A tensor decomposition-based feature extraction method to predict neurological recovery from coma after cardiac arrest using EEG signals

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Abstract

Electroencephalogram (EEG) patterns can reveal important details regarding the level of neurological recovery in comatose individuals who have undergone cardiac arrest hospitalization. Automated algorithms based on EEG signal processing and machine learning can be used to estimate a patient's chances of regaining consciousness. This study uses tunable Q-factor wavelet transform (TQWT)-based signal refinement and Tensor decomposition-based feature extraction from EEG records to construct probability-based favorable or bad outcome labels for prognosis. TQWT-based signal decomposition into sub-bands of EEG signals employing optimal settings for feature extraction to enhance critical care patterns. A 3-way tensor per record is created using scattering transform, which captures time-frequency information. The core tensor from Tucker decomposition of the produced tensor is utilized to get 1-D feature vectors along with other time and frequency domain features for bagging ensemble classifier learning. We participated in the George B. Moody PhysioNet Challenge 2023 as team 'Medics' and obtained 7^{th} ranking with challenge score of 0.69 on challenge hidden test data for prognostication 72 hours after return of spontaneous circulation (ROSC).

1. Introduction

Patients suffering cardiac arrest undergo sudden unexpected fading of cardiac activity, respiration and consciousness. The number of people who experience a cardiac arrest every year on a global scale is approximately 6 million [1, 2]. Survival rates for such patients range from 1% to 10%, depending on the patient's geographic location [3]. Cardiac arrest survivors frequently suffer brain damage and coma. The majority of cardiac arrest survivors admitted in intensive care unit (ICUs) are comatose. For comatose cases, doctors often have to guess if the patient will eventually recover consciousness. The patient will get continuous care for good prognosis results and withdrawal of life support for poor prognosis causing death. However, a high rate of false positive predictions has been a major concern with regard to such subjective forms of prognostication.

For medical decision-making, EEG signals can be analysed for attenuated voltage, burst suppression, and seizure-like patterns. However, manually analysing lengthy EEG recordings with numerous channels is laborious, expensive, engaging, and requires expertise which is unavailable in most of the healthcare centers[4]. In order to tackle this issue and achieve better prognostication of coma, electroencephalogram (EEG) signals can yield predictive information by means of automated analysis[5, 6]. Thus, the role of automatic EEG signal analysis in clinical practice has huge scope for better comatose patient care with accurate and prompt prognosis [4].

Recently, many such automated methods have been proposed but results portrayed were merely for a few numbers of patients that too from a particular hospital setting [5,7,8]. Pham et al. [7] in their study computed nine predefined, automatically calculated, quantitative EEG features to train a random forest model. A convolutional neural network (CNN) was also trained using 10s segments of EEG signals. Similarly, Tjepkema et al. [8] performed the prognosis of good and poor outcomes using CNN trained using 5min EEG data which was downsampled to 64 Hz sampling rate. However, these methods can not be generalized for unseen and diverse data. To overcome these limitations, George B. Moody PhysioNet Challenge 2023 (GBMP Challenge 2023) has provided an opportunity to develop an open source algorithm to predict neurological recovery of comatose patient by disclosing a large multicenter international database.

In this paper, in line with GBMP Challenge 2023 objective [9, 10], we developed a binary classification model using TQWT-based signal refinement and tensor decomposition-based feature extraction from EEG records to generate probability and good or bad outcome prognoses. To begin with, TQWT based signal decomposition is applied on EEG signals to get relevant sub-bands for enhancement of the meaningful clinical patterns. The tensor based features is obtained by applying scattering transform on TQWT sub-bands to get time-frequency based information. Scattering transform of EEG signal epochs are used to create a 3-way tensor per record. The core tensor resulting from Tucker decomposition of the formed tensor is then used to get 1-D feature vectors along with the other time and frequency domain features for learning of ensemble bagging classifier model.

Rest of paper is organized as follows. Our methodology is in section 2. Through numerous experiments, we provide our results and evaluations in section 3. Finally, section 4 presents conclusions and future directions.

2. Methodology

The major steps involved in the proposed methodology are pre-processing, TQWT based decomposition, applying scattering transform on TQWT sub-bands, tensor based feature extraction, and regression with binary classification. The overall system design is shown in Figure 1 and the details of each involved step is described below.

2.1. Data

The data for this challenge comprises of 1,020 adult patients in ICUs who suffered cardiac arrest either out-of-hospital or in-hospital and attained normalcy of their heart activity but remained comatose. The data acquisition was done from seven academic hospitals in the U.S. and Europe by researchers in the International Cardiac Arrest REsearch consortium (I-CARE) [11]. The dataset includes 19-channel continuous EEG signals obtained up to 72 hours from return of spontaneous circulation (ROSC). It also includes ECG, EMG and/or other clinical time-series signals. The recordings have quality deterioration from various artifacts. The data was partitioned into training, validation, and test sets. Approximately 60% of the patients are in the publicly available training set, 10% in the hidden validation set, and 30% in the hidden test set.

2.2. Pre-Processing

For this study, 19-channel continuous EEG signals obtained up to 72 hours from ROSC along with the meta data variables viz. age, gender, ROSC, out-of-hospital cardiac arrest (OHCA), shockable rhythm, and targeted temperature management (TTM) are used. One minute EEG signal segment per hour is pre-processed to generate 10 seconds epochs for further analysis. The pre-processing covers filtering, re-sampling, normalization, and epoching. A notch filter is applied to remove utility frequency from the EEG signals. A band pass filter with cut-off frequency of 0.1 Hz and 30 Hz is used to remove artifacts. The EEG signals were re-sampled to 128/125 Hz frequency depending upon even/odd sampling frequency of the data. Bipolar montages are derived from given channels. The signal scaling is done with min-max normalization scheme to bring all the signals in the range [-1,1].

2.3. Tensor and Tucker decomposition

Wavelet transformations (WTs) have achieved success in time-frequency analysis of nonstationary signals in several applications. In this work, on one hand, discrete and adaptive wavelet transform TQWT is used to analyze the oscillatory components of EEG signals [12]. The Q-factor (Q), redundancy (r), and decomposition levels (J) of this transformation are easy to change. And tuning these input parameters can give enhanced information in the decomposed sub-bands for further signal processing.

On the other hand, this study also investigates applying the WT based Scattering Transform (ST) to build the tensor for tucker decomposition-based feature extraction. ST is a non-linear mathematical operator based on convolutional networks [13]. ST uses low-pass filter averaging, complicated modulus procedures, and many wavelet transform layers. Its major goal is to create a translation-invariant and compact time-warping-stable representation. A signal and its shifted counterpart have the same feature space representation with ST.

A tensor is a multi-way array of data, and is the natural generalization of a matrix when the order is higher than two. In this work, the ST images of the TQWT sub-bands are clubbed and stacked channel-wise to form the 3-way tensor $\underline{\mathbf{X}}$ for subsequent tensor decomposition. Similar to Singular value decomposition, Tucker tensor decomposition yields orthogonal factor matrices such as unitary matrices along with a core tensor. The core tensor can be represented as: $\underline{\mathbf{C}} \approx \underline{\mathbf{X}} \times_{\mathbf{1}} \mathbf{U}^{(\mathbf{1})\mathbf{T}} \times_{\mathbf{2}} \mathbf{U}^{(\mathbf{2})\mathbf{T}} \times_{\mathbf{3}} \mathbf{U}^{(\mathbf{3})\mathbf{T}} = \underline{\mathbf{X}} \times \left\{\mathbf{U}^{\mathbf{T}}\right\}$, where $\mathbf{U}^{(\mathbf{n})}$ are the unitary factor matrices. The optimized rank setting of core tensor $\underline{\mathbf{C}}$ is found with an objective to maximize the classification performance between two classes with respect to f-score for the problem at hand.

2.4. Feature Extraction

In the proposed methodology, three distinct feature sets are derived from the available I-CARE dataset: (a) time- and frequency- domain features, (b) time-frequency domain using tensor representation via ST of EEG data, and (c) given patients' metadata. The pre-processed one minute EEG data, which is further divided into six epochs of ten second each, undergoes the TQWT decomposition. For each sub-bands of decomposed epochs, the statistical feature set is extracted which includes the mean, standard deviation, variance, skewness, kurtosis, entropy, Hjorth mobility, complexity, and activity. Along with this, power spectral density feature set is extracted from one minute EEG data for four frequency ranges 0.5-8 Hz, 4-8HZ, 8-

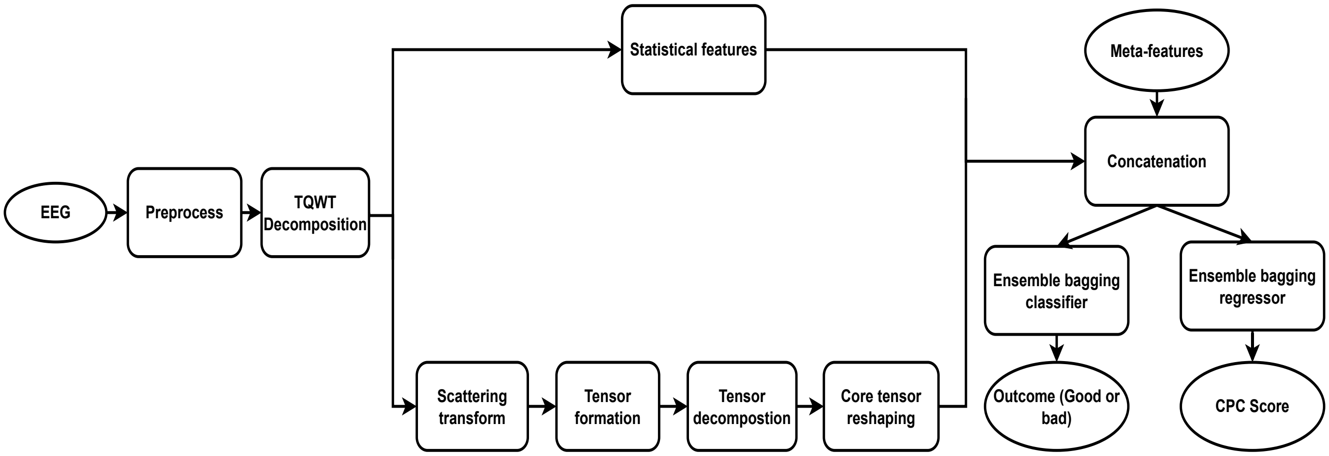

Figure 1. The proposed coma prognostication scheme for cardiac arrest patients.

12Hz, and 12-30Hz corresponding to delta, theta, alpha, and beta rhythms respectively.

ST is applied on the subbands to get the time-frequency representation of the same and stacked channel wise to form a 3-way tensor. Further, to obtain the compressed time-frequency information from the tensor, Tucker decompostion is applied as explained in the previous section. Subsequently, obtained core tensor is flattened as an array to form the second set of features. Finally, the patient metadata feature set includes age (in years), sex, return of spontaneous circulation (ROSC) in minutes, out-of-hospital cardiac arrest (OHCA), shockable rhythm, targeted temperature management(TTM) in Celsius.

2.5. Prognostication Models

In this study, bagging decision tree ensembles are used to generate neurologic prognostication following cardiac arrest. Decision trees are non-parametric supervised learning methods most widely used for regression and classification tasks due to its interpretability and the availability of efficient and scalable learning algorithms [14]. Bagging is a ensemble learning method based on decision trees which creates many random subsets of the dataset with replacements. Each subset of data is used to develop a decision tree learner. Finally, an ensemble of weak learners are selected to improve generalizability over a single estimator in terms of prediction performance. On an average, variance of the combination of estimators is usually lower than any of the single weak learner. All the features extracted as discussed in the section 2.4 are concatenated and fed as input to the ensemble schemes. The first scheme is to classify clinical data into poor and good outcomes using bagging decision tree ensemble classifier. Further, to obtain the CPC scores in the range from 1-5 bagging decision tree ensemble regressor is used in the second scheme.

3. Results and Discussion

An experimental study was carried out to obtain the optimal setting for the TQWT decomposition, ST based tensor creation, and tensor decomposition which in-turn produces the discriminating features between the two classes for classification. The objective of this experimental study was to enhance the classification performance in terms of average of the f-scores of considered two classes. Thus, grid search based obtained optimal TQWT decomposition parameters values are found to be $Q = 1$, $r = 4$, and $J = 11$. Similarly ST parameters j and q are empirically chosen as 2, where q is the number of wavelets per octave and 2^j is the averaging scale. Finally, for Tucker decomposition of the formed tensor the required optimal rank setting was derived as $10 \times 2 \times 21$ using grid search based optimization. The proposed neurologic prognostication involves classification of patients' data as "Good" and "Poor" outcome and generation of CPC score from 1-5 using regression method, therefore two bagging ensemble models are used. The bagging ensemble models are used with default settings in python library scikit-learn except the 'number of base estimators' training parameter which was empirically set to 300.

The average results of the ten-fold cross-validation performed on the individual extracted feature sets and combined feature set are shown in Table 1.

Table 1. Performance measures for ten-fold cross validation using training data.

Feature set	Accuracy	F-measure	Challenge Score
Metadata features	0.65	0.61	0.42
Time and frequency domain features	0.77	0.74	0.60
Tensor based features	0.67	0.64	0.45
Combination of features	0.78	0.75	0.66

The proposed methodology was evaluated on challenge hidden test data for prognostication 72 hours, 48 hours, 24 hours and 12 hours after ROSC and the obtained results are tabulated in Table 2.

Table 2. Performance measures for prognostication after several hours of ROSC using test data.

Hours after ROSC	Accuracy	F-measure	Challenge Score
72 hours	0.77	0.70	0.69
48 hours	0.76	0.68	0.67
24 hours	0.74	0.63	0.32
12 hours	0.67	0.45	0.23

4. Conclusion

In this study, we developed a tool to generate neurological prognostication outcomes along with the CPC score for the cardiac arrest comatose patients. The quantitative EEG methods like TQWT based signal decomposition and Tensor decomposition based feature extraction are capable of detecting early signs of neurological recovery while coma persists. The classification results demonstrates that a competitive solution for such prognosis can be built using proposed methodology. The proposed methodology is designed for only one minute data which in turn reduces the processing time as compared to the hourly data. The choice of epoch, parameters of TQWT, scattering transform and tensor decomposition could be further investigated in the future work along with the exploration of other feature sets and classification/regression technique.

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