by using NSE with EN. This value is better than the accuracy rates obtained with other neural networks [4], [5].

II. METHODS

A. EEG data acquisition and selection

Four patients are anesthetized by the intra-venous infusion of propofol after premedication with 10mg of morphine and 0.4 mg of atropine [5]. It is then followed by the induction of anesthesia with thiopentone (2-4 mg kg^{-1}). Seven to ten minutes after the induction, propofol is infused in five equal 10-min steps, starting at 40 mg kg^{-1} min^{-1} to the final rate of 200 mg kg^{-1} min^{-1}. The blood concentration of propofol is measured by taking venous blood samples from the arm opposite to the one receiving the infusion. Based on the blood concentration values, the patient is considered to be in one of the three different levels of anesthesia, namely, low, medium, and high level and the corresponding EEG data are recorded. The recorded EEG data are then labeled according to the three different levels of anesthesia based on blood concentration of propofol. For experimental analysis, the final 5 min of each 10 min recording period is used, since during these periods the measured concentration of propofol was near constant.

The EEG signal [5] is recorded from the forehead to the left mastoid (with right mastoid as common) using an 82dB preamplifier, having a bandwidth of 0.5-400 Hz (first-order high-pass filter and third-order Butterworth low-pass filter) and converted to a digital signal using a 12 bit analogue to digital converter. Incoming EEG data are sampled at 1 KHz, downsampled to 250Hz and then digitally filtered with a low-pass cutoff at 100Hz using a finite impulse response filter (47 coefficients). The recordings were split into 75% overlapping windows of two seconds length (giving an effective time resolution of 0.4 seconds). Figs.1-5 show five specimens of EEG signals corresponding to three different levels of anesthesia

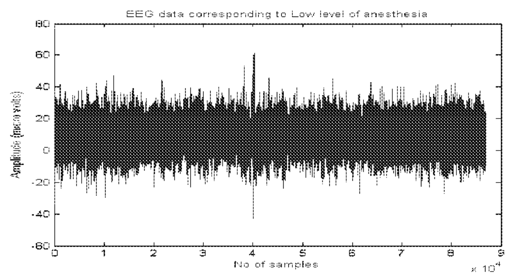

Fig.1. EEG corresponding to low level of anesthesia

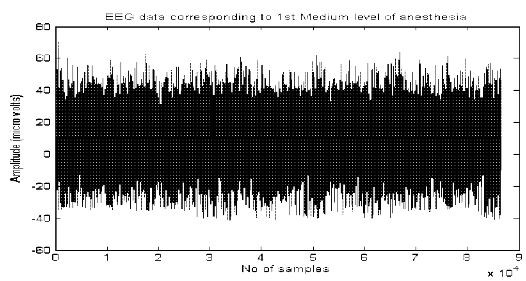

Fig.2. EEG corresponding to 1^{st} medium level of anesthesia

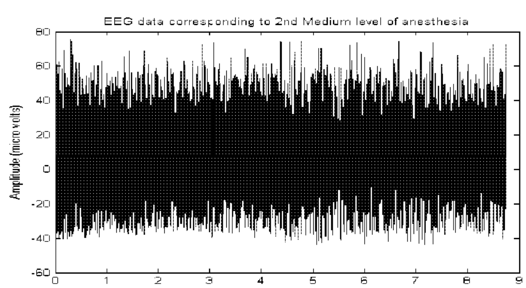

Fig.3. EEG corresponding to 2^{nd} medium level of anesthesia

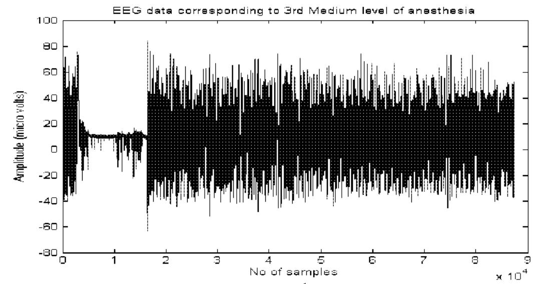

Fig. 4.EEG corresponding to 3^{rd} medium level of anesthesia

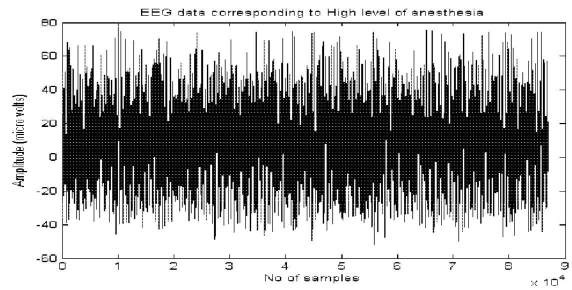

Fig.5. EEG corresponding to high level of anesthesia

B. Feature extraction

Short sections of one-sec EEG epoch are used for the feature extraction. This short sections help in approximating the stationarity of the EEG signal [7]. In the determination of the frequency domain feature, namely, NSE it is assumed that the input EEG signal remains stationary during each epoch. The steps involved in the determination of NSE are given below:

1. The spectral entropy (SE) [6] of each EEG epoch is calculated in the frequency range $[f_1, f_2]$ by using (1)

$$\text{SE} = \sum_{f_i=f_1}^{f_2} P_n(f_i) * \log\left(\frac{1}{P_n(f_i)}\right) \qquad (1)$$

where

f_i represents the frequency component ranging from f_1 to f_2 and $P_n(f_i)$ represents the value of the normalized power spectral component at f_i.

2. The NSE for each epoch is obtained as shown in (2)

$$\text{NSE} = \frac{SE}{\log(N)} \qquad (2)$$

where

N represents the total number of frequency components in the range $[f_1, f_2]$.

C. Artificial neural network implementation

The ANNs are considered to be good classifiers due to their inherent features such as adaptive learning, robustness, self-organization and generalization capability [7].The ANN considered in this paper for the detection of anesthetic levels is a special type of recurrent neural network known as EN. Fig.6 shows the basic architecture of a recurrent neural network. The frequency domain feature, namely, NSE obtained from the pre-processed EEG segments is used as the input for the neural network. For the two layered EN, the activation functions used are tan-sigmoidal and log-sigmoidal for the hidden and output layers respectively. The number of neurons used in the hidden layer and the output layer are 90 and 1 respectively. Gradient descent algorithm with an adaptive learning rate is used for training the EN [8]. The neural network target and threshold values for the different anesthetic levels are shown in Table I. The neural network training parameters are shown in Table II.

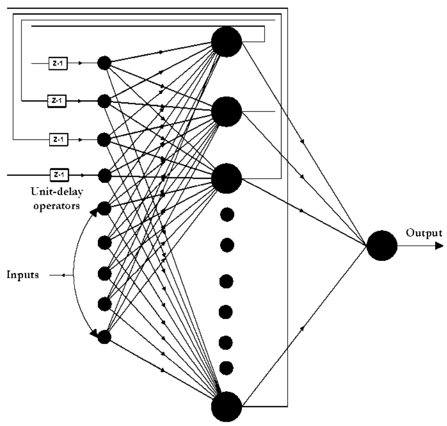

Fig.6. Recurrent neural network architecture

Table I. Elman network target and threshold values

Level of anesthesia	Target value	Threshold values used for classification
Low	0	<0.1
Medium	0.5	0.1 – 0.9
High	1	>0.9

Table II. Elman network training parameters

Training Parameters	Value
Initial Learning rate	0.5
Learning rate increase (LRI)	1.05
Learning rate decrease (LRD)	0.7
Momentum constant (MC)	0.90
Maximum error ratio (MER)	1.04
Performance goal (MSE)	0.01

III. RESULTS

The EN is trained with the NSE feature values obtained from the pre-processed EEG segments of 1sec duration. A total number of 4500 training patterns of 1-sec duration corresponding to three patients have been used as the training data-set and a total number of 1500 test patterns of 1-sec duration corresponding to a new patient have been used as the test data-set for evaluating the performance of the neural network. The classification results are show in Table III.Fig.7 shows the output of EN corresponding to the three levels of anesthesia when tested with the unseen test data of 1500 test patterns. The average value of the overall detection accuracy rate obtained with EN is 99.6%.

Table III. Classification results

Anesthetic levels	Total applied patterns (T_{AP})	Correctly detected patterns (C_{DP})	Overall accuracy (%) = $\frac{C_{DP}}{T_{AP}}$
Low	300	300	100
Medium	900	894	99.33
High	300	300	100
Average overall accuracy			99.6

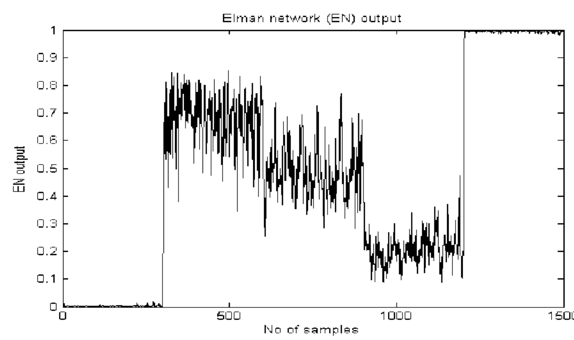

Fig.7. Elman network output

IV. DISCUSSION

This experimental study demonstrates that EN trained with EEG data-sets of three patient's, is able to detect the levels of anesthesia in an unseen test data-set corresponding to a new subject with an high accuracy rate of 99.6% which is better than the values of 77% and 98$\pm$0.2% obtained with feed-forward neural network and radial basis classifier respectively [4],[5].

V.CONCLUSION

In this paper a recurrent type of neural network known as Elman network has been used for the automated detection of anesthetic levels. Pre-processed EEG segments of one-sec duration have been used as test patterns. A frequency domain feature, namely, normalized spectral entropy has been used to characterize the EEG data corresponding to the different levels of anesthesia. Our experimental results show that an overall detection accuracy rate of 99.6% can be obtained using Elman network with a single input feature. This overall accuracy rate is higher than those obtained with other types of neural networks, namely, feed-forward neural network and radial basis classifier. As this automated detection scheme of anesthetic levels is based on a single input feature, it would be more suitable for real time applications as the overall processing time would be considerably reduced.

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