Using PCA on EEG Data to Differentiate Sleep Stages

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***Abstract*—**

I. Introduction

II. Study of Literature

A substantial body of scientific research has been devoted to exploring Principal Component Analysis (PCA). The foundation of this method was laid by Pearson[9] and Hotelling[4].

An introduction to PCA as well as a good overview on how to derive the formula used to compute the Principal Components (PC) used in Section **??** is given by Shlens[11]. Recent applications and variants of PCA are explored by Jolliffe et. al.[6].

A short discussion on the limitations of PCA as well as example in which PCA fails is given by Shlens[11]. One of the limitations mentioned is that the given data must be linearly dependent. Tenenbaum proposes a non-linear method to combat this problem[12].

Generally speaking the variables must not have third or higher order dependencies between them. In order to reduce a problem dealing with higher order dependencies to a second order one, where we can use PCA as described in this paper, we can transform the data beforehand. This method is called kernel PCA[11].

Another method for combating this problem is Independent Component Analysis (ICA) which is discussed by Naik et. al.[8].

TODO

first work on pcscholkopf1997kernela [9] and [4]

given paper [6]

when does pca fail? [11] and [12] (non-linear method)

book containing sleep phases eeg [2]

Review Paper on Sleep Stage Classification Methods [1]

papers trying to solve similar problem [13] and [10] and [7]

competition using similar data set [3]

winner of competition [5]

III. Mathematical Basics

IV. Principal Component Analysis

V. Sleep Stages and EEG Data

VI. Data and Algorithm

1) subdivide eeg signals in the temporal domain
2) apply fft transforming into frequency domain
3) pca
4) achive dimensinality reduction
5) classification of sleep stages
6) visulisation

VII. Results

VIII. Conclusion

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