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Data Mining in EEG signal Processing technique with Epilepsy and Coma Patients

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Abstract: This study deals with the application of principal components analysis (PCA) to the field of data mining in electroencephalogram (EEG) processing. Alternatively, they can be estimated by a neural network (NN) configured for extracting the first principal components. Instead of performing computationally complex operations for eigenvector estimation, the neural network can be trained to produce ordered first principal components. Possible application include separation of different signal components for feature extraction in the field of EEG signal processing, adaptive segmentation, epileptic spike detection, longterm EEG monitoring evaluation of patient in coma.

Keywords: Epileptic spike, Electroencephalogram, Principal components analysis.

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1. Introduction

Data mining techniques are carried out to study EEG signals of patients with epilepsy and coma. A comparison is made in the pattern of the waves [1]. Electroencephalography (EEG) is a widely used medical technique, for monitoring electrical brain activity produced by neurons. Technically an EEG consists of multiple channels that monitor neurons' activities in a region, each channel represent an electrode on a patient's scalp. Epilepsy is a neurological disorder manifesting in uncontrolled seizures. These seizures lead to a discharge in the brain, generating a disturbance in the EEG. The analysis of EEG looking for the spikes over background activity is the main method of epilepsy diagnosis and treatment. A regular EEG can have from up to 20 electrodes and last more than an hour [2]. Comas are caused by an injury to the brain. Brain injury can be due to increased pressure, bleeding, loss of oxygen, or buildup of toxins. The injury can be temporary and reversible. It also can be permanent.

2. Electroencephalogram

An electroencephalogram (EEG) is a recording of spontaneous brain electrical activity by means of electrodes located on the scalp [1]. The placing of the electrodes is constrained by natural physical limits, namely by the size of the electrodes, which limits he maximum number of electrodes that can be used. Another limitation is the mutual influence of electrodes located close to each other. Standardized placement of the basic number of electrodes is done in accordance with the scheme designed by Dr. Jasper (Jasper, 1958). This is nowadays known as the International 10-20 system. The frequency domain can be distinguished in four basic frequency bands on an EEG Signals, namely delta, theta, alpha, and beta activities [2], [3] and [4].

2.1 Delta Band

The delta band corresponds to the slowest waves in the range of 0-4 Hz. Its appearance is always pathological in an adult in the waking state. The pathological significance increases with increasing amplitude and localization [5]. The existence of a delta wave is normal for children up to three years of age, in deep sleep and hypnosis. During sleep the waves can be higher than 100 µ V in amplitude.

2.2 Theta Band

The theta band corresponds to waves in the range of 4-8 Hz. Their existence is considered as pathological if their amplitude is at least twice as high as the alpha activity or higher than 30 µ V if alpha activity is absent. The presence of a theta wave is normal if its amplitude is up to 15 µ V and if the waves appear symmetrically [6], [7], [8] and [9]. In healthy person they appear in central, temporal and

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parietal parts. This activity is characteristic for certain periods of sleep.

2.3 Alpha Band

The alpha band corresponds to waves in the range of 18-13 Hz. In the waking state in mental and physical rest the maximum appears in the occipital part of the brain. Its presence is highly influenced by open or closed eyes. The amplitude is in the range of 20-100 µ V, most frequently around 50 µ V.

2.4 Beta Band

The beta band corresponds to the fastest waves in the range of 13-20 Hz. The maximum of the activity is mostly localized in the frontal part, and it decrease in the backward direction. The rhythm is mostly symmetrical or nearly symmetrical in the central part. The amplitude is up to 30 µ V. The activities are characteristic for concentration, logical reasoning and feeling of anger and anxiety.

The measurements given by an EEG are used to confirm or rule out various conditions, including [10]:

- Seizure disorders(such as epilepsy)
- A head injury
- Encephalitis(an inflammation of the brain)
- A brain tumor
- Encephalopathy(a disease that causes brain dysfunction)
- Memory problems
- Sleep disorders
- Stroke
- Dementia
- EEG may be performed to determine the level of brain activity; the test can also be used to monitor activity during brain surgery.
- EEG of Normal patients

The normal EEG is fundamentally a recording of the electrical activity of a highly complex system. This electrical activity is being recorder at the scalp and, although accurate, it is not the same as the recording of activity directly from the surface of brain or at the single cell level. Therefore, from person to person, a variation is expected of waveforms and occasional typical waveforms that still fall within what would be considered normal.

3. EEG of Epileptic patients

The term epilepsy refers to a group of neurological disorder characterized by the recurrence of sudden reactions of brain function caused by abnormalities in its electrical activity, which is clinically manifested as epileptic seizures. Epileptic seizures vary greatly, ranging from a brief lapse of attention to a prolonged loss of consciousness; this loss is accompanied by abnormal motor activity affecting the entire body or one or more extremities [11]. The basic classification of epilepsy and epileptic seizures into partial and generalized seizures is widely accepted. Among generalized epilepsy, grand mal and petit mal seizures are the most prevalent.

4. EEG of Coma patients

Coma is a state of brain function. It can be compared to sleep. However an individual cannot be awaken purposefully from a coma, using either internal or external stimulus. This state can occur due to number of causes, from head injury, through diseases, infectious diseases, brain tumours, metabolic disorders, hypoglycemia, to drug overdose, degenerative diseases, and many more. Great efforts have been taken to scaling comatose states into different levels according to the seriousness, depth and prediction of the probable development of the patient [12]. The first attempt to unify coma classification was the Glasgow classification of unconsciousness (Glasgow Coma Scale-GCS) [13], [14] and [18]. GCS has become widely used, and is reliable scale for classifying coma depth.

5. Phases of EEG signal processing

It is complex process with several steps: Data acquisition, Pre-processing, Digital Filtering, Segmentation, Principal Component Analysis, Extraction of descriptive features and Classification. We focus on segmentation, feature extraction and classification as the most important steps that are decisive for the success of the whole process.

5.1 Data Acquisition: An EEG signal is recorded digitally and saved in a defined format in files on a PC.

5.2 Pre-processing: The aim of pre-processing is to remove noise and thus prepare the signal for further processing. The operations include removal of the DC part of the signal, signal filtering, and removal of certain artifacts [5].

5.3 Digital Filtering: A digital filter is a computer program or algorithm that can remove unwanted frequency components from a signal. As in the case of analog filters, they may be classified as low-pass, high-pass, and band –pass, or notch filters.

5.4 Segmentation: If we use a signal divided into intervals of constant length for acquisition of informative attributes, non-stationariness of the signal may distort the estimation of the characteristics. Segments may contain a mixture of waves of different frequencies and shapes [15]. It depends strongly on the segment length. Therefore it is dividing the signal into segments of different interval length that are quasi-stationary. EEG signals are stochastic signals. Stochastic signals can be divided into two basic

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groups: stationary and non-stationary. Stationary stochastic signals do not change their statistical characteristics in time [16] and [7]. Non-stationary signals may have variable quantities in time, for example mean value, dispersion or frequency spectrum. EEG signals are non-stationary, like most real signals. Therefore spectral analysis or other similar techniques cannot be directly applied to the signal [17].

5.5 Principal Component Analysis: It is a technique used to reduce multidimensional data sets to lower dimensions for analysis and to extract informative features. The principal components may be computed ether using a covariance matrix or using artificial neural networks [18].

5.6 Classification:

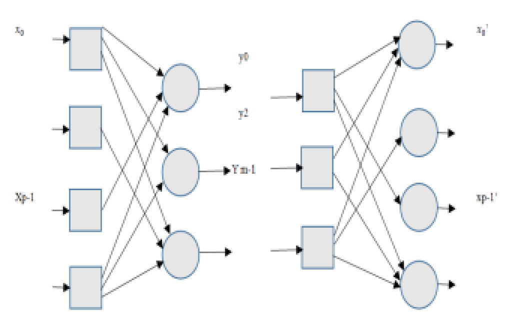
In the following section we use an application of adaptive segmentation and PCA to two types of EEG signals: EEGs of comatose and epileptic patients [19].

Figure 1. Structure of a neural net for PCA computing

Original signal $X = [x_o, x_1, \ldots, x_{p-1}]$

Projection to principal components $Y = [y_o, y_1, \ldots, y_{M-1}]$

Reconstructed signal $X' = [x'_o, x'_1, \ldots, x_{p-1}']$



6. EEG of Comatose Patients

EEG monitoring is employed to control the proper depth of narcosis in coma. The objective is to prepare a set of robust EEG indicators for automatic assessment of coma scales [20]. There is a correlation between the EEG indicators and the clinical scores in comatose patients. One possible approach to pattern recognition is to apply a learning classifier [22]. In mild disturbance of consciousness, diffuse alterations with decrease in alpha and increase in theta and delta activities prevail; more characteristic patterns come with deeper stages of somnolence, spoor, and coma [21]. Faster activities at this stage are most often due to benzodiazepines and barbiturates.

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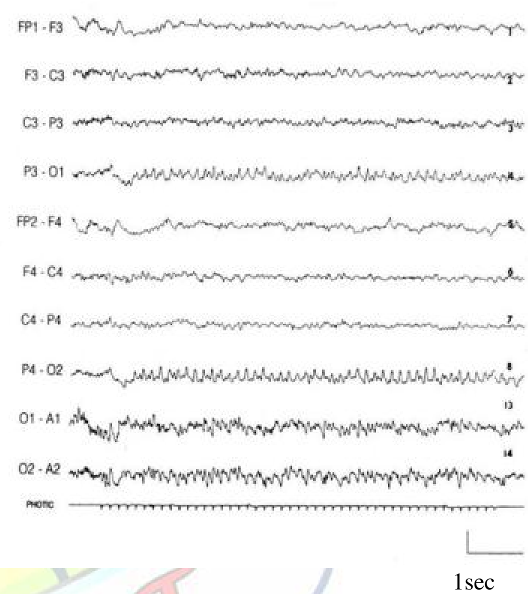
Figure 2. Unusual patterns in coma patient.



6.1 Intermittent rhythmic delta activity

Intermittent rhythmic delta activity occurring most often over the frontal regions, occasionally also posteriorly, is found in more superficial stages of coma (i.e., obtundation, somnolence, and spoor) and deep midline lesions affecting the thalomocortical projections[24],[27].they may also be found in patients with epilepsy but clearly do not represent an ictal pattern[28] (Fig.2).

6.2 Prolonged bursts of slow-wave activity

Prolonged burst of slow-wave activity can occur in a variety of etiologies in deeper stages of coma [23],[24] and [25]. They are most often diffuse but can also be lateralized without any spatiotemporal evolution.

6.3 Stimulus-induced rhythmic, periodic, or ictal discharges (SIRPIDs)

In comatose patients, ictal-appearing or periodic discharges may be evoked after any altering stimulus. They are reproducible and often correlate with the duration of the stimulation [36].

6.4 Generalized periodic and rhythmic discharges

Generalized periodic and rhythmic discharges are frequently found in various stages of coma because of a wide range of etiologies [23], [29], [14] and [18]. Periodic discharges (PDs) can be defined as waves with "relatively

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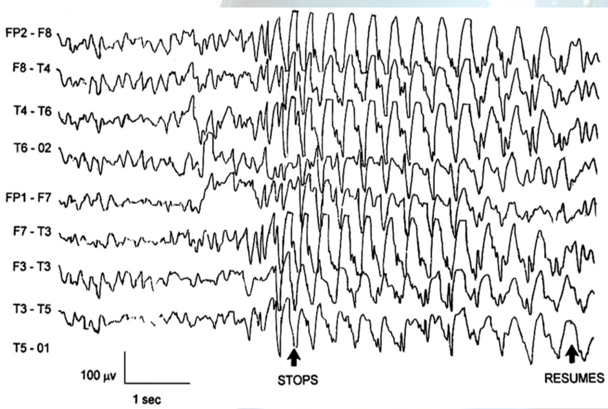
uniform morphology and duration with quantifiable interdischarge interval between consecutive waveforms and recurrence of the waveform at nearly regular intervals between consecutive waveforms and recurrence of the waveform at nearly regularly intervals" [2].

7 EEG of Epileptic Patients

In this example, we borrow an approach used in [13]. It consists in signal pre-processing (conditioning) by enhancing the frequency components that are common for epileptic graphoelements. The resulting signal is then squared and smoothed and compared with a threshold. Threshold crossing indicates the possible presence of spike. This translation is usually achieved using a pattern recognition approach, whose main two main steps are the following:

Figure 3. Electroencephalogram demonstrating benign rolandic epilepsy. Note the characteristic spike and waves seen in drowsiness.



7.1 Feature Extraction

The first signal-processing step is known as 'feature extraction" and aims at describing the EEG signals by (ideally a few relevant values called "features". Such features should capture the information embedded in EEG signals that is relevant to describe the mental states to identify, while rejecting the noise and other non-relevant information.

7.2 Classification

The second step, denoted as "classification," assigns a class to a set of features (the feature vector) extracted from the signals [30]. This class corresponds to the kid of mental state identified. This step can also be denoted as " feature translation". Classification algorithm is also known as "classifiers".

Conclusion

This paper addresses some of the most important issues in EEG signal processing. By its nature, an EEG signal is the most complex signal that can be measured on the human body. The classification on two EEGs signal containing epileptic graphoelements, and EEGs of comatose patients are made. For further there are still more open issues. The first of these is development of new preprocessing methods that can detect artifacts easily and efficiently, and separate them from the useful signal. The second issue is better detection of typical graphoelements that have a specific morphological structure. Finally it is desirable to develop new hierarchical hybrid or multiple classifiers.

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