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RESEARCH ARTICLE

A New Feature Definition for Classification of Multi-channel EEG Signals and its Application to Epileptic Seizure Detection

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Abstract

In this study, a new feature definition for classifying multi-channel EEG waveforms is introduced. New definition relies upon using the second-order statistics, e.g. autocorrelation, as a random process that represents temporal behavior of EEG signals. A spatially invariant representation of multi-channel time-series associated to EEG waveform components with class labels is obtained based on respective statistics. As an application of proposed feature vector description, a simple multivariate Gaussian classifier is designed to identify normal and epileptic EEG waveforms. Experiments with a publicly available dataset indicate that the proposed method with randomly selected lag vectors of random length within chosen ranges yields high classification success in statistical terms.

Introduction

Feature extraction for electroencephalogram (EEG) signals has drawn considerable attention and emphasis as a research topic in developing research tools such as brain-computer interface (BCI) or human-computer interaction (HCI) systems to identify sources of major neurophysiological events, [1]. Due to excessively large number of cortical neurons involved in generating electrical signals as source against relatively small number of electrodes to collect and record in short duration, temporal samplings usually are of limited capability in recognition of involved processes, [2]. Moreover, sources of most cortical activities in EEG signals are to a great extent obscured due to relatively higher-amplitude artifacts. With such disguised sources and temporal behavior, EEG signals are considered to be of non-stationary nature. Various feature definitions and extraction methods have been proposed to represent and recognize supposedly distinct components involved: Joint time-frequency techniques and wavelet transforms (WT) have been known in obtaining relevant spectral contents in a number of representative frequency bands for modeling spatio-temporal characteristics, [3]. For example, statistical attributions of WT coefficients are a means of spatial representation and, hence, recognition for EEG waveforms. Autoregressive (AR) linear predictive coefficients (LPC), [4], and its variants, e.g. cepstral coefficients, [5], for non-stationary signals have also been widely adopted in EEG waveform classification. Above parametric methods mostly suggest a time-varying linear relationship between electrophysiological excitatory cerebral current sources and the observed scalp potential with optimally suppressed artifact and noise components. They perform with relatively short-time window segments in which statistically invariant cues need to be extracted with temporally sparse, almost noise-like components. For example, as a problematic issue, visually evoked-response potential (ERP) components, which are usually around 10μV low-frequency theta- and alpha-rhythmic beats, are generally observable within a time window of about 10s, [6]. In the case of epileptic seizures, recurring alpha- and delta-rhythmic beats may transiently occur accompanied with interictal electrical discharge (IED), which makes it more involved to extract invariant features within observation time interval, [7]. In most cases, these phenomena become more complicated when involved with other abnormalities or inferences caused by varying brain regions, [8]. On the other hand, nonparametric methods, such as amplitude distribution, spike interval distribution, correlation analysis etc., offer versatility and flexibility for developing a spatial representation of individual EEG waveforms, [9].

In this study, a new and simple nonparametric feature definition for modeling multi-channel EEG waveform components is presented. The method implicitly exploits the notion of predictive, autoregressive model for non-stationary signals and it is based on estimated second-order statistics for a process of random time lags. Proposed definition is extended to describe a random vector, which is then utilized with a simple multivariate Gaussian classifier in identifying normal and epileptic-seizure components involved in EEG waveforms from a publicly available dataset. Results demonstrate that the new feature vector definition formed with random lags yields spatially invariant statistics that can be exploited for successful classification of event sources, i.e. components involved in an EEG waveform.

New Feature Description and Gaussian Multivariate Classifier

Given a discrete-time signal vector $\mathbf{x} = [x_1\ x_2\ \dots\ x_N]$ within an N-sample time slot, the sample value x_n at time stamp n, can be predicted or modelled as output of an autoregressive filter driven by past samples as

$$\hat{x}_n = -\sum_{j=1}^{p} a_j x_{n-j} = x_n + \varepsilon_n \tag{1}$$

where p and ε_n are the prediction order and error, respectively. The prediction error ε_n is assumed to be a (normally distributed) white-noise random process. The model parameters in vector $\boldsymbol{a} = [a_1\ a_2\ \dots\ a_p]$ are called linear predictive coefficients (LPCs). They can be estimated based on least-squares by minimizing the prediction error power $E_p = \sum_{i=1}^{N} |\varepsilon_i|^2$ subject to $\partial E_p / \partial a_j = 0$, where $j = 1, \dots, p$, which yields Yule-Walker equations, [5]. The solution to Yule-Walker equations is usually obtained with recursive methods, e.g. Levinson-Durbin algorithm, in terms of estimated autocorrelation vector $\hat{\boldsymbol{r}} = [\hat{r}(0)\ \hat{r}(1) \dots \hat{r}(p)]$ where $\hat{r}(|m-s|) = \frac{1}{N}\sum_{i=1}^{N} x_{i-m} x_{i-s}$, $0 \leq m, s \leq p$. It is noticed that the vector $\hat{\boldsymbol{r}}$ is fully informative about $\boldsymbol{a}$, that is, it suffices to have $\hat{\boldsymbol{r}}$ to uniquely determine the modelling vector $\boldsymbol{a}$. Furthermore, from the solution of Yule-Walker equations, it is known that the farthest autocorrelation term $\hat{r}(p)$ is a random quantity expressible in terms of smaller-lag autocorrelation terms, i.e. $\hat{r}(0), \dots, \hat{r}(p-1)$ once $\boldsymbol{a}$ has been known. Thereby, we can suggest a feature to represent an L-channel EEG waveform as

$$v(p) = \frac{1}{\sum_{l=1}^{L} \sigma_l^2} \sum_{l=1}^{L} \hat{r}_l(p) - \sigma_l^2 \tag{2}$$

where σ_l^2 and $\hat{r}_l(p)$ are the variance and the p-lag autocorrelation of the EEG waveform in time slot for the l-th channel. Equation (2) implies a norm of vector whose contributions/coordinates are due to merely p-lag correlation terms against the variance for the signal considered. Recently, in [10], it has been demonstrated that above feature definition can be successfully exploited in estimating human emotion states involved in EEG waveforms with a simple regression classifier.

In order to visualize the spatial characteristics of new feature definition for classification task of a multi-channel EEG waveform, we consider a conditional likelihood multivariate Gaussian probability density function (pdf)

$$f\left(\mathbf{v} \middle| \mathbf{p}^{(k)}, C_i\right) = \frac{1}{(2\pi)^{\frac{k}{2}} |\Delta_v|^{\frac{1}{2}}} e^{-\frac{1}{2}(\mathbf{v}-\boldsymbol{\mu}_\mathbf{v})^T \Delta_v^{-1} (\mathbf{v}-\boldsymbol{\mu}_\mathbf{v})} \tag{3}$$

In (3), the random feature vector $\mathbf{v} = [v(p_{k,1}), \dots, v(p_{k,k})]$ is formed by using a k-tuple, nonempty distinct sub-vector $\mathbf{p}^{(k)} = [p_{k,1}, \dots, p_{k,k}]$, i.e. $p_{k,i} \neq p_{k,j}$ for $i \neq j$, where each $p_{k,i}$ has been chosen from a random lag vector $\mathbf{p} = [p_1, \dots, p_d]$ and each member $v(p_{k,i})$ of $\mathbf{v}$ can be extracted as defined in (2). The class label C_i refers to either normal or epileptic seizure components in EEG waveform. Model parameter $\boldsymbol{\mu}_v$ and $|\Delta_v|$ refer to the mean vector and the determinant of the covariance matrix Δ_v of training feature vectors, respectively. These two model parameters, i.e. $\boldsymbol{\mu}_v$ and Δ_v, both can be estimated with the procedure given in [11]-[12]. The density in (3) trained as a classifier, can be tested and assessed in terms of Bayesian *a posteriori* probability term $P(C_i|\mathbf{v})$for a test vector $\mathbf{v}$. In case the number of EEG waveforms used in training for every subset of $\mathbf{p}$ for each class is equal, the class label for test vector $\mathbf{v}$ corresponding to an EEG waveform becomes

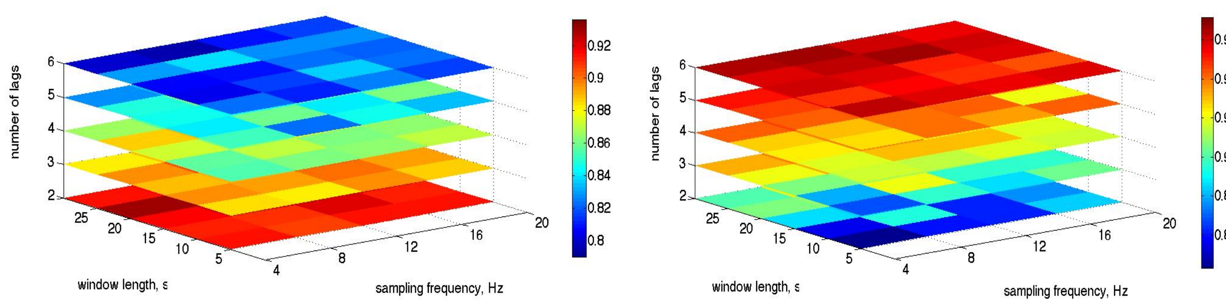
$$P(C_i|\mathbf{v}) \propto f(\mathbf{v}|C_i) = \sum_{\forall k \neq 0} \alpha(k) f\left(\mathbf{v}\middle|\mathbf{p}^{(k)}, C_i\right) \tag{4}$$

In (4), the parameter $\alpha(k) = P\left(\mathbf{p}^{(k)}|C_i\right) = \frac{\binom{d}{k}}{2^{d}-1}$ is the *a priori* probability associated to random selection of non-empty k-member partition $\mathbf{p}^{(k)}$ such that $\sum_{\forall k} \alpha(k) = 1$.

Experiments with a Real EEG Dataset with Epileptic Seizures

Above classifier with new feature vector definition was used on a task of detecting epileptic seizures in real-world EEG waveforms. The waveforms were randomly picked from CHB-MIT Scalp EEG Database, which is publicly available at http://www.physionet.org/pn6/chbmit/. Each dataset covers EEG recordings of 23 cases for each of 22 pediatric subjects of varying-age 5 males and 17 females. Subjects were tracked and monitored for up to several days upon withdrawal of anti-seizure medication for observing seizures. The international 10-20 system of EEG electrode positions and nomenclature were used in M=23-channel recordings. Each subject recording of almost an hour length is sampled 256 times per second and then digitised and stored into an '.edf' type file in 16-bit resolution. In this study, each digitised waveform to be processed was down-sampled to 8 samples per second for reducing possible noisy artifacts. That is, preprocessing waveforms was carried out with N=256 samples or equivalently 32-second long time slots. The previously described vector $\mathbf{p}$ was set to be composed of time lags from 0 to 7.5 seconds (60 samples), with increment of 1.5 seconds (12 samples), i.e. d=6 and k=2, …, 6. For each k-tuple vector $\mathbf{p}^{(k)}$, 10 experiments were conducted, that yields identical $\alpha(k)$. In each experiment, the classifier in (3) was trained (tested) with randomly picked 25 (100) EEG waveforms for each class label.

It is desirable to demonstrate the usefulness and robustness of the classifier with new feature definition given in against variations in design or operating parameters such as sampling frequency, window length in samples and the number of lags in seconds with chosen classifier. Fig. (1) illustrates behaviour of average *a posteriori* probability terms given in (4) in sidebar out of 100 experiments with 50 EEG waveform components randomly chosen from dataset for normal and epileptic seizure for each triplet of above parameters, respectively.



(a) (b)

Fig. 1. Variation of classification success for (a) normal and (b) epileptic seizure EEG waveform components versus preprocessing and classifier parameters.

From the above figure, it is seen that the proposed feature vector definition yields highly successful classification scores for both components, which is higher than 85% for wide range of parameter variations. For normal EEG waveform components, high classification success of 90% or higher is achieved for autocorrelation length 2 and 3 while similar success is attained for increased number of lags, almost regardless window length and the sampling frequency. Therefore, it can be inferred that proposed feature description allows highly successful classification performance, which solely depends on randomly chosen number of time lags of individual waveform autocorrelation terms. The success of the classifier with proposed feature definition in discriminating the normal and epileptic seizure components is depicted as histogram in density profile, f (sid), as shown in Fig. 2. The argument 'sid' in density profiles stands for the relative frequency in percent, i.e. $P(C_i|\mathbf{v} \in C_i)$, of successfully classified/identified test waveform in each experiment.

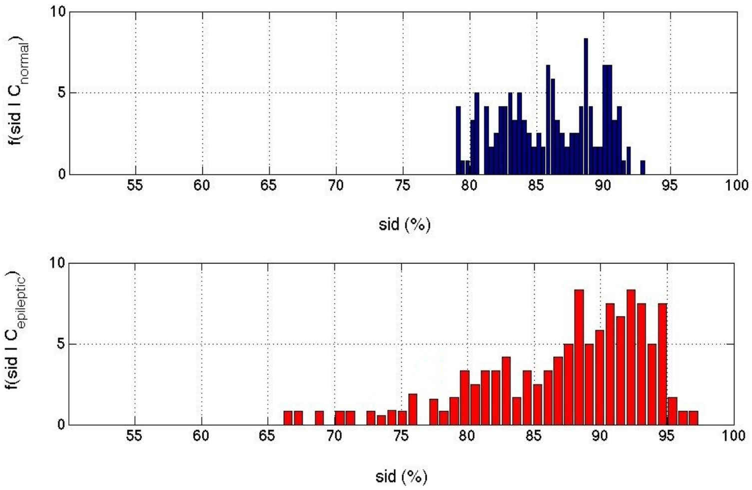


Fig. 2. The density profile histograms in testing multivariate Gaussian classifier with new feature definition for class labels of EEG waveform components where 'sid' refers to successful classification.

Besides the presented histograms above, Table I summarises the major statistical quantities for classification success in testing, which also includes 90% confidence interval as a measure of success. The confidence interval was computed as the range in which the nearest 90% *a posterior* probability values reside with respect to the mean.

EEG waveform component	90% confidence interval, %	Avg. success in classification, %	Std. deviation of success in classification, %
Normal	82.4-90.5	86.5	2.2
Epileptic	80.5-94.3	90.4	4.7

Table I. Some important characteristics and statistical measures of successful classification of EEG component waveforms based on new feature definition with a simple multivariate Gaussian classifier.

It is seen that normal (epileptic) EEG waveforms were identified such that 90% of successful recognition in *a posteriori* probability resides within a range of almost 8.1% (13.8%) around the average of 86.5% (90.4%). This outcome indicates that randomly selected lags at randomly selected tuples with the second-order statistics can be directly utilised as a feature in successful identification of EEG waveform components involving epileptic seizures. Despite considerable variation range in classifier parameters, it is seen that successful recognition of EEG waveforms is possible around 85% with a narrow range. It is also seen that as the number of autocorrelation lags vary the EEG waveforms will exhibit saliency in classifier performance for each waveform components and this observation can be further employed.

Conclusions

A new feature definition for multi-channel EEG waveforms, which is based on estimated second-order statistics, e.g. autocorrelation, of individual channel waveforms as a random process, is presented. With use of new feature definition, a vector description with randomly chosen length and time lags is provided for modeling normal and epileptic EEG waveforms. A simple multivariate Gaussian classifier is designed for identifying these waveform components based on the proposed feature vector. Experiments with a real-world publicly available dataset reveal that the new feature and associated vector descriptions with chosen classifier allow successful.

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