Expert Systems With Applications 89 (2017) 205–221

Contents lists available at ScienceDirect

Expert Systems With Applications

journal homepage: www.elsevier.com/locate/eswa

Optimal configuration of multilayer perceptron neural network classifier for recognition of intracranial epileptic seizures

Shivarudhrappa Raghu, Natarajan Sriraam*

Center for Medical Electronics and Computing, Ramaiah Institute of Technology (Affiliated to VTU Belgaum), Bangalore, 560054, India

ARTICLE INFO

Article history:
Received 29 April 2017
Revised 15 July 2017
Accepted 19 July 2017
Available online 27 July 2017

Keywords:
Entropy
Epileptic seizures
MLP
Mutual range of coefficient
Training function
Transfer function

ABSTRACT

Background: This paper presents optimized configuration of multilayer perceptron neural network (MLP-NN) as a pattern classifier for recognition of intracranial electroencephalogram (iEEG) epileptic seizures. Though qualitative analysis of intracranial recordings from the patients involves cumbersome procedure, it provides significant neuronal activities of the brain that is essential for clinical decision making.
Methods: This study considered three epileptic seizures stages, namely, pre-ictal (set C), post-ictal (set D) and epileptic (set E) iEEG from the University of Bonn, Germany database. Four entropies, Shannon, log energy, spectral and Renyi entropies were considered as features to evaluate MLP-NN network. Four classification tasks with the dataset were formed, namely CE, DE, CDE, and CD. In order to identify the optimal configuration of MLP-NN for classification, network parameters such as input-hidden layer activation/transfer functions, hidden-output layer activation/transfer functions, network training/learning functions, the number of hidden neurons were considered and the optimality was arrived based on the mean square error (MSE), classification accuracy (CA). The efficiency of the entropy features was exploited by the parameters, mutual range of coefficient (γ), p-value, and z-score, which showed the band discrimination for various classification tasks.
Results: Simulations results showed that the tan sigmoid, pure linear were found to be optimal input-hidden, hidden-output transfer function and Levenberg-Marquardt learning algorithm as optimal training function for all the four classification tasks. It was inferred from the proposed study that the CA indirectly varies with γ value, p value, and MSE, and directly varies with z-score. From the experimental study, the best CA of 97.68%, 94.56%, 84.58%, and 57.8% was obtained for case CE, DE, CDE, and CD respectively. It can be concluded that proposed features with optimally configured MLP-NN found to be helpful for real-time iEEG classification.

1. Introduction

About 1% of the world population is affected by epilepsy which is characterized by a tendency for recurrent seizures (WHO, 2015). Epilepsy is excessive and abnormal brain cell activity characterized by unpredictable seizures and can cause other health problems (Fisher et al., 2005). An electroencephalogram (EEG) is a signal that conveys the information of brain in term of electrical activity (Andrzejak, 2001). The EEG is widely used to assess the neurological disorders and to detect brain abnormalities. Usually EEG is recorded by placing electrodes on the scalp using 10–20 International system. According to neurologists, scalp EEG is very sensitive to artifacts and noise, and has poor spatial resolution (Janjarasjitt, 2014). The best way to overcome this issue is implanting the electrodes on the cortex and measure the electrical activity, which is referred as intracranial EEG (iEEG). In the clinical environment, any brain related disorders were annotated using EEG recordings through qualitative visual inspection by the specialist. One has to have the knowledge of temporal patterns and characteristics to study the abnormalities of the brain. Temporal characteristics of EEG may be interpreted by variety of advanced signal processing techniques and machine learning algorithms. The EEG signals activities under epilepsy condition were divided into four states, namely, normal, pre-ictal (an event just before the ictal), post-ictal (an event just after the ictal), and epileptic states (Health Communities, 2014). Ictal is the period of time from the start to the end of the seizure activity (Health Communities, 2014).

The essential part of the epilepsy is recognition of pre-ictal, post-ictal and epileptic seizures from iEEG. Detecting pre-ictal activity state certainly benefit the patient to take precaution or treatment and for neurologist to assess the patient immediately. Several feature extraction parameters, supervised and unsupervised algo-

* Corresponding author.
E-mail addresses: raghu.sidda@gmail.com (S. Raghu), sriraam@msrit.edu, natarajan.sriraam@gmail.com (N. Sriraam).

http://dx.doi.org/10.1016/j.eswa.2017.07.029
0957-4174/© 2017 Elsevier Ltd. All rights reserved.

rithm based classification methods have been applied for epileptic seizures problem in the past (Acharya, Molinari, Vinitha, & Chattopadhyay, 2012a; Kumar, Dewal, & Anand, 2014; Nicolaou & Georgiou, 2012; Srinivasan, Eswaran, & Sriraam, 2007; Ubeyli, 2009; Yoo et al., 2013). In particular, combination of entropy and neural network based studies showed impressive results (Acharya et al., 2012a; Kumar et al., 2014; Nicolaou & Georgiou, 2012; Pravin, Sriraam, Benakop, & Jinaga, 2010). Majority of the studies in the past have classified extracranial EEG against iEEG, whose recording environment is completely different. Whereas, this study emphasizes on classification of iEEG alone under various epileptic seizure conditions.

2. Related background

Several attempts have been made by making use of University of Bonn, Germany, database for classification of EEG into normal, pre-ictal, post-ictal and epileptic using supervised and unsupervised pattern classifiers. In Tzallas, Tsipouras, and Fotiadis (2007), Ubeyli (2009), Nicolaou and Georgiou (2012) and Yoo et al. (2013), time frequency analysis, Eigen vector method, permutation entropy and energy sub bands were computed for classification of iEEG into different states. Most of the studies have focused on extracranial EEG against iEEG to classify between normal and epileptic EEG (Acharya et al., 2012a; Pravin et al., 2010; Raghu, Sriraam, & Pradeep Kumar, 2016; Srinivasan et al., 2007). Five sets of EEG signals were decomposed using discrete wavelet transform (DWT) into different sub-bands to obtain detail and approximation coefficients (Kumar, Dewal, & Anand, 2012). Support vector machine (SVM), feed forward back-propagation neural network, K-nearest neighbor and decision tree classifiers were considered to classify EEG signals using relative wavelet entropy and wavelet entropy. Six different classification tasks were formed for classification of epileptic seizures using DWT and approximate entropy (ApEn) (Kumar et al., 2014). In Janjarasjitt (2014), the characteristics of spectral exponent obtained from wavelet based approach was examined for intracranial EEG. The mean sensitivity and mean specificity of 99.01% and 92.40% was obtained respectively using spectral exponent difference. One of the study make use of wavelet packet decomposition to extract Eigen values from the wavelet coefficient using principal component analysis (Acharya, Sree, Suri, & Alvin, 2012b). Significant features were selected using ANOVA test and 99% classification accuracy was obtained using Gaussian mixture model (GMM) classifier with 10-fold cross validation.

The effect of wavelet packet decomposition on EEG signals was studied using log energy entropy (Raghu, Sriraam, & Pradeep Kumar, 2015). Three non-linear features including wavelet entropy, sample entropy, and spectral entropy were explored using artificial neural networks (Pravin et al., 2010). In Acharya et al. (2012a), four entropies namely ApEn, sample entropy, phase entropy 1, and phase entropy 2 were considered for automated detection of normal, pre-ictal and ictal conditions. Seven different classifiers were employed and an overall accuracy of 98.1% was achieved. The studies (Acharya et al., 2012a; Kannathal, Lim, Rajendra Acharya, & Sadasivan, 2005; Raghu et al., 2016; Srinivasan, Eswaran, & Sriraam, 2005) have shown the importance of various entropies for detection and classification epileptic seizures using iEEG. Acharya, Vidya, Fujita, Bhat, and Joel (2015) made an extensive review on different features have been used in the past with various transformation techniques. Another study (Greene et al., 2008), extracted 19 significant features for 17 patients for neonatal seizure detection which showed a sensitivity of 81.08% and specificity of 82.23% classifier performance using linear discriminant classifier model. This study proved that combining all features together into a classifier led to superior performance than that of individual features taken alone.

Through the literature survey it was noticed that the studies have not attempted to find optimized classifier functions for iEEG classification. Our study selected four entropy features based on their previous results in classification of epileptic seizure to evaluate the performance of MLP-NN classifier.

3. Materials and methods

3.1. EEG dataset

This study makes use of EEG database from University of Bonn, Germany (Andrzejak, 2001). Three conditions, namely, pre-ictal (set C), post-ictal (set D) and epileptic (set E) were considered for the experimental study. These recordings were recorded with intracranial electrode placement from five different subjects undergoing presurgical evaluations (Andrzejak, 2001). The depth electrodes were implanted symmetrically into the hippocampal formations and strip electrodes were implanted onto the lateral and basal regions of the neocortex. The implantation of electrodes was carried out to exactly localize the seizure generating area which is termed as epileptogenic zone. The EEG was recorded during epileptic seizures termed as ictal activity. The pre-ictal and post-ictal data sets were recorded during seizure-free intervals (interictal periods) from within the epileptogenic zone and opposite the epileptogenic zone of the brain respectively. The summary of the dataset used in present study is shown in Table 1. Figs. 1–3 show sample recordings of datasets C, D and E respectively. Each dataset contains 100 single channel files with a duration of 23.6 s and a sampling rate of 173.6 Hz (Andrzejak, 2001).

3.2. Proposed method

In our study, both binary and multi-class (3-class) classification using entropy based features were considered to evaluate the performance of MLP-NN. Entropy is a common method in many fields, especially in signal processing applications. Entropy indicates the amount of information which is stored in signal (Coifman & Wickerhauser, 1992). Entropy from time series data can be of probability or energy based. The entropy based features such as Shannon entropy (Pravin et al., 2010; Shannon, 1948), log energy entropy (Raghu et al., 2016; Shannon, 1948), spectral entropy (Pravin et al., 2010; Shannon, 1948), and Renyi entropy (Renyi, 1961) were considered as a feature extraction parameters. The four entropy-based features were considered due to their inherent ability to detect epileptic activities in the past (Acharya et al., 2012a; Das & Bhuiyan, 2016; Raghu et al., 2016; Srinivasan et al., 2007). All four features were used as inputs to the MLP-NN classifier. The network was then configured optimally by considering the hidden neurons, transfer functions at input-hidden layer and hidden-output layers and supervised training/learning algorithms. Four different transfer functions namely, hyperbolic tangent sigmoid (tansig), log sigmoid (logsig), linear (purelin) and Elliot symmetric sigmoid (elliotsig) were used. The weights and bias were updated using different training functions namely, conjugate gradient backpropagation (CGB), gradient descent with momentum and adaptive learning rate backpropagation (GDX), Levenberg-Marquardt (LM), scaled conjugate gradient (SCG), Broyden-Fletcher-Goldfarb-Shanno quasi-Newton backpropagation (BFGS) and resilient backpropagation (RP). A parameter called mutual range of coefficient was derived to establish correlation between *p*-value, z-score, mean square error (MSE) and classification accuracy (CA). The network was examined using multi features with all possible combinations of training and transfer functions. Fig. 4 shows the flow framework conveying a step-by-step overview of the proposed method. With the available three states of iEEG data, four different classification tasks were formed as follows: