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Pre-Processing Based Wavelets Neural Network for Removing Artifacts in EEG Data

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Abstract

The electroencephalogram (EEG) is a record of brain activity; however, because the electric potential of cerebral activity has a low amplitude and occurs at frequencies between 4 to 60 Hz, it is easily masked by other environmental noise signals and non-cerebral signals. This work presents to minimize noise by pre-processing new wavelets which are numerically stable and orthogonal bases will be proposed using Morelette wavelets and classified using convolutional neural networks (CNN). For experimentation, wavelet transforms are done to the original EEG signals from the public EEG database using Python scripts. Performance measures like SNR and MSE, which are determined for various step sizes of signal and filter orders, are used to measure and analyse the performance of filters. Compared to existing methodologies, wavelet analysis techniques perform better.
Keywords: EEG, Noise removal, Morelette wavelets, CNN, SNR and MSE.

1 Introduction:

Electroencephalogram (EEG) depicts the brain states of a person's mental state. EEG signals are cerebral's electrical potentials, which are contaminated by other bio-potentials such the electrocardiogram, electromyogram, and electroculogram (EOG, ECG) [1].Artifacts are undesirable components that come from other sources and misrepresent current recorded EEG data's depiction of cerebral activity. As a result, EEG data analysis becomes more difficult. In order to recognise patterns in and increase classification accuracy, machine learning techniques are applied.The two approaches that are most frequently used to handle EEG artefacts are support vector machines (SVM) and artificial neural networks [2]. A promising strategy for handling automatic artefacts is a hybrid approach that combines ICA and SVM.Support vector machines (SVMs) are supervised statistical learning algorithms that are commonly used to categorise unknown data using decision boundaries that are created from rules that divide data into discrete classes. The analysis of biomedical data, such as multi-channel EEG recordings, can benefit from SVM's strong generalisation capacity, which is independent of input space dimension [3].

2 Related works:

Deep learning (DL) is utilised extensively in computer vision and natural language processing (NLP), but application of DL techniques to EEG denoising is still relatively new. We only discovered four

DL-based studies on EEG denoising, to the best of our knowledge [4]. Particularly for EOG artefacts, they provided performance that was comparable to that of conventional denoising approaches.Previous research has described the use of a convolutional autoencoder, a 5-layer neural network, and an unique end-to-end 1D-ResCNN model to eliminate various forms of artefacts [5, 6, 7]. EEG denoiseNet, a benchmark dataset for deep learning approaches to EEG denoising, has recently been suggested [8-10].

3 Methodology:

To create pairs of clean and noisy EEG signals for training and testing the suggested neural network, we used data from the EEG denoised Net. Particularly, noisy EEG with myogenic artefacts was simulated using 4514 EEG epochs and 5598 EMG epochs. We obtained 5598 pairs of EEG and myogenic artefact epochs by reusing some of the data at random to create 5598 EEG epochs. 10 data pairings totaling 5598 pairs were randomly divided into 8 training set (4478 pairs), 1 validation set (560 pairs), and 1 test set (10 parts). The letters y, x, n, and in the calculations stand for the combined signal of EEG and myogenic activity, the clean EEG signal, the myogenic signal, and the relative contribution of the EMG artefact by eq. (1).

$$C(a,\tau)=\langle x,\psi_{a,\tau}\rangle=\int_{\Re} x(t)\psi^{*}_{a,\tau}(t)dt$$

$$w(s,\tau)=\langle X,\ \psi_{\tau,s}(n)\rangle=\sum_{n=0}^{N-1} x_n \psi^{*}\left(\frac{(n-\tau)dt}{s}\right) \tag{1}$$

where "*" denotes complex conjugation and s and stand for scale and translation, respectively. We can extract a collection of different frequency components by adjusting the scale factor's value by eq. (2)

$$\psi_0(n)=\pi^{-\frac{1}{4}}e^{j\omega_0 n}e^{-\frac{1}{2}n^2}$$

where f0 is the frequency of the wavelet's centre angle. Additionally, based on the time-domain convolution theorem, inner production of transformed frequency series of two series can be used to indirectly compute the time-domain convolution of two series.

The decision tree technique benefits those who can quickly analyse and categorise an observed dataset. An appropriate pruning factor and confidence factor are controlled in a decision tree algorithm to provide the best classification result. In this instance, the decision tree was created using the best attribute selection practises and a nominal result-appropriate pruning factor. To improve the decision tree, the classification accuracy was compromised for a relatively narrow range.

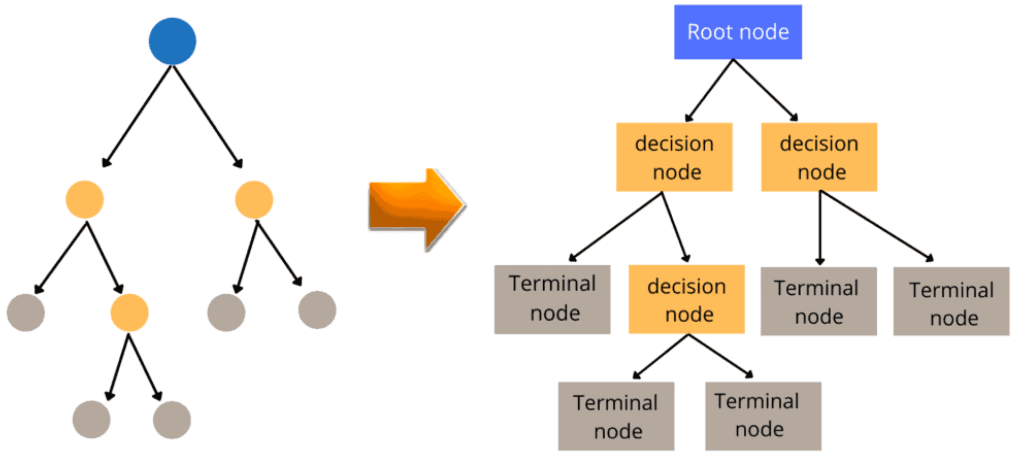

Figure 1: Decision tree

4 Performance Evaluation:

MATLAB is the simulation tool used on a desktop with Intel i7 processor at 1.8 GHz and 16GB of RAM and represents a synthetic information gathering problem in an area of 30 m × 30 m.

Table.1. Comparison of Existing and Proposed

Metrics	Existing Without Preprocessing (%)	Proposed With Preprocessing (Morlet Wavelet De-Noise) (%)
Accuracy	95	98
Precision	81	86
Recall	75	81
RMSE	55	58
F-Measure	83	88

The above table-1 shows comparative analysis between proposed and existing techniques in terms of accuracy, precision, recall, F_1 score, RMSE. Here analysis has been carried out based on number of epochs. Accuracy calculation is done by the general prediction capability of projected DL method. For calculating F-score, number of images processed are EEG signal for both existing and proposed technique. The F-score reveals each feature ability to discriminate independently from other features. For the first feature, a score is generated, and for the second feature, a different score is obtained. However, it says nothing about how the two elements work together. Here, calculating the F-score using exploitation has determined the prediction performance. It is created by looking at the harmonic component of recall and precision. If the calculated score is 1, it is considered excellent, whereas a score of 0 indicates poor performance. The actual negative rate is not taken into consideration by F-measures. The accuracy of a class is calculated by dividing the total items classified as belonging to positive class by number of true positives. Probability that a classification function will produce a true positive rate when present. It is also known by the acronym TP amount. In this context, recall is described as ratio of total number of components that genuinely fall into a positive class to several true positives. How well a method can recognise Positive samples is calculated by recall. Recall increases as more positive samples are determined. MSE squared root is used to calculate RMSE. The RMSE calculates the change in each pixel as a result of processing.

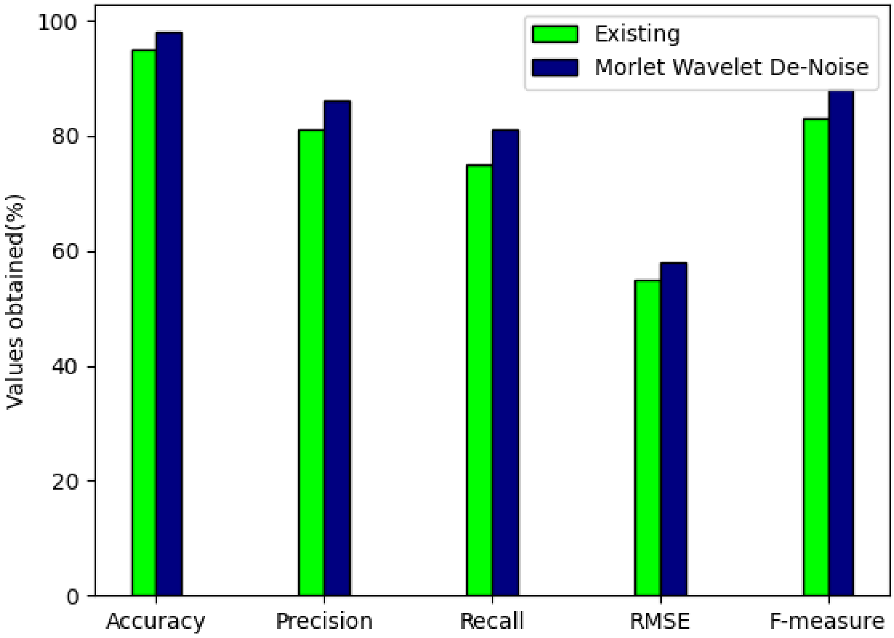

Figure 2: Comparative analysis

From above figure 2 shows comparative analysis between proposed and existing technique. the proposed technique attained accuracy of 95%, precision of 81%, recall of 75%, F-1 score of 83%, RMSE of 55%. While the existing ICPE attained accuracy of 98%, precision of 86%, recall of 81%, F-1 score of 88%, RMSE of 58%.

5 Conclusion:

Digital evaluation has replaced physical assessment as the method for evaluating patients. The evaluation of the depth of anaesthesia is one important illustration (DoA). The assessment has switched from a physical to a digital one employing a DoA monitor. The electroencephalogram (EEG) signal is sent into the DoA monitor.The procedures involve signal analysis, filtering, and digitization. In order to reduce noise in the EEG signal, this study focuses on filtering techniques. EEG signal noise may reduce the DoA monitor's accuracy. Noises in the EEG signal are caused by muscular contractions, blinking and eye movement, power lines, and device interference. As a result, monitoring DoA without eliminating noise could produce an inaccurate evaluation. The noise in EEG signals cannot be completely eliminated by a straightforward filtering technique like a band pass filter. Here, we introduce wavelets-based signal pre-processing and categorization along with adaptive filtering.It is evident from the classification that machine learning is more feasible when using fewer EEG datasets than in the prior classification, which required more sensors. This was done by comparing experimental results of various wavelets decompositions at level 1 and level 2.

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