

# Chapter VIII

## EEG Data Mining Using PCA

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### **ABSTRACT**

*This chapter deals with the application of principal components analysis (PCA) to the field of data mining in electroencephalogram (EEG) processing. The principal components are estimated from the signal by eigen decomposition of the covariance estimate of the input. 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 applications include separation of different signal components for feature extraction in the field of EEG signal processing, adaptive segmentation, epileptic spike detection, and long-term EEG monitoring evaluation of patients in a coma.*

## INTRODUCTION

Computer-assisted processing of long-term electroencephalogram (EEG) recordings has been gaining in importance. The aim is to simplify the work of a physician who needs to make a visual evaluation of EEG recordings many hours in length. At present, EEGs of patients may be recorded over a time span of tens of minutes up to 24 or 48 hours, depending on their purpose. Automatic systems cannot fully replace a physician, but aim to make his/her work more efficient. They identify segments of the signal where there are deviations from standard brain activity, and in this way they save some of the time that would be required for visual inspection of the whole recording.

This chapter deals with the issue of applying advanced methods to the analysis of EEG signals. It describes the design and implementation of a system that performs an automatic analysis of EEG signals.

First, EEG is briefly introduced. Then there is a description of the phases of EEG signal processing. The chapter focuses on the most important parts of this process, namely segmentation, application of principal component analysis (PCA) to feature extraction, and shape detection. The explanation is illustrated by examples of EEGs of comatose and epileptic patients. The chapter concludes with a look at future trends and problems to be addressed in EEG processing.

## ELECTROENCEPHALOGRAM

An electroencephalogram (EEG) is a recording of spontaneous brain electrical activity by means of electrodes located on the scalp. The placing of the electrodes is constrained by natural physical limits, namely by the size of the electrodes, which limits the 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.

In the frequency domain we can distinguish four basic frequency bands on an EEG signal, namely delta, theta, alpha, and beta activities.

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. 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  $\mu\text{V}$  in amplitude.

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  $\mu\text{V}$  if alpha activity is absent. The presence of a theta wave is normal if its amplitude is up to 15  $\mu\text{V}$  and if the waves appear symmetrically. In healthy persons they appear in central, temporal and parietal parts. This activity is characteristic for certain periods of sleep.

The alpha band corresponds to waves in the range of 8-13 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  $\mu\text{V}$ , most frequently around 50  $\mu\text{V}$ .

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 decreases in the backward direction. The rhythm is

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