北京郵電大學 Beijing University of Posts and Telecommunications

Queen Mary University of London

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Undergraduate Project Report
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Dimension Reduction Methods Applied to Sleep Stage Analysis

Name:	Zekuan Liu
School:	International School
Programme:	Internet of Things Engineering

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Abstract

Sleep is critical to the human body, but sleep disorders bother people frequently in modern daily life. To diagnose sleep disorders, the proportion between sleep stage duration as well as the content of physiological signals are used. A sleep cycle consists of several stages: wake, rapid eye movement (REM), stage 1, stage 2, stage 3, and stage 4. The sleep cycle is repeated several times overnight. Recently, Polysomnography (PSG) is widely used in sleep stage analysis and further address sleep disorders. It records a wide range of physiological signals at the same time, e.g., Electroencephalography (EEG), Electrocardiography (ECG), blood oxygenation, airflow, etc. However, multiply measurements in PSG add data redundancy, and features extracted from physiological data can be very high dimensional compared to the number of data records. In order to tackle this problem, this project has applied dimension reduction methods to high dimensional data, thereby reducing data redundancy, saving computational resource and preventing overfitting. In addition, the complete procedure for sleep stage analysis, including data pre-processing, feature extraction, and downstream classification are implemented as well. Experiments demonstrated the effectiveness of the sleep staging procedure and verified the necessity and superiority of dimension reduction under the sleep stage analysis scenario.

摘要

睡眠对人体非常重要，但是在现代生活中人们经常被睡眠障所困扰，而不同睡眠阶段持续时间的比例与生理信号本身可被用于诊断睡眠障碍。一个睡眠周期包括以下几个阶段：清醒期，快速眼动期（REM），睡眠 1 期（S1），睡眠 2 期（S2），睡眠 3 期（S3）和睡眠 4 期（S4）。睡眠周期会在一晚的睡眠中循环多次。近年来，多导睡眠监测仪被广泛用于睡眠分期并进一步诊断睡眠障碍。多导睡眠监测仪可以同时记录多种生理信号，例如：脑电图（EEG），心电图（ECG），血氧饱和度，呼吸气流等。但多导睡眠监测仪中测量的多种信号会增加数据冗余，且相比于生理信号本身从信号中提取的特征可能有非常高的维度。该项目为解决此问题，将降维方法应用于高维数据，以减少数据冗余，节省计算资源并防止过拟合。此外，该项目还实现了完整的睡眠分期程序，包括数据预处理，特征提取和下游分类。实验证明了睡眠分期程序的有效性，并验证了在睡眠分期场景中降维的必要性和优越性。

Chapter 1: Introduction

1.1 Motivation

Sleep is important for the human body. It is a prerequisite for both physical and mental health. During sleep, the body will protect the metabolizable energy, mature the neuronal connections, and consolidate learning and memory (Faust et al., 2019). However, due to the quickened life rhythm and unhealthy lifestyle, sleep disorders become an increasingly frequent problem in modern daily life. Demographic research reveals that up to 24% of people are faced with regular sleep problems (Willemen et al., 2014), due to sleep apnea, insomnia, hypersomnia, etc. Sleep disorders associated with not only disturbances in cognitive and psychological function, but also increased morbidity and mortality (Hillman and Lack, 2013). For instance, obstructive sleep apnea syndrome (OSAS) has a significant side effect of increased risk of cardiovascular diseases (Boostani et al., 2016). In addition, adverse effects of sleep disorders threaten people's safety, productivity, and quality of life. A study shows that drowsy driving is a key factor in about 100,000 traffic accidents occurring each year in the United States, resulting in thousands of deaths and injuries (Stutts et al., 2003)A French research found that employees with sleep problems missed as twice many as workdays in a year compared to normal sleepers (Faust et al., 2019). Baldwin et al. found that subjective sleep symptoms are comprehensively associated with poorer quality of life (Baldwin et al., 2001).

Nowadays, overnight Polysomnography (PSG) is considered the gold standard in sleep research and allows accurate assessment of sleep. It is widely adopted in sleep stage analysis and further sleep disorders diagnosis (Agarwal and Gotman, 2001; Sulistyo et al., 2017). PSG is a multi-parametric measurement equipment that records a wide range of physiological signals at the same time, including Electroencephalography (EEG), Electrocardiography (ECG), Electrooculography (EOG), Electromyography (EMG), airflow, blood oxygenation, respiratory effort, etc. In conventional systems, PSG sleep stage analysis is carried out manually by experts. However, more and more computer automatic sleep stage analysis systems have replaced humans to perform this tiring and time-consuming task in recent years. In addition to saving the cost of labour, computer systems can help to reduce intra- and inter-observer variability, and further improve the quality of the analysis (Faust et al., 2019). Despite the superiorities, problems still exist. One of the problems is that multiple measurements add data redundancy, i.e., the ECG merely confirms the information already extracted from an EEG signal. Similarly,

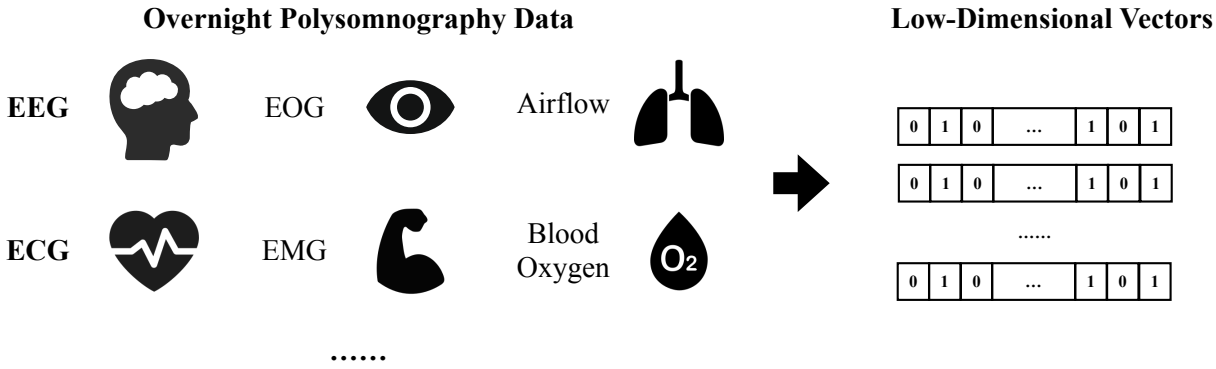


Figure 1 Dimension Reduction on PSG Data

features extracted from physiological data are redundant as well. Therefore, as Figure 1 shows, this project aims to apply dimension reduction methods in computer-based automatic sleep stage analysis, in order to reduce data redundancy, save computational resource, and avoids the issue of over-fitting. Specifically, this project only focused on EEG and ECG of polysomnography data. Finally, obtained data will be used in the downstream classification of different sleep stages.

1.2 Overview

Figure 2 shows the overview of this project. The project is divided into four parts: pre-processing, feature extraction, dimension reduction, and classification.

Data pre-processing is required because a lot of interferences and artefacts could affect the record of the raw data. On top of these, signals have to be segmented into regular 30s epochs as units of further classification.

After pre-processing, various features can be extracted for each epoch of obtained cleaned data. For instance, powers in the frequency band of different waves and Hjorth parameters are estimated from EEG data, so that high dimensional feature vectors are obtained.

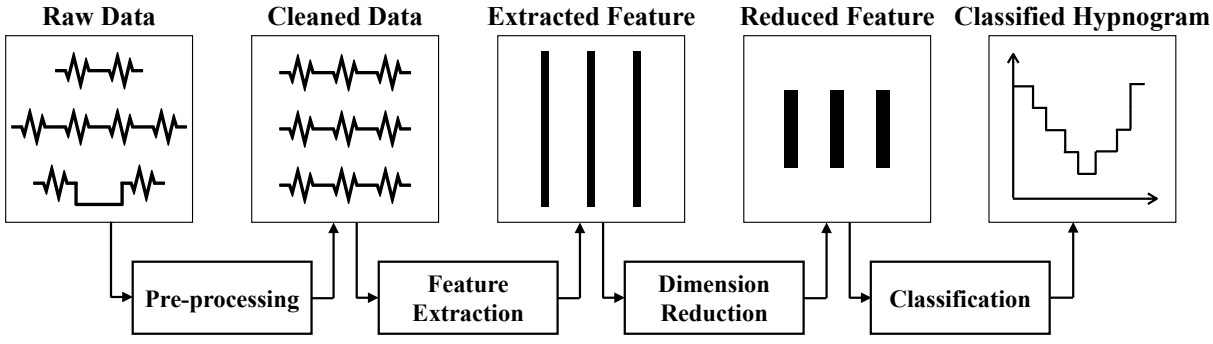


Figure 2 Project Overview

Regarding dimension reduction, the key component of this project, high dimensional vectors are compressed, reducing the size of vectors but preserving most of the information required.

The final step of this project adopted machine learning models to classify overnight sleep into different stages based on the dimension reduced vectors. According to the classification results, overnight hypnograms can be plotted.

1.3 Achievement

In general, the achievements of this project are as follow.

1. Established a pre-processed dataset for sleep stage analysis from raw physiological data.
2. Implemented the feature extraction and dimension reduction processing step of EEG and ECG data.
3. Implemented the classification processing step for various type of classification with multiple classifiers and evaluation matrices.
4. Verified the necessity and superiority of dimension reduction under the sleep stage analysis scenario.
5. Designed a variable weighted PCA based on mutual information, which outweighs conventional PCA in most cases.
6. Proposed an improved representation of hypnogram which is easier to read compared to conventional hypnogram.

Chapter 2: Background

2.1 Polysomnography

Polysomnography (PSG) data is adopted to analyse the sleep stages of patients in this project. PSG is a multi-parametric measurement apparatus that records a wide range of physiological signals simultaneously, Electroencephalogram (EEG), Electrocardiogram (ECG), Electromyogram (EMG), Electrooculogram (EOG), blood oxygenation, respiratory effort, airflow and so on. Despite the variety of data, most of the studies focus on EEG and/or ECG, because sleep is caused by significant changes in brain activities (Faust et al., 2019). Therefore, this project only focused on sleep stage analysis with EEG and ECG signals.

2.1.1 Electroencephalography

Electroencephalography (EEG) signals are recordings of the electrical activity of the human brain. The special device called Electroencephalogram records the signals through electrodes or leads placed on the scalp. Generally, several electrodes are arranged according to standards, but in this project, to simplify the problem, only one channel (C3-A2) of EEG signal is analysed. EEG patterns show different characteristics during sleep stages. EEG waveforms are classified based on their frequency.

Delta wave (0.1 – 4 Hz) is the slowest wave but has the highest amplitude. It is related to the grey matter in the brain. It can be observed in all sleep stages especially in stage 3 and 4, but not in the stages of awake.

Theta wave (5 – 7 Hz) is associated with subconscious activities. It is found in deep relation and meditation. It can increase in sleep stage 1.

Alpha wave (8 – 12 Hz) is observed in awake but relaxed adults. It represents white matter activities of the brain and serves as a bridge between the subconscious and conscious mind.

Sigma wave ranges from 13 to 15 Hz. Sleep stage 2 is characterized by sleep spindles, i.e., transient runs of rhythmic activity in sigma wave.

Beta wave (16 – 30 Hz) is regarding action and behaviour. It is commonly observed during conscious behaviours (e.g., speaking, thinking, and decision making).

Gamma wave (30 – 100 Hz) occurs during the integration of sensory inputs and hyper-alertness. It seldom occurs in normal sleep (Kumar and Bhuvaneswari, 2012).

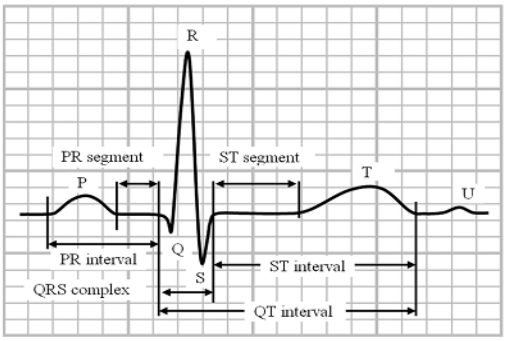


Figure 3 ECG Waveform

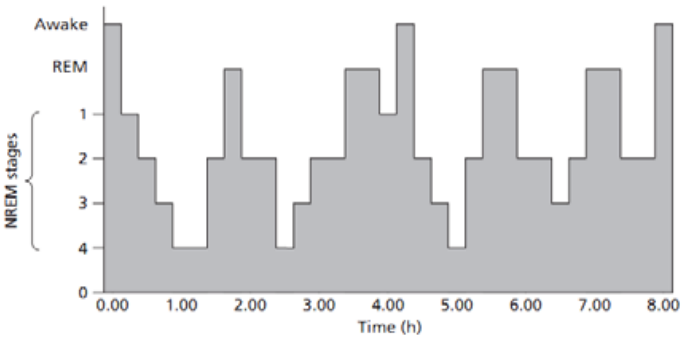


Figure 4 Hypnogram

2.1.2 Electrocardiography

Electrocardiography (ECG) is a recording of the electrical activity of the heart. Similar to EEG signal, single-lead ECG is applied. ECG signals of healthy human are highly structured, and each signal component can be identified via visual inspection (Noviyanto et al., 2011). ECG waveform and its attributes are shown in Figure 3. Sleep stages are also indicated in subtle changes in ECG signals. For instance, the absolute voltage for the P, Q, R, S and T points of the ECG signal in the stage of awake are greater than the stage of sleep. Additionally, the number of samples in the P-QRST interval in the stage of awake is lesser than the stage of sleep. Furthermore, the total amount of R peaks in the constant time interval is also distinguishing between the two stages (Yücelbaş et al., 2018). These difference in the physiological signal provides the foundation of sleep stage analysis in this project.

2.2 Sleep Stage Analysis

Sleep specialists analyse sleep stages following well-established guideline (Berry et al., 2015). Overnight sleep is scored in 30-second epochs. Each epoch is labelled as either wakefulness, rapid eye movement (REM) sleep or one of four stages during non-rapid eye movement (NREM) sleep, including stage 1 (S1), stage 2 (S2), stage 3 (S3), and stage (S4). In some scenarios, stage 1 and stage 2 were merged to Light Sleep (LS), while stage 3 and stage 4 were merged to stage 3, also known as Slow Wave Sleep (SWS) (Faust et al., 2019). The scoring result plotted in temporal consequence is a hypnogram. Figure 4 provides an example of hypnogram (Noviyanto et al., 2011). In this project, sleep stage analysis is completed automatically with computer programs.

Table 1 Signal length of subjects in 30-second epochs

Subject	Epoch	Subject	Epoch	Subject	Epoch	Subject	Epoch	Subject	Epoch
1	748	6	768	11	811	16	852	21	908
2	882	7	925	12	774	17	752	22	711
3	826	8	907	13	916	18	913	23	838
4	808	9	900	14	789	19	787	24	893
5	813	10	864	15	822	20	861	25	721

2.3 Dataset

This project adopted St. Vincent's University Hospital / University College Dublin Sleep Apnea Dataset, which is publicly accessible in PhysioNet (Goldberger et al., 2000). The dataset contains twenty-five overnight polysomnograms with synchronised three-channel Holter ECG, from adult subjects with suspected sleep-disordered breathing.

Subjects were arbitrarily selected over 6 months (from Sept. 2nd to Feb. 3rd) from patients referred to the Sleep Disorders Clinic at St Vincent's University Hospital, Dublin, for potential diagnosis of central sleep apnea, obstructive sleep apnea, or primary snoring. Subjects had to be over 18 years of age, without known autonomic dysfunction and cardiac disease, and not on medication known to interfere with heart rate. Twenty-five subjects (twenty-one males and four females) were selected (age: 50 ± 10 years, range 28 - 68 years; AHI: 24.1 ± 20.3, range 1.7 - 90.9; BMI: 31.6 ± 4.0 kg/m², range 25.1 - 42.5 kg/m²). The signal length of each subject in 30-

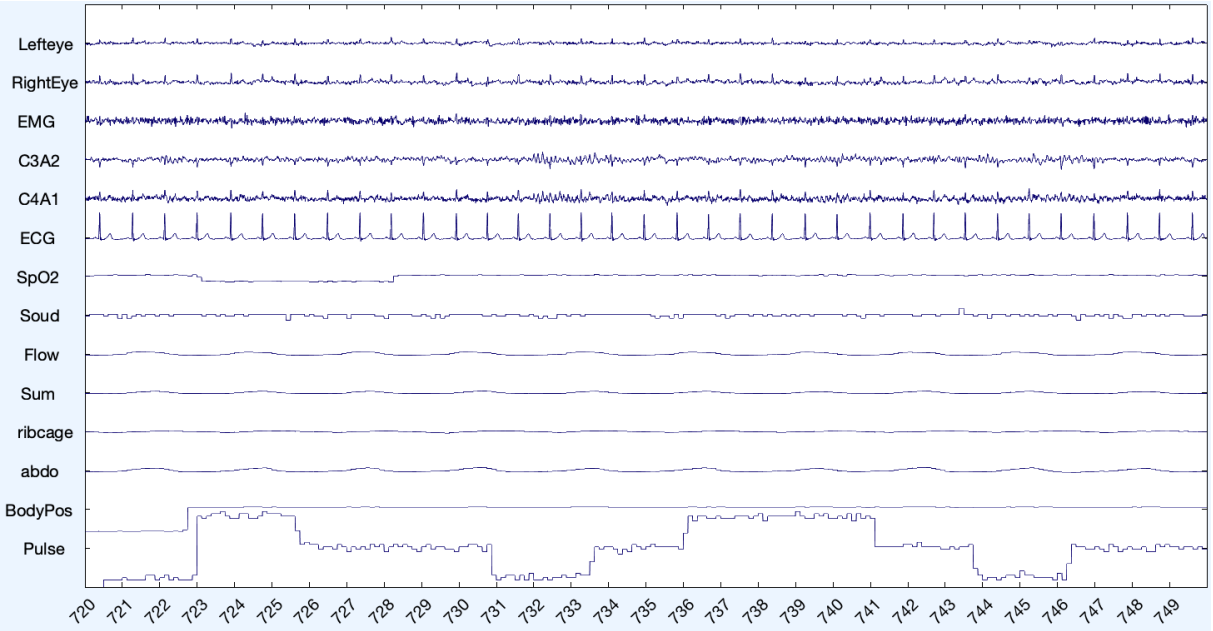


Figure 5 A 30-second sample of the PSG dataset

second epochs is shown in Table 1.

Polysomnograms were acquired with the Jaeger-Toennies system (Erich Jaeger GmbH, Germany). Figure 5 shows a piece of the dataset. Signals recorded were EEG (C4-A1), EEG (C3-A2), left and right EOG, submental EMG, ECG (modified lead V2), oronasal airflow (thermistor), ribcage movements, abdomen movements (uncalibrated strain gauges), oxygen saturation (finger pulse oximeter), snoring (tracheal microphone) and body position. The files are stored in EDF format. In this project, only EEG (C3-A2) and ECG signal are used, and the labels were scored by a skilled sleep technologist according to standard Rechtschaffen and Kales rules. The original dataset is open access at https://doi.org/10.13026/C26C7D.

2.4 Related Work

This project aims at computer-based sleep stage analysis, which stages the sleep with physiological data automatically. In recent years, numerous researches and experiments have published on this task. For instance, Hassan and Bhuiyan have decomposed EEG signals and built a sleep classification system using the RUSBoost classifier (Hassan and Bhuiyan, 2017). The accuracy has been improved in (Bajaj and Pachori, 2013) with an alternative SVM classifier, and Mousavi et al. proposed a model to classify sleep stages further enhanced the performance with the introduction of deep learning (Michielli et al., 2019). Although most of the works were concerning with EEG signals for the reason that changes in brain activities are the origin of sleep and sleep stages, ECG signals are also widely adopted by many researchers because they pick up sleep-related changes in the automatic nervous system and relatively easy to collect compared to EEG signals (Faust et al., 2019). Yücelbaş et al. applied ECG signals to score the sleep (Yücelbaş et al., 2018). Mendez et al. have implemented sleep stage analysis based on heart rate variability (HRV), which is even simpler and cheaper to access (Mendez et al., 2010). In addition to EEG and ECG signals, other signals, e.g., EOG and respiratory effort, are adopted in sleep stage analysis as well (Long et al., 2014; Rahman et al., 2018). Some researchers use multiple types of data at the same time. Phan et al. used multi-modal learning on both EEG and EOG data for sleep staging (Phan et al., 2019). However, most of these works have not focused on dimension reduction.

Chapter 3: Design and Implementation

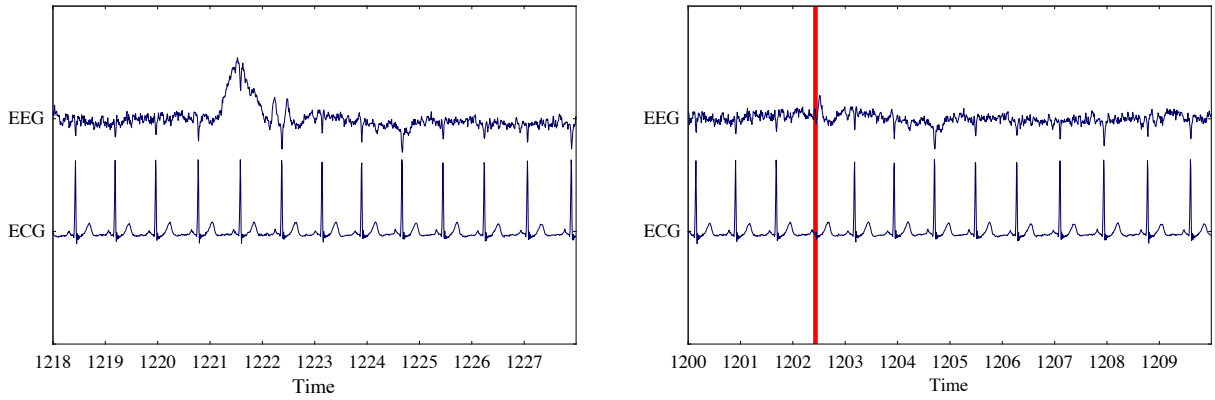
The program in this project is implemented in MATLAB R2021a under macOS Big Sur, with Statistics and Machine Learning Toolbox, Bioinformatics Toolbox, Signal Processing Toolbox, Wavelet Toolbox and DSP System Toolbox. The code is available at https://github.com/kayzliu/DRSleep.

3.1 Pre-processing

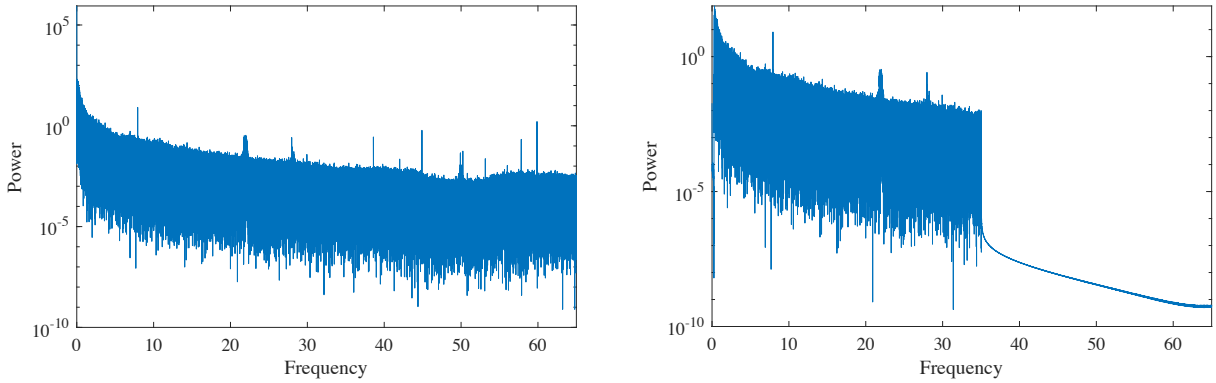
Electroencephalogram (EEG) and electrocardiogram (ECG) are recorded by sensitive electrodes. Due to the complication of the sensing environment, artefacts are inevitable. Basically, there are two types of artefacts, biological artefacts, and environmental artefacts. As the EEG electrodes are placed on the scalp, it will not only record brain neuron electrical activities but also those from eyes (ocular artefacts), muscles (muscle artefacts), even heart (ECG artefacts). These are called biological artefacts. On the other hand, environmental artefacts refer to the artefacts that originated outside of the body, e.g., body movement, 50 or 60 Hz artefacts from the power supply, etc. These artefacts may lead to significant variation to the signal (Motamedi-Fakhr et al., 2014). To reduce the influence of artefacts, three methods can be used in pre-processing of the raw data, rejecting bad data, filtering, and Independent Component Analysis (ICA). In addition to the pre-processing stated above, other commonly used pre-processing steps are also performed, including normalisation, calibration, etc. Furthermore, the signals are required to be divided into uniform 30-second epochs for the later procedure. In this project, EEGLAB (a toolbox developed by UCSD) is applied to implemented part of pre-processing, including selecting channels, removing DC offset, filtering, rejecting bad segment, etc (Delorme and Makeig, 2004).

3.1.1 Removing Bad Data

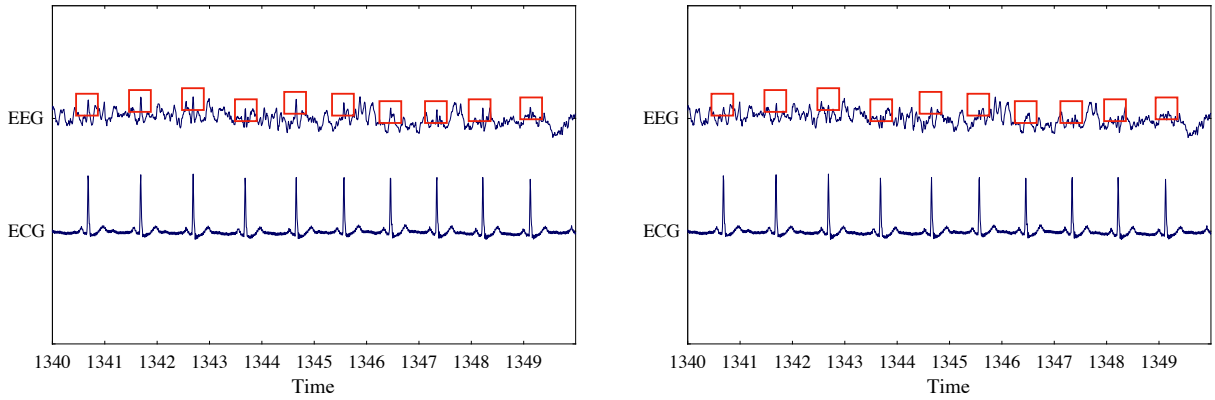
Due to various artefacts, there could be short-time bursts in the recorded signals. For instance, as Figure 6 (a) Left shows, there is an abnormally large value between 1221 second and 1222 second in the EEG channel. To prevent the negative effect on the later procedure, the standard deviation within a 0.5-second window is estimated. When the estimated result exceeds the threshold (20 in this case), the corresponding signal segment will be considered as a bad segment and removed from all channels. As Figure 6 (a) Right shows, the segment is removed



(a) Removing Bad Data



(b) Filtering



(c) Independent Component Analysis

Figure 6 Signal comparison between before and after pre-processing

and replaced with a red vertical line in its original position. Similarly, flatlines, noise and low-frequency drifts can also be removed by this mean.

3.1.2 Filtering

Although the method used in the last step can remove most of the artefacts, some artefacts remain, e.g., alternating current power supply, which has a small volume but continuously exists

during the record of the signal. Hence, filtering is used to further reduce the artefacts. As for EEG signal, a band-pass filter (0.3 – 35 Hz) is used. As Figure 6 (b) Right shows, the high-frequency components and direct current component in Figure 6 (b) Left have been removed after filtering. Similarly, regarding ECG data, a high-pass filter of 0.3 Hz is applied.

3.1.3 Independent Component Analysis

Another approach that can be conducted is Independent Component Analysis (ICA) which uses the multi-channel property of signals to decompose the dataset into several components which are maximally independent. The electromagnetic property of EEG and ECG signals indicates that these signals satisfy the assumptions of the ICA algorithm, i.e., ones based on an instantaneous mixture model (Motamedi-Fakhr et al., 2014). In addition, a variant sequential independent component analysis, which takes temporal dependence into account can be used to improve the performance (Safont et al., 2014). The crucial application of ICA is the suppression of other electromagnetic characters (e.g., ECG) from EEG signal. As Figure 6 (c) shows, the impulses in red boxes of EEG signal in Figure 6 (c) Left, which are result from ECG signal, are diminished in Figure 6 (c) Right after ICA. The red boxes are in the exact same position in the two figures. However, the main problem of ICA is the lack of automatic and reliable identification of different components, i.e., which component is related to EEG and which component is related to ECG. The incorrect identification can result in an inconsistency problem of the data.

3.1.4 Segmentation

The non-stationary property of PSG signals is not compatible with lots of signal processing algorithms, which suppose the processing signals are stationary. This problem is met in plenty of applications of signal processing and a widely used solution is to segment the signals into small epochs in the time domain such that they can be considered as being nearly stationary (a so-called assumption of quasi-stationarity) within each signal (Motamedi-Fakhr et al., 2014). In this project, the dataset also labelled the data based on 30-second epochs. Hence, rather more practically the study of PSG signals needs to identify the approximate temporal location or time range of events, as a result, naturally any processing scheme uses data corresponding to a certain finite duration window.

3.2 Feature Extraction

Features are parameters that provide information about the underlying structure of the signal of interest. Feature extraction is an important step in the whole procedure, which can significantly affect the final classification outcome. There are different methods to extract features from ECG and EEG signals respectively. As for the ECG signal, autoregressive (AR) coefficients, Shannon entropy, wavelet leader estimates are applied. Regarding the EEG data, both temporal features and spectral features are used. Specifically, frequency domain features are the powers in the frequency band of delta wave, theta wave, alpha wave, sigma wave, and beta wave. On the top of that, Hjorth parameters are estimated in the time domain, including activity, mobility, and complexity.

3.2.1 Autoregressive Coefficient

Autoregressive coefficients, also known as reflection coefficients, are obtained from the autoregressive (AR) model. In an AR model of order p, the output of current is a linear combination of the outputs of past p stages plus a white noise input. The weights on the p past outputs minimize the mean squared prediction error of the autoregression. Its mathematical formula is:

$$y(n) + \sum_{k=1}^{p} a(k)y(n-k) = x(n) \tag{1}$$

where $y(n)$ is the current value of the output; $a(k)$ is autocorrelation coefficient and $x(n)$ is a zero-mean white noise input. The reflection coefficients are the partial autocorrelation coefficients scaled by -1. They indicate the time dependence between $y(n)$ and $y(n-k)$ after subtracting the prediction based on the intervening $k-1$ time steps. In this project, the order of the AR model is 4, and Burg's method is used to calculate the coefficients. It estimates the reflection coefficients and uses the reflection coefficients to estimate the AR parameters recursively (Liang et al., 2012).

3.2.2 Wavelet Leader

Discrete Wavelet Transform (DWT) is a linear operator that decomposes the original signal into two components: approximation coefficients (ACs, which are the low frequency, high scale information of the initial signal) and detail coefficients (DCs, which capture the high frequency, low scale information in the original signal). Then, the DCs remain while the ACs are

recursively decomposed into new DCs and ACs. Owing to its great time and frequency localization ability, DWT can reveal the local characteristics of the input ECG signal. In addition, the multi-level decomposition of an ECG signal into different scales by DWT generates multi-scale features, each of which represents particular characteristics of the signal (Li and Zhou, 2016).

Wavelet leaders are derived from the critically sampled discrete wavelet transform (DWT) coefficients. Wavelet leaders offer significant theoretical advantages over wavelet coefficients in the multifractal formalism. Wavelet leaders are time- or space-localized suprema of the absolute value of the discrete wavelet coefficients. The time localization of the suprema requires that the wavelet coefficients are obtained using a compactly supported wavelet. The Holder exponents, which quantify the local regularity, are determined from these suprema. The singularity spectrum indicates the size of the set of Holder exponents in the data (Serrano and Figliola, 2009; Wendt and Abry, 2007).

3.2.3 Shannon Entropy

In this section, Shannon entropies of the wavelet packet coefficients of discrete wavelet packet transform (WPT) of the ECG signal are estimated. Instead of DWT, which is used in the last section, WPT, an extension of DWT is applied. Since DWT decomposes ACs only at each level, it is hard to extract distinctive information from DCs. On the other hand, in the WPT, the filtering operations are applied to not only ACs but also DCs. Therefore, the WPT has the same frequency bandwidths in each resolution while DWT does not. This property makes WPT not increase and lose information compared to original signals, resulting in the features from WPT having more discrimination power than those from DWT. The mathematical representation of WPT is:

$$\begin{cases} d_{0,0}(t) = y(t), \\ d_{i,2j-1}(t) = \sqrt{2}\sum_{k} h(k) d_{i-1,j}(2t-k), \\ d_{i,2j}(t) = \sqrt{2}\sum_{k} g(k) d_{i-1,j}(2t-k), \end{cases} \tag{2}$$

where $h(k)$ and $g(k)$ are high-pass and low-pass filter respectively, and $d_{i,j}$ is the reconstruction coefficients of WPT at the ith level for the jth node.

Although the coefficients by DWT or WPT can reveal the local characteristics of an ECG signal, the number of such coefficients is usually so huge that it is hard to use them as features for

classification directly. Therefore, Shannon entropy, which measures the uncertainty of the information contained in given systems, may derive from these coefficients for better classification. Mathematically, the Shannon entropy *E* is represented as:

$$E = -\sum_i {d_i}^2 \log\left({d_i}^2\right) \tag{3}$$

where d_i is the wavelet packet coefficients, with the convention 0log(0) = 0 (Li and Zhou, 2016).

3.2.4 Power in Frequency Band

Powers in the frequency band of various waves in EEG signal are estimated, including delta wave (0-4 Hz), theta wave (5-7 Hz), alpha wave (8-12 Hz), sigma wave (13-15 Hz) and beta wave (16-30 Hz). As 2.1.1 illustrated, different waves may have different amplitude, during different sleep stages. Thus, their power in the frequency band can reveal the current sleep stage. To calculate the power of different waves, Fast Fourier transform (FFT) is first conducted, to convert the signal from the time domain to the frequency domain. FFT is a rapid discrete Fourier transform algorithm factorizing the transform matrix into a product of sparse factors. Hence, it reduced the computational complexity from $\mathrm{O}(N^2)$ to $\mathrm{O}(N \log N)$, where *N* is the size of the data. The mathematical formula of discrete Fourier transform is:

$$Y_k = \sum_{n=0}^{N-1} y_n e^{-i2\pi kn/N} \tag{4}$$

where *k* equals to 0 to *N*-1; $e^{i2\pi/N}$ is a primitive *N*th root of 1. After the Fourier transform, the power of different waves (different frequency range) can be obtained by:

$$P = \frac{1}{T}\int_b^a |Y(f)|^2 \mathrm{d}f \tag{5}$$

where *T* is the time range (30 seconds); *a* and *b* are upper bound and lower bound of the wave frequency range, respectively.

3.2.5 Hjorth Parameters

The interpretation of EEG data, consisting of a sequence of observed electrical potentials, is complicated by the lack of a sufficient model to explain how states of the central nervous system are reflected in the measured signals. To resolve this problem and effectively represent the EEG

data, Hjorth parameters, including activity, mobility, and complexity, are proposed (Hjorth, 1973).

Activity parameter is the variance of the signal in the time domain, indicating the surface of the power spectrum in the frequency domain, which means the value of activity parameter is proportional to the number of high-frequency components. Its mathematical definition is:

$$activity = var(y(t)) \tag{6}$$

Mobility parameter is described as the square root of the ratio of the variance of the derivative of the signal and that of the signal. It positively proportions to standard deviation of the power spectrum. Its formula is:

$$mobility = \sqrt{\frac{var(y'(t))}{var(y(t))}} \tag{7}$$

Complexity parameter is the shape similarity between a signal and a pure sine wave. Its value converges to 1 as the shape of the signal becomes more similar to a sine wave.

$$complexity = \frac{mobility(y'(t))}{mobility(y(t))} \tag{8}$$

While these three parameters contain information about the frequency spectrum of a signal, they also help analyze signals in the time domain. In addition, they have lower computational complexity.

3.3 Dimension Reduction

Dimension reduction in this project is implemented with principal component analysis (PCA) and weighted PCA.

3.3.1 Principal Component Analysis

Principal component analysis (PCA) is a common linear dimension reduction algorithm. The idea of the PCA is to find the most important components in the data through linear transformation and to sort the obtained principal component vectors according to their explained variances. Based on the required number of components, the first serval components are remained, while other components are discarded. The original high dimensional data is finally transformed into a linearly independent representation of each dimension of the group, revealing the intrinsic structure behind the high dimensional data. The dimensionality reduction

of the data through PCA can achieve the effect of removing noise and redundancy and simplifying the model while maintaining the information of the original data to the greatest extent. Its optimization goal is maximizing the explained variance of the data in low dimensional space. It can be represented in the formula:

$$w = argmax \frac{w^T X^T X w}{w^T w} \tag{9}$$

where the w is the parameter, and the X is the data (Alickovic and Subasi, 2018).

3.3.2 Weighted Principal Component Analysis

There are briefly two types of weighted PCA (WPCA), sample-wise weighted PCA and variable-wise weighted PCA. In order to adapt to the trend and continuously learn the new information, sample-wise weighted PCA adopt moving window, recursing or EWMA (Exponentially Weighted Moving Average) filter and so on (Fan et al., 2011). As for variable-wise weighted PCA, the weightings are determined by a customized formula, with consideration given not to over-weight variables. In this project, the variable-wise weighted PCA is adopted, and mutual information is used as weights while performing the principal components analysis. The weights are defined as:

$$weight_i = I(X_i, Y) = \sum_{j,k} P(X_i = x_j, Y = y_k) \log \frac{P(X_i = x_j, Y = y_k)}{P(X_i = x_j) P(Y = y_k)} \tag{10}$$

where I is the mutual information of feature variable X_i and label Y. As the features are continuous variables. They are discretized into 256 bins or the number of unique values in the variable if it is less than 256. The function finds optimal bivariate bins for each pair of variables using the adaptive algorithm (Darbellay and Vajda, 1999).

3.4 Classification

In the classification stage, the leave-one-out classification based on the 30s epochs is used. First, the data splitting is based on leave-one-out, which means in each experiment one subject is used as the testing set, while others are used as the training set. For instance, in a dataset of 10 subjects, the training set is subject 2 to subject 10, while subject 1 is the testing set; in the next experiment, subject 2 is specified as the testing set, and others (subject 1 and subject 3 to 10) are defined as the training set. Then, according to different classification type, the label of the data has to be modified. In this project, three types of classification are investigated, including

three classification (Wake, REM, and NREM), four classification (Wake, REM, LS, SWS), and full six classification (Wake, REM, S1, S2, S3, and S4). After the specification of the classifier, the relabelled training data can be imported into the classifier and start training. Depending on the classifier, the computing period may vary. Next, the testing dataset is predicted by the trained model. By comparison of predicted values and actual values, evaluation metrics (confusion matrix and average accuracy, in this project) can be obtained. A visualisation of hypnogram can be obtained by plotting the classification result in temporal sequence (sample result can be found in Figure 10 in Chapter 4).

Despite it is critical to select a suitable classifier to achieve better performance, the emphasis of this project is on dimension reduction instead of classification. Therefore, only several classical classifiers are used, and delicate deep learning classifiers are not included. Classification only serves as a downstream task, which is used to evaluate the result of the previous procedure.

3.4.1 Linear Discriminant Analysis

Linear discriminant analysis (LDA) is an algorithm that finds a linear combination of features that characterizes or separates two or more classes of objects. It also frequently used on dimension reduction. It is suitable when the data of different classes are Gaussian distributed and have similar variances. The model predict classifies so as to minimize the expected classification cost:

$$\hat{y} = \underset{y=1\ldots K}{\operatorname{argmin}} \sum_{k=1}^{K} \widehat{P}(k|x) C(y|k), \tag{11}$$

where $\hat{y}$ is the predicted classification; K is the number of classes; $\hat{P}(k|x)$ is the posterior probability of class k for observation x; and $C(y|k)$ is the cost of classifying an observation as y when its true class is k (Singh et al., 2016).

3.4.2 Quadratic Discriminant Analysis

Quadratic Discriminant Analysis (QDA) is similar to LDA. It also assumes the data of different classes are normally distributed, but QDA can tackle various means and covariances, which is more difficult to handle. Unlike LDA, which separates the classes using a linear surface, QDA separates the classes using a quadratic surface (i.e., a conic section) (Singh et al., 2016).

3.4.3 *k*-Nearest Neighbour

k-Nearest Neighbour (*k*NN) is a non-parametric classification method. The predicted class of specific unlabelled sample point is depending on the most common class of its k nearest neighbours (k is a positive integer). If $k = 1$, the sample is simply assigned to the class of the nearest neighbour. The nearest neighbour can be measured in multiple distances, but Euclidean distance is usually used. It is suitable for classification with multiple labels as well as multi-modal classification. However, it is simple and low efficient. The selection of optimal hyperparameter k is also a problem. The algorithm is sensitive to noise and unstable on performance (Singh et al., 2016).

3.4.4 Naïve Bayes Classifier

Naïve Bayes (NB) is a classifier based on Bayes' theorem, assuming strong independence between the features. Its mathematical formula is:

$$\hat{y} = \underset{k=1\ldots K}{\operatorname{argmax}} P(C_k) \prod_{i=1}^{n} P(x_i|C_k) \tag{12}$$

where $\hat{y}$ is the predicted classification; K is the number of classes; C_k is the kth class; and x_i is features of the ith sample. Naïve Bayes classifier is highly scalable. It requires a number of parameters linear in the number of features in a learning problem, taking less computational time (Singh et al., 2016).

3.4.5 Support Vector Machine

Support Vector Machine is a sophisticated algorithm, providing high accuracy with an appropriate kernel. It maps training samples to points in high dimensional space to maximise the gap width between classes and separates different classes with a hyperplane. In the testing stage, new samples are mapped into the same space and categorised based on the region they located. Unlike some algorithms (e.g., *k*-NN), the performance of SVM is independent of the size of the data as well as feature dimension, but the number of training cycles. It provides a high generalisation ability, preventing overfitting problem theoretically. However, it requires relatively longer computational time, and its performance also depends on the parameters (Singh et al., 2016).

Chapter 4: Results and Discussion

To validate the design and implementation described in the last chapter, several comparison experiments are conducted.

4.1 Classifier

According to the last chapter, Linear Discriminant Analysis (LDA), Quadratic Discriminant

Table 2 Comparison result of different classifiers

LDA	Wake	REM	S1	S2	S3	S4
Wake	1107	134	524	78	1	1
REM	216	1322	616	761	11	7
S1	311	246	475	286	1	1
S2	106	210	372	2980	158	125
S3	54	67	91	851	224	434
S4	64	31	62	246	141	950

(a)

QDA	Wake	REM	S1	S2	S3	S4
Wake	533	73	221	99	9	15
REM	503	1434	969	967	13	13
S1	668	193	457	176	1	5
S2	84	214	358	2727	153	139
S3	38	51	66	806	195	310
S4	32	45	69	427	165	1036

(b)

*k*NN	Wake	REM	S1	S2	S3	S4
Wake	826	218	468	191	6	10
REM	228	825	410	455	13	20
S1	500	436	566	612	29	52
S2	267	484	618	3277	274	417
S3	15	15	37	266	59	166
S4	22	32	41	401	155	853

(c)

NB	Wake	REM	S1	S2	S3	S4
Wake	552	57	191	72	6	4
REM	421	1367	802	822	2	1
S1	664	184	511	151	0	0
S2	137	331	534	3584	278	254
S3	35	17	21	129	41	72
S4	49	54	81	444	209	1187

(d)

SVM	Wake	REM	S1	S2	S3	S4
Wake	1080	106	474	95	3	5
REM	198	1069	427	299	0	3
S1	338	273	462	171	2	7
S2	223	539	739	4374	364	492
S3	0	0	0	0	0	0
S4	19	23	38	263	167	1011

(e)

ACC	WRN	WRLS	ALL
LDA	74.1	62.5	53.2
QDA	68.3	55.7	48.1
***k*NN**	71.4	60.0	48.3
NB	71.0	61.9	54.6
SVM	**77.2**	**68.4**	**60.3**

(f)

Analysis (QDA), *k*-Nearest Neighbour (*k*NN), Support Vector Machine (SVM), and Naïve Bayes Classifier (NB) can be applied in downstream classification. However, different classifiers can have diverse performance under various scenarios. The comparison results of different classifiers in the same settings (only EEG data, without dimension reduction) is shown in Table 2. Sub-table (a) to (e) show the confusion matrixes (summation of all subjects) of different classifiers, and sub-table (f) shows the average accuracies (the number of correct epochs divided by the number of all epochs) of classifiers in WRN (Wake, REM, and NREM), WRLS (Wake, REM, LS, SWS), and ALL (Wake, REM, S1, S2, S3, and S4), respectively. Despite SVM cannot distinguish S3, SVM significantly outperforms other classifiers in accuracy in all types of classification. Therefore, SVM is selected for follow-up experiments.

4.2 Pre-processing

In order to verify the effectiveness of the pre-processing, three variants of the procedure are implemented. The first one is the raw data without any pre-processing (RAW). The second one is the data with only filtering (FLT). The third one is the data with only removing bad segments (RMD). Same settings (SVM classifier, only EEG data, without dimension reduction) are used

Table 3 Comparison result of different pre-processing

RAW	Wake	REM	S1	S2	S3	S4
Wake	3097	339	840	323	31	69
REM	415	1172	538	429	6	3
S1	269	294	284	169	0	0
S2	796	1116	1654	5826	543	1360
S3	0	0	0	0	0	0
S4	145	95	87	238	93	558

(a)

FLT	Wake	REM	S1	S2	S3	S4
Wake	3032	354	829	303	23	76
REM	446	1247	547	383	0	0
S1	288	348	278	184	0	0
S2	798	1000	1663	5734	491	867
S3	0	0	0	0	0	0
S4	158	67	86	381	159	1047

(b)

RMD	Wake	REM	S1	S2	S3	S4
Wake	1164	131	535	121	6	6
REM	208	1347	519	379	8	5
S1	370	246	430	179	1	1
S2	257	577	762	4258	374	670
S3	0	0	0	0	0	0
S4	27	35	51	300	147	836

(c)

ACC	WRN	WRLS	ALL
RAW	72.5	61.8	52.6
FLT	73.0	64.2	54.5
RMD	75.4	65.4	57.6
FULL	**77.2**	**68.4**	**60.3**

(d)

in three variants except for the difference in pre-processing. Table 3 shows the final classification results of these variants and fully pre-processed data (FULL). Sub-table (a) to (c) show the confusion matrixes of different pre-processing, and sub-table (d) shows a summary of the average accuracy of each pre-processing. As the confusion matrix of FULL is the same as Table 1 (e), it is not shown in Table 3. According to Table 3, it is obvious that FULL performs better than others in all three classification types, indicating that both pre-processing, filtering and removing bad segments, are necessary.

4.3 Dimension Reduction

In this section, the influence of dimension reduction of different numbers of components is investigated. In order to facilitate the experiment, a pre-processed sub-dataset of 10 subjects is used in the experiments described in this section. Figure 7 shows how explained variance decrease with the reduction of the number of components in three types of data, EEG, ECG and COM (linear combination of EEG and ECG). The blue curve shows the change with conventional PCA, while the orange curve shows the weighted. Although the explained variance monotonically decreases, it changes slightly at the beginning and remains a high value after significantly reducing the number of components, which demonstrated the necessity of dimension reduction. Moreover, the orange curve is always above the blue curve, proving that weighted PCA helps information compact in first serval components better than the conventional one.

Figure 8 describes the relationship between the classification performance and the number of components with different data and different classification types. Sub-figure (a) shows the results of ALL (six classes full classification), sub-figure (b) shows WRLS (Wake, REM, LS, and SWS), and (c) shows WRN (Wake, REM, and NREM). In each sub-figure, the result of EEG, ECG, and COM (linear combination of EEG and ECG) data are shown in the Left, Middle, and Right, respectively. In the figure, blue curves represent the results of PCA, while orange

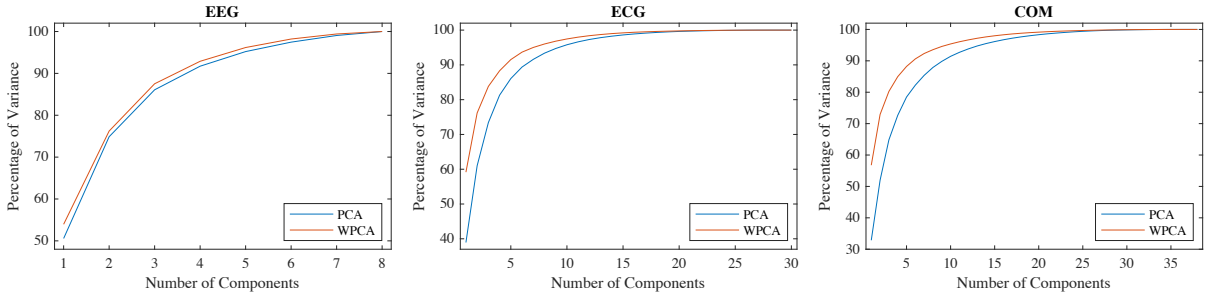


Figure 7 Percentage of variance verse number of components

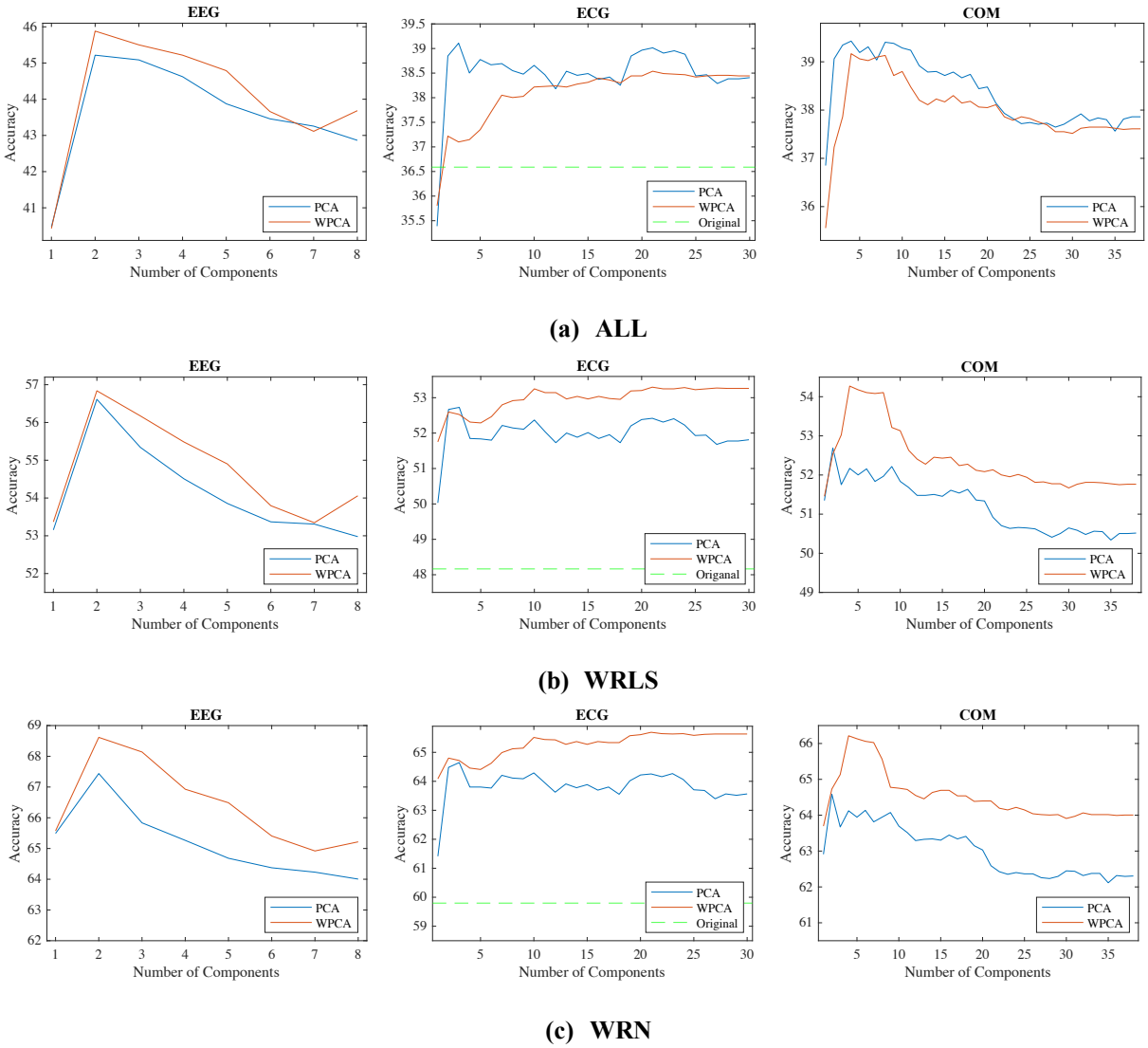


Figure 8 Classification accuracy verse number of components

curves represent WPCA's, and green horizontal lines show the results before dimension reduction. Table 4 shows the comparison optimal results of different data in different classification types.

From Figure 8 and Table 4, several conclusions can be drawn. First, in most curves, the optimal result is achieved with a relatively small number of components instead of maximum. The decrease in the performance with the increasing number of components could result from the noise contained in the latter components. It demonstrates the necessity and superiority of dimension reduction in general circumstances. Second, in the cases of relatively poor performance (e.g., ECG data shown in Figure 8 Middles and bold accuracy in Table 4), dimension reduction helps improve the performance of downstream classification. However, in the circumstances that original data has already achieved a high performance, the accuracy can

Table 4 Comparison of optimal accuracy of different dimension reduction methods

	WRN			WRLS			ALL		
	EEG	**ECG**	**COM**	**EEG**	**ECG**	**COM**	**EEG**	**ECG**	**COM**
Original	75.8	59.8	74.1	69.1	48.2	66.0	60.3	36.6	55.2
PCA	67.4	64.6	64.6	56.6	52.7	52.7	45.2	**39.1**	39.4
WPCA	68.6	**65.7**	66.2	56.8	**53.3**	54.3	45.9	38.5	39.2

drop after dimension reduction. The conclusion further proves the necessity and superiority of dimension reduction in specific scenarios. Third, the weighted PCA (WPCA) designed in this project has improved the classification accuracy in most cases. However, the performance can still decline in the case of both high dimension with many classes (e.g., Middle and Right in sub-figure (a)). In general, the effectiveness of weighted PCA has been verified.

4.4 Hypnogram

Hypnogram is a graph that plot the sleep stage results in a temporal consequence, which allows the different stages of sleep to be identified during the sleep cycle as was explained in Chapter 2. Figure 2 provides a sample of conventional hypnogram, an ideal model, which has perfect cycles of sleep. However, in reality, the sleep cycle of patients may not that predictable. Figure 9 shows the hypnogram of a sample in the dataset. The sleep could frequently switch between two or more stages within a short period of time, and the sleep cycle may not follow the constant sequence. Hence, the hypnogram can be very messy, and hard to extract useful information, especially in those periods of irregular stage switching. Fortunately, it is easy to obtain by analysis that the vertical lines in the hypnogram are the main reason for the confusion, but they seldom contain information related to sleep stages. Therefore, in this project, points, instead of

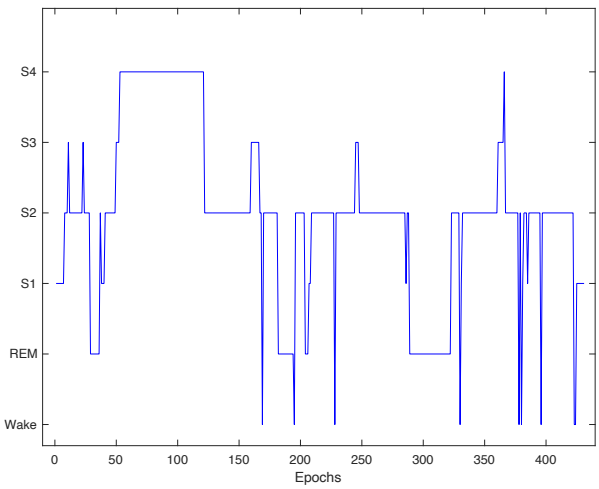


Figure 9 Conventional Hypnogram

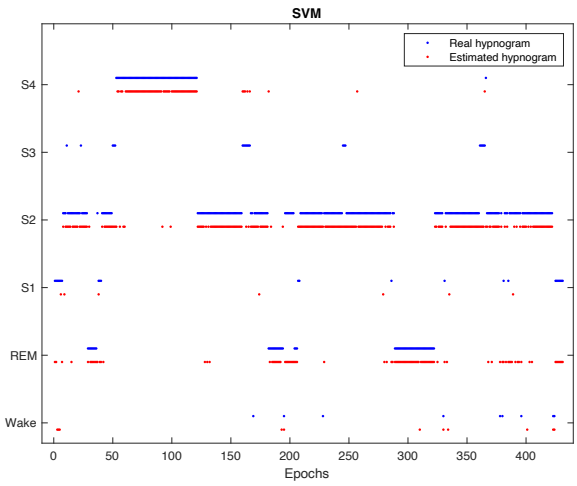


Figure 10 Comparison Hypnogram

lines, are used to represent the sleep stage in a specific time range, and the sample result is shown in Figure 10. Sleep stages are more clearly shown in the figure.

Figure 10 shows the hypnogram of overnight sleep of subject 5. the red points represent the classification result (Estimated hypnogram), while the blue points are ground truth results labelled by an expert (Real hypnogram). The accuracy reaches 77% in this subject. According to the figure, the result is relatively favourable, which is consistent with its accuracy. The estimated hypnogram has basically restored the real hypnogram, but approximate stages which are too hard to distinguish (e.g., S3 and S4) are sometimes confused. The effectiveness of the procedure has been proved.

Chapter 5: Conclusion and Further Work

5.1 Conclusion

In this project, the complete procedure of sleep stage analysis based on PSG data is investigated, including data pre-processing, feature extraction, dimension reduction, and stage classification, emphasizing dimension reduction. A series of experiments demonstrate the achievements of the project. The pre-processing of the dataset is effective, significantly improving the quality of the data and downstream classification performance. The features extracted from the data successfully represented the necessary information in both EEG and ECG signals for staging. Dimension reduction using PCA and designed weighted PCA has conserved the computational resource and facilitate the analysis process, even improved analysis performance in some cases. Classification of different models are compared, and the optimal one reaches satisfactory matrices. The result of such sleep stage analysis procedure can be used in further assistance for clinic diagnosis of sleep disorders (e.g., sleep apnea), reducing inter- and intra-observer variability and decreasing the need for interpreting multiple signals. In addition to the sleep stage analysis procedure, the pre-processed dataset and extracted feature data of St. Vincent's University Hospital / University College Dublin Sleep Apnea Database have established and can be used in further study as well. Furthermore, a novel form of hypnogram is proposed. It is more straightforward compared to a traditional hypnogram.

5.2 Further Work

Although the project is completed to the largest extent since the limitation of project duration and other unavoidable factors, further work of the project can be conducted from several aspects.

1. In this project, only conventional statistic machine learning classifiers are used. However, in recent years, deep learning has been applied in plenty of scenarios and achieved surprising performance, such as computer vision and natural language processing and so on. Introducing deep learning may significantly improve the result of the staging.
2. This project has not considered the temporal relations between the epochs in the signal. However, PSG data has a strong temporal dependence. To take information in previous epochs into account, Hidden Markov Model (HMM) can be used. Combining with deep learning, the neural network model which considered temporal relation (e.g., recurrent

neural network, LSTM, etc.) can be attempted as well.

3. In order to simplify the problem, only EEG and ECG signal in PSG is used in this project. However, other signals in PSG, such as EOG, can provide additional information related to sleep. The synthesis of these data may also enhance the outcome of the procedure.
4. Dataset adopted in this project is collected with suspicious patients. However, a normal sleeper can have a more typical sleep pattern. Adding normal sleepers' data can help model better learn the physiological signal pattern of each sleep stage.

References

Agarwal R and Gotman J (2001) Computer-assisted sleep staging. *IEEE Transactions on Biomedical Engineering* 48(12): 1412–1423. DOI: 10.1109/10.966600.

Alickovic E and Subasi A (2018) Ensemble SVM Method for Automatic Sleep Stage Classification. *IEEE Transactions on Instrumentation and Measurement* 67(6): 1258–1265. DOI: 10.1109/tim.2018.2799059.

Bajaj V and Pachori RB (2013) Automatic classification of sleep stages based on the time-frequency image of EEG signals. *Computer Methods and Programs in Biomedicine* 112(3): 320–328. DOI: 10.1016/j.cmpb.2013.07.006.

Baldwin CM, Griffith KA, Nieto FJ, et al. (2001) The Association of Sleep-Disordered Breathing and Sleep Symptoms with Quality of Life in the Sleep Heart Health Study. *Sleep* 24(1): 96–105. DOI: 10.1093/sleep/24.1.96.

Berry RB, R. B, E. GC, et al. (2015) The AASM Manual for the Scoring of Sleep and Associated Events: Rules, Terminology and Technical Specifications. American Academy of Sleep Medicine. Available at: http://www.aasmnet.org/.

Boostani R, Karimzadeh F and Torabi-Nami M (2016) A Comparative Review on Sleep Stage Classification Methods.pdf. Available at: https://hal.archives-ouvertes.fr/hal-01390384.

Darbellay GA and Vajda I (1999) Estimation of the information by an adaptive partitioning of the observation space. *IEEE Transactions on Information Theory* 45(4): 1315–1321. DOI: 10.1109/18.761290.

Delorme A and Makeig S (2004) EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis. *Journal of Neuroscience Methods*.

Fan Z, Liu E and Xu B (2011) Weighted Principal Component Analysis. In: *Artificial Intelligence and Computational Intelligence*, 1 September 2011.

Faust O, Razaghi H, Barika R, et al. (2019) A review of automated sleep stage scoring based on physiological signals for the new millennia. *Computer Methods and Programs in Biomedicine* 176: 81–91. DOI: 10.1016/j.cmpb.2019.04.032.

Goldberger AL, Amaral LAN, Glass L, et al. (2000) PhysioBank, PhysioToolkit, and PhysioNet. *Circulation* 101(23): E215-20. DOI: 10.1161/01.cir.101.23.e215.

Hassan AR and Bhuiyan MIH (2017) Automated identification of sleep states from EEG signals by means of ensemble empirical mode decomposition and random under sampling boosting. *Computer Methods and Programs in Biomedicine* 140: 201–210. DOI: 10.1016/j.cmpb.2016.12.015.

Hillman DR and Lack LC (2013) Public health implications of sleep loss: the community burden. *Medical Journal of Australia* 199(S8): S7–S10. DOI: 10.5694/mja13.10620.

Hjorth B (1973) The physical significance of time domain descriptors in EEG analysis. *Electroencephalography and Clinical Neurophysiology* 34(3): 321–325. DOI: 10.1016/0013-4694(73)90260-5.

Kumar JS and Bhuvaneswari P (2012) Analysis of Electroencephalography (EEG) Signals and Its Categorization–A Study. *Procedia Engineering* 38: 2525–2536. DOI: 10.1016/j.proeng.2012.06.298.

Li T and Zhou M (2016) ECG Classification Using Wavelet Packet Entropy and Random Forests. *Entropy* 18(8): 285. DOI: 10.3390/e18080285.

Liang S-F, Kuo C-E, Hu Y-H, et al. (2012) Automatic Stage Scoring of Single-Channel Sleep EEG by Using Multiscale Entropy and Autoregressive Models. *IEEE Transactions on Instrumentation and Measurement* 61(6): 1649–1657. DOI: 10.1109/tim.2012.2187242.

Long X, Foussier J, Fonseca P, et al. (2014) Analyzing respiratory effort amplitude for automated sleep stage classification. *Biomedical Signal Processing and Control* 14: 197–205. DOI: 10.1016/j.bspc.2014.08.001.

Mendez MO, Matteucci M, Castronovo V, et al. (2010) Sleep staging from Heart Rate Variability: time-varying spectral features and Hidden Markov Models. *International Journal of Biomedical Engineering and Technology* 3(3/4): 246. DOI: 10.1504/ijbet.2010.032695.

Michielli N, Acharya UR and Molinari F (2019) Cascaded LSTM recurrent neural network for automated sleep stage classification using single-channel EEG signals. *Computers in Biology and Medicine* 106: 71–81. DOI: 10.1016/j.compbiomed.2019.01.013.

Motamedi-Fakhr S, Moshrefi-Torbati M, Hill M, et al. (2014) Signal processing techniques applied to human sleep EEG signals—A review. *Biomedical Signal Processing and Control* 10: 21–33. DOI: 10.1016/j.bspc.2013.12.003.

Noviyanto A, Isa SM, Wasito I, et al. (2011) Selecting features of single lead ECG signal for automatic sleep stages classification using correlation-based feature subset selection. *International Journal of Computer Science Issues* 8(5): 139.

Phan H, Chén OY, Koch P, et al. (2019) Towards More Accurate Automatic Sleep Staging via Deep Transfer Learning. *arXiv*. DOI: 10.1109/tbme.2020.3020381.

Rahman MM, Bhuiyan MIH and Hassan AR (2018) Sleep stage classification using single-channel EOG. *Computers in Biology and Medicine* 102: 211–220. DOI: 10.1016/j.compbiomed.2018.08.022.

Safont G, Salazar A, Vergara L, et al. (2014) Mixtures of Independent Component Analyzers for Microarousal Detection. *IEEE-EMBS International Conference on Biomedical and Health Informatics (BHI)*: 752–755. DOI: 10.1109/bhi.2014.6864473.

Serrano E and Figliola A (2009) Wavelet Leaders: A new method to estimate the multifractal singularity spectra. *Physica A: Statistical Mechanics and its Applications* 388(14): 2793–2805. DOI: 10.1016/j.physa.2009.03.043.

Singh A, Thakur N and Sharma A (2016) A Review of Supervised Machine Learning Algorithms. In: *Proceedings of International Conference on Computing for Sustainable Global Development*, New Delhi, India, 18 March 2016. IEEE.

Stutts JC, Wilkins JW, Osberg JS, et al. (2003) Driver risk factors for sleep-related crashes. *Accident Analysis & Prevention* 35(3): 321–331. DOI: 10.1016/s0001-4575(02)00007-6.

Sulistyo B, Surantha N and Isa SM (2017) Sleep Apnea Identification using HRV Features of ECG Signals. *International Journal of Electrical and Computer Engineering (IJECE)* 8(5): 3940–3948. DOI: 10.11591/ijece.v8i5.pp3940-3948.

Wendt H and Abry P (2007) Multifractality Tests Using Bootstrapped Wavelet Leaders. *IEEE Transactions on Signal Processing* 55(10): 4811–4820. DOI: 10.1109/tsp.2007.896269.

Willemen T, Deun DV, Verhaert V, et al. (2014) An Evaluation of Cardiorespiratory and Movement Features With Respect to Sleep-Stage Classification. *IEEE Journal of Biomedical and Health Informatics* 18(2): 661–669. DOI: 10.1109/jbhi.2013.2276083.

Yücelbaş Ş, Yücelbaş C, Tezel G, et al. (2018) Automatic sleep staging based on SVD, VMD, HHT and morphological features of single-lead ECG signal. *Expert Systems with Applications* 102: 193–206. DOI: 10.1016/j.eswa.2018.02.034.

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