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Automatic classification of human sleep recordings combining artifact identification and relevant features selection

Lukas Zoubek

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presented and sat by

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AUTOMATIC CLASSIFICATION OF HUMAN SLEEP RECORDINGS
COMBINING ARTIFACT IDENTIFICATION AND RELEVANT FEATURES
SELECTION

CLASSIFICATION AUTOMATIQUE D'ENREGISTREMENTS DE
SOMMEIL HUMAIN COMBINANT L'IDENTIFICATION D'ARTEFACTS
ET LA SELECTION DE CARACTERISTIQUES PERTINENTES

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Summary

This thesis describes the research focused on development of an automatic system for classification of polysomnographic recordings into different sleep/wake stages. Polysomnographic recordings are typically composed of three signals (EEG, EOG and EMG) and are used to characterize whole night sleep of a person. The aim of the thesis is to propose a complex classification system that would be capable to deal with various artifacts that are rather common in the real physiological signals (EEG, EOG and EMG). Moreover, employment of only the relevant parameters computed from the analyzed signals is desired so as to perform accurate classification of the recordings.

The manuscript is composed of six main chapters. The general overview presented in chapter 1 describes the background of the polysomnography. The chapter clearly presents all the information and terminology needed to understand the field of sleep analysis. It mainly introduces physiological signals monitored, individual sleep/wake stages, rules of visual sleep classification as well as the overview of actual state of automatic sleep analysis. Database of polysomnographic recording analyzed in this thesis is presented at the end of the chapter.

Chapter 2 introduces the difficulty related to the existence of artifacts that can be present in the real polysomnographic recordings. Existence of artifacts can significantly decrease reliability of the automatic sleep/wake stage classification performed using parameters computed from the contaminated signals. In the first part of the chapter, several possible artifacts are categorized and characterized and after it various artifact processing methods are presented. Then, artifact processing strategy employed in this thesis is introduced in detail. In the last part, performance of the strategy applied to a database composed of several polysomnographic recordings is presented and analyzed.

Chapter 3 focuses on the selection of the most relevant features. In the first part, a list of all features extracted from the monitored signals (EEG, EOG and EMG) is presented. Then, the importance of the selection of the most relevant features is discussed and the feature selection methodology proposed in this thesis is presented in detail. At the end of the chapter, the most relevant features selected by the selection method are listed and their importance for automatic classification is discussed.

The complex automatic classification system proposed in this thesis is presented in chapter 4. The system is designed so as to combine the artifact identification strategy proposed in chapter 2 and the feature selection strategy developed in chapter 3. The complex classification system is then able to effectively deal with artifacts and to perform accurate classification of the recordings.

Chapter 5 describes the results obtained on a database composed of 47 polysomnographic recordings. The results present evident improvement in classification of NREM I and REM stages whose discrimination is traditionally difficult. The improved classification is especially caused by employment of only artifact-free EOG and EMG signals as well as by employment of nontraditional time domain parameters like mobility, entropy and kurtosis.

The last chapter concludes the research performed in the thesis and discusses further possible improvements in the field of automatic human sleep analysis.

Keywords: decision making, diagnosis, medical applications, pattern recognition, signal processing

Résumé

Cette thèse décrit notre recherche sur le développement d'un système de classification automatique d'enregistrements de signaux poly-somnographiques en phases de sommeil/éveil. Les enregistrements poly-somnographiques sont composés de trois signaux (EEG, EOG et EMG) et sont classiquement utilisés pour décrire une nuit de sommeil. Le but de cette thèse est de proposer un système de classification capable de prendre en compte les nombreux artefacts présents dans les signaux physiologiques de type EEG, EMG et EOG, tout en n'utilisant que les caractéristiques extraites des signaux les plus discriminantes, en proposant une méthode judicieuse de sélection de celles-ci.

Le manuscrit est composé de 6 chapitres. Le chapitre 1 décrit de manière générale l'analyse polysomnographique. Il présente les informations nécessaires à la compréhension de l'analyse du sommeil ainsi que la terminologie du domaine. Plus particulièrement, il détaille les signaux physiologiques enregistrés, les différentes phases de sommeil/éveil, les règles de classification visuelles utilisées par les experts ainsi qu'un état de l'art de l'analyse automatique du sommeil. La base de signaux utilisée pour mettre au point et valider les méthodes proposées dans cette thèse est introduite à la fin du chapitre.

Le chapitre 2 met en évidence, dans un premier temps, les difficultés liées à l'occurrence d'artefacts dans les signaux enregistrés. Ceux-ci peuvent diminuer de manière significative la fiabilité des classifieurs automatiques. En début de chapitre, plusieurs artefacts parmi les plus courants sont décrits et quelques méthodes de détection et de rejet sont présentées. Ensuite, la méthode de détection utilisée dans cette thèse est décrite en détail et les performances obtenues sur la base de signaux disponible sont présentées et discutées.

Le chapitre 3 s'intéresse plus particulièrement à la sélection des caractéristiques les plus discriminantes. Dans un premier temps, une liste de caractéristiques qu'il est possible d'extraire des signaux polysomnographiques est réalisée puis une méthode judicieuse de sélection de caractéristiques spécialement adaptée aux signaux polysomnographiques est proposée. A la fin du chapitre, les caractéristiques retenues par la méthode sont listées et leurs effets sur les performances en classification en phases de sommeil/éveil sont discutées.

Le système de classification en deux étapes est décrit au chapitre 4. Ce système combine la stratégie de rejet d'artefacts développée au chapitre 2 avec les résultats de la sélection de

caractéristiques présentés au chapitre 3, ce qui lui permet d'être robuste à la présence d'artéfacts dans les signaux et de réaliser une classification performante.

Les résultats obtenus sur la base de signaux constituée de 47 enregistrements de nuits de sommeil sont résumés au chapitre 5. Ils mettent en évidence une nette amélioration de la classification des phases NREM I et REM, traditionnellement difficiles à discriminer, grâce à l'utilisation de signaux EOG et EMG non corrompus ainsi qu'à l'utilisation de caractéristiques temporelles peu classiques, comme la mobilité, l'entropie ou le kurtosis.

Enfin, le dernier chapitre conclut sur les travaux réalisés au cours de cette thèse et ouvre des perspectives pour de nouvelles recherches en classification automatique de sommeil humain.

Les mots clés: décision, diagnostic, application médicales, reconnaissance de formes, traitement du signal

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List of symbols and abbreviations:

ANN	Artificial neural network
AVR	Averaged reference
A/D	Analog to digital
CNC	Central nervous system
CR	Common reference
CRISP-DM	Cross Industry Standard Process for Data Mining
ECG	Electrocardiography
EEG	Electroencephalography
EMG	Electromyography
EOG	Electrooculography
f_s	Sampling frequency
f_N	Nyquist frequency
ICA	Independent component analysis
IQR	Interquartile range
MLP	Multilayer perceptron
MSEC	Multiple Source Eye Correction
NREM	Non Rapid eye movement sleep
NREM I	Non rapid eye movement sleep stage I
NREM II	Non rapid eye movement sleep stage II
NREM III	Non rapid eye movement sleep stage III
NREM IV	Non rapid eye movement sleep stage IV
PCA	Principal component analysis
pk-pk	peak-to-peak amplitude
PS	Paradoxical sleep
PSG	Polysomnography
QRS	Phenomenon in the electrocardiogram
REM	Rapid eye movement sleep
REMs	Rapid eye movements
SBS	Sequential backward selection
SEF	Spectral edge frequency
SEMs	Slow eye movements
sEMG	Surface electromyography
SFS	Sequential forward selection
SWS	Slow wave sleep

Introduction

Sleep is an important human behaviour that not only positively affects the quality of human life but can also be indicative of some health diseases. Human interest in sleep, its role, its mechanism or its importance has been joined to the mankind since the beginning of its existence. The fact that this phenomenon considered to be self-evident in our lives is not well-researched till now can be thus really surprising. There is no doubt that it is caused by the fact that the clinical sleep medicine and sleep research are relatively young fields compared to the other branches of science.

A detailed analysis and an exact interpretation of a human whole night sleep can contribute to the identification or the diagnosis of a wide spectrum of sleep diseases and disorders and can also subsequently give to the physicians some precise instructions on how to treat the patients suffering from sleep disorders. Sleep analysis and its results can also be important for the medical diagnosis of some serious diseases, because they are frequently accompanied by sleep disorders as accessory symptoms.

This thesis deals with the process and analysis of physiological recordings recorded during the whole night sleep. The set of measured signals is denoted as a polysomnographic recording and the information contained in it is used to characterize the actual state of the person during the sleep or to diagnose and treat the disorders in the organism. The analysis of the polysomnographic recordings is essentially aimed at classifying the whole recording into a succession of sleep/wake stages. The physician or medical expert typically splits the polysomnographic recordings into segments with a constant duration - epochs. Then, the physician classifies the epochs into sleep/wake stages on the basis of information extracted from the signals monitored. An experienced physician is also able to deal with possible artifacts or noise that can occur in the polysomnographic recording. He should be able to ignore the artifacts and make his classification upon the information directly associated with the actual state of the sleeping subject. The visual analysis of the polysomnographic recordings is typically a tedious task, because the human expert must analyze long-time recordings representing the whole night sleep of the person. In order to facilitate the work of the physician, an automatic classification system would be worthwhile. The existence of such

an automatic system would also avoid differences in the inter-expert classification which occur when visual analysis is performed.

Though many researches have been made on the choice of the best classifiers to perform automatic sleep classification and many results were published, there are still problems to be solved. One of them corresponds to the occurrence of artifacts in the polysomnographic signals. The artifacts should be excluded from the signals so as to avoid the devaluation of the information contained in them. Another problem encountered during processing of the polysomnographic signals is the selection of the most relevant information to be used for subsequent classification. This thesis focuses on both these problems – proper processing of artifacts as well as selection and application of relevant features computed from the available signals, in order to design a complex automatic classifier of human polysomnographic recordings.

The first part of the research realized in this thesis focuses on the identification of artifacts and rejection of contaminated segments from the signals monitored (electroencephalogram, electrooculogram and electromyogram). Artifact identification methods capable to detect several technical and biological artifacts are employed in order to separately clean up the individual signals contained in the polysomnographic recording. A strategy evaluating artifact contamination of the epochs is then proposed so as to reduce loss of data caused by presence of artifacts.

The second part of the thesis focuses on the process of extraction and selection of relevant features used for classification. A selection strategy based on a suitable classification criterion is proposed in order to determine the relevant features that discriminate the individual sleep/wake stages the most accurately. The application of only the relevant features can lead to an increase in the classification accuracy as well as to a decrease in the computational time needed to perform classification.

In the last part of the thesis, a complex automatic classification system combining artifact identification with extraction of relevant features from available signals is presented. Since artifact identification and rejection is performed separately on each monitored signals, some values can be missing in the feature set containing features computed from all three signals. To be able to deal with possible missing values, a classification system using a bank of

classifiers is proposed as a suitable solution. The structure of the system will be presented in detail later.

The outline of this thesis is the following. Chapter 1 provides a general introduction to polysomnography. The chapter contains all the terminology and information needed to understand the field of sleep analysis. Physiological signals, individual sleep/wake stages and characteristic of visual sleep classification are presented.

In chapter 2, some problems connected with the existence of artifacts are introduced. Firstly, a number of possible artifacts are categorized and characterized. Then, several artifact processing methods are presented. In the last part, the artifact processing strategy employed in this thesis is characterized in detail and the results obtained when applying this strategy on a data set composed of several polysomnographic recordings are presented.

Chapter 3 focuses on the selection of the most relevant features. In the first part, a list of features extracted from the monitored signals (EEG, EOG and EMG) is presented. Then, the importance of the selection of relevant features for automatic classification is discussed and the feature selection methodology proposed in this thesis is presented in detail. At the end of the chapter, the most relevant features selected by our method are listed and the importance of each of them is discussed.

The complex automatic classification system is presented and characterized in detail in chapter 4. It combines the artifact identification strategy proposed in chapter 2 and the feature selection strategy developed in chapter 3 to design a classifier able to deal with artifacts without losing too many data.

Chapter 5 describes the experiments performed in order to evaluate and compare the performances of the complex two-step automatic classification system. The results obtained in this thesis are summarized at the end.

The last chapter concludes the research performed in the thesis and discusses further possible improvements in the field of automatic sleep analysis.

Chapter 1

Polysomnography

The basic diagnostic method used to analyze the human sleep is the polysomnographic examination – polysomnography. The principle of this method can be evident from the name. During polysomnographic examination are simultaneously monitored and recorded several physiological parameters related to the sleep and vigilance states. Most commonly, this examination takes place in the specialized sleep laboratories and is indicated to analyze the whole night sleep. Then, its results can lead to diagnosis of various sleep disorders [RBRM95], [BBJCC05], [Ling].

First chapter of the thesis will introduce the field of sleep analysis. Before any sophisticated proposition of automatic classification system can be done, it is necessary to understand the theoretical background characterizing the whole process of sleep staging. So, firstly the polysomnographic signals and single sleep/wake stages will be characterized. Such a general description is also needed so as to be able to evaluate the actual state of research in the field of automatic sleep/wake stage classification and to find out the possibility of potential improvements that could be done.

1.1 History of modern polysomnography

The history of the modern polysomnography is closely connected with the first successful experiments of human brain activity monitoring (Electroencephalogram or EEG) realized by German physician H. Berger in 1920s and 1930s [Berger29]. In the middle of 1930s, team of authors chaired by Loomis observed that the electrical activity of the brain is not homogenous during a night sleep [LHH37a]. This finding led to the determination of different sleep stages

characterized on the basis of the EEG analysis. In 1953, E. Aserinsky and N. Kleitman observed presence of rapid eye movements (REMs) during the sleep [AK53]. With a discovery of the rapid eye movements was determined a new state of sleep – rapid eye movement sleep. At the end of 1950s, the sleep analysis was extended by a new monitored physiological signal – electromyogram (EMG). Importance of the EMG for sleep analysis is mainly related to the discovery of muscle atonia during the REM sleep stage characterized in the work of Jouvet *et al.* [JM59], [JMC59]. During the early evolution of the sleep analysis there was not any worldwide accepted set of criteria used for both description of sleep/wake stages and for subsequent classification of polysomnographic recordings. It was the main reason why the inter-rater agreement between the different laboratories was low [Monroe67]. As lately as in 1968, Rechtschaffen and Kales published “A Manual of Standardized Terminology, Techniques and Scoring System for Sleep Stages of Human Subjects” [RK68]. This manual defines a set of rules, criteria and guidelines for classification of the sleep/wake stages in humans. This manual is regarded as the golden standard used for human sleep evaluation. Since 1968, several supplements and updates of this manual have been published especially in order to increase intra- and inter-rater agreement as well as to facilitate development of automatic systems for sleep analysis [HSKS+01], [PHHC+07]. Implementation of the unified system created for sleep analysis and sleep/wake stages classification made possible wide and effective expansion of the polysomnography as the universal diagnostic method.

1.2 A polysomnographic examination

A polysomnographic examination consists in simultaneous monitoring of several physiological parameters during a whole night sleep. According to the international standardization, standard polysomnographic recording is formed by monitoring of three essential physiological signals:

- Electroencephalogram (EEG) – monitoring of brain activity
- Electrooculogram (EOG) – monitoring of eye movements
- Electromyography (EMG) – monitoring of muscle activity.

Comparing these three polysomnographic signals, the electroencephalogram characterizing the human brain activity during the sleep can be thought of as the most important information

source for classification and discernment of the sleep/wake stages. Application of only the EEG signal gives us rather precise information for initial sleep/wake stages classification. This is in conformity with the historical development of the polysomnography that is mainly based on the different signs in the brain activity monitored during the night sleep. The EOG and EMG signals have indispensable contribution in the classification of the stages characterized by the similar brain activity. It concerns for example with detection of rapid eye movements using the EOG signal and classification of the REM sleep stage.

If there is a need of a concrete or special diagnosis assessment, the number of monitored physiological parameters can be arbitrarily extended. Polysomnography can be for example indicated to diagnose some breath disorders during the sleep (e.g. snoring) and occurs then demand on simultaneous monitoring of some breath parameters of the sleeping subject. There are many other physiological signals or parameters that can be monitored during the extended polysomnographic examination at the same time with the three initial signals listed above. The arbitrary parameters include the following:

- Electrocardiogram (ECG) – monitoring of heart activity
- Breath parameters
- Oxygen Saturation measurement
- Blood Pressure measurement
- Monitoring of body position and movements
- Sound recordings to measure snoring
- Core body temperature measurement

Polysomnographic recording containing predefined number of monitored signals is the main basis for analysis and classification of the sleep. The analysis of polysomnographic recording is divided into several phases. To be able to observe and evaluate all changes in the state of the sleeping subject during the whole night, the polysomnographic recording (all recorded signals) is fragmented into the succession of shorter segments. In the medical practice is the recording split into the succession of segments with a constant length. The segments of the recording are called epochs and most frequently last 20 seconds. The length of the epoch can vary depending on the actual medical application, aim of the analysis, recording devices used or the custom practice (e.g. in the USA the common length of epoch is 30 seconds). So that for example a sleep recording that lasts 8 hours is subsequently represented by the means of

1440 epochs with the uniform duration of 20 sec. In the next phase, each epoch prepared from the whole night recording is classified into one of the predefined sleep/wake stages. There are six traditional sleep/wake stages discerned in the human sleep. They are: wakefulness, NREM sleep stages I, II, III and IV, and REM sleep. Classification is performed on the basis of the characteristics of the monitored signals in the intervals corresponding to the currently processed epoch. Thanks to the development of computer science and information technology over the last decades is the whole process of pre-processing, analysis and evaluation of the polysomnographic recordings partially automated. Nowadays, computer assistance is especially common in the visualization of the monitored parameters (signals and variables). All of them can be on-line displayed and initially analysed with a help of the computer. In the case of sleep analysis, physician or sleep expert can use the computer to extract different parameters and attributes from the polysomnographic recording. The extracted characteristics then can be used to describe and classify the epochs of the recording. Until now, the analysis and classification of the whole night sleep is made visually by the physician, who scores every 20sec epoch into one of the sleep/wake stages. The classification is performed epoch by epoch according to the classical sleep/wake stages classification manual [RK68]. When the polysomnographic recording is classified into the sleep/wake stages, it is possible to represent the sleep structure graphically by the means of the hypnogram, an example of which is presented in the Fig. 1. Thus, hypnogram is an overall representation of the sleep architecture and presents chronological succession of the sleep/wake stages recognized in the whole night recording. The results of the sleep analysis presented in the form of a hypnogram can be consequently used to diagnose some sleep disorders that can be characterized by atypical distribution of the sleep/wake stages during the night sleep.

The manual classification of the polysomnographic recordings is a tedious and time-consuming task. It is possible to tell, that the main principle of the manual classification performed by the physician consists in the analysis and evaluation of the EEG signal course. During the visual analysis, the physician primarily focuses on the evaluation of brain activity. In the concrete, the expert observes and analyses the rhythmic activity of the EEG signal. If the information and characteristics extracted from the EEG signal give ambiguous information about the actual sleep/wake stage, the expert focuses more precisely on the other available data (electrooculogram and electromyogram). The precise description of all sleep/wake stages is presented in section 1.4.

The classification performed by the physician is partly influenced by its internal opinion as well as by its experience. This influence can be significant mainly at classification of the stages which are not characterized by some dominant feature or parameter as well as at classification of the transitions between individual sleep/wake stages. Transitions between the two consecutive stages are mostly slow and gradual and can last for several epochs. This fact causes ambiguities at classification of some epochs during the transition states.

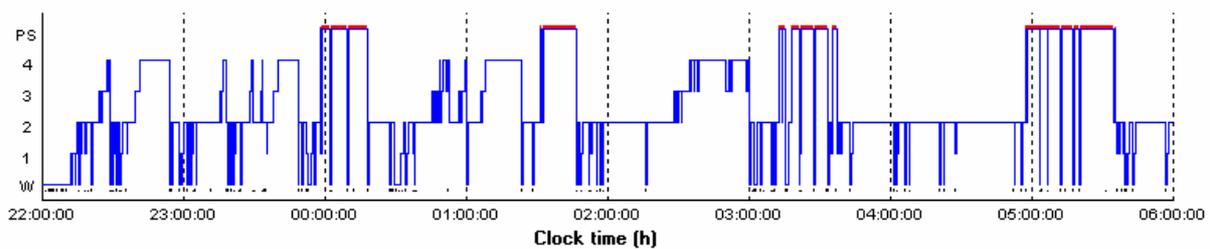


Fig. 1 An example of a hypnogram obtained from a night-time PSG recording.

1.3 Polysomnographic signals

Modern polysomnography is based on monitoring and recording of three physiological parameters; electroencephalogram, electrooculogram and electromyogram. From the primary description of the sleep analysis mentioned above can be evident, that correct and precise analysis of the EEG signal is required for initial classification of the sleep recordings. Therefore the description of electroencephalographic signal will be the most detailed. The signals will be characterized especially from polysomnographic point of view.

1.3.1 Electroencephalography

Electroencephalography is the neurophysiologic diagnostic method used to monitor electrical potentials that arise during the brain activity. In the other words, it monitors electric activity of the brain. The signal registered during this measurement is called Electroencephalogram (EEG). Electroencephalogram reflects the complex spatio-temporal biopotential changes that rise at signal regulation and processing of information in the Central nervous system (CNS). EEG presents an electrical signal from a large number of structurally and hierarchically interconnected neurons and cellular structures of the Central nervous system.

To the main advantages of the EEG belongs not only simplicity and reliability of the method, but also availability and noninvasive realization of this method (invasive measurement is not common in the sleep medicine). The main advantage and importance of the EEG is the fact that it monitors functional manifestations of the brain activity. Thus, the electroencephalography is a function test and therefore can be indicated as a diagnostic method used to diagnose various malfunctions and injuries of the brain.

The conventional scalp EEG measurement is realized by means of surface electrodes placed on the scalp of a person. The scalp area should be abraded and special conductive gel should be applied before the electrodes are attached. EEG electrodes must be placed according to the predefined system. The best known and worldwide used system is the International 10-20 EEG System of Electrodes Placement defined by H. Jasper in 1958 [*Jasper58*]. The title of the system is derived from the principle of electrode placement. Distances on the scalp, from the outer limits in both longitudinal and transversal planes, are divided into segments with a length of 10% and 20% of the total measured distance. The outer limits represent the nasion,inion and the preaurical points nearby the ear lobes. The EEG montage contains 21 electrodes, 19 of them are placed on the skull and the two other (reference electrodes) are placed on the ear-lobe. Position of each electrode is labeled with a letter identifying the concrete brain lobe and with a number or another letter identifying the hemisphere. Electrodes labeled with the odd numbers are placed on the left hemisphere and electrodes placed on the right hemisphere are labeled with even numbers (Fig. 2). The middle of the skull is labeled with index *z*. For the need of electroencephalography, brain activity is monitored from six areas of the brain corresponding to the main brain lobes. The main areas are labeled as follows:

- **F**: Frontal
- **Fp**: Fronto-polar
- **C**: Central
- **P**: Parietal
- **O**: Occipital
- **T**: Temporal

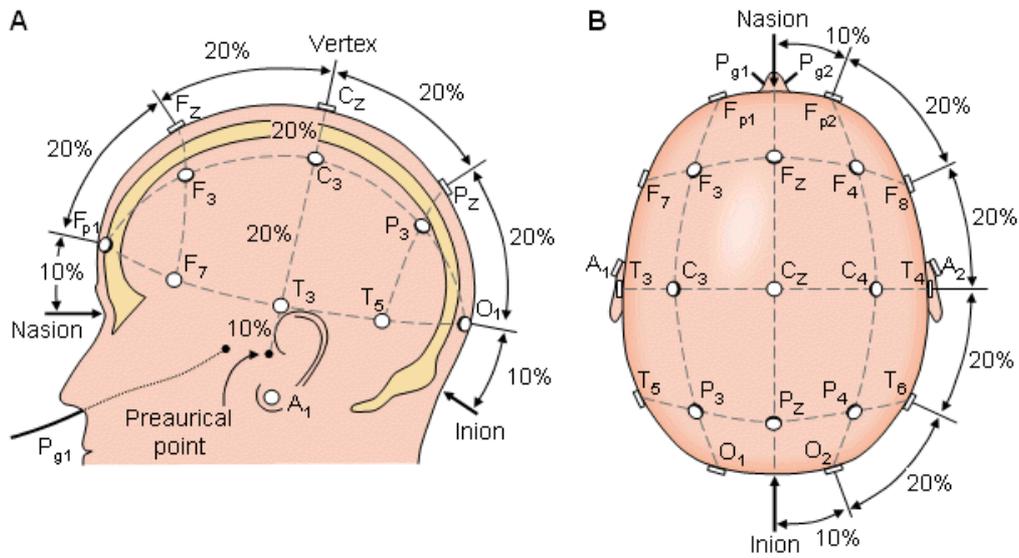


Fig. 2 EEG - electrode placement; 10-20 system. [MP95]

The electrode placement is the first parameter that affects the resulting EEG signal trace. The second important parameter is an electrode montage. It corresponds to the manner how the pairs of electrodes are connected to the amplifiers in the EEG machine. In actual practice, there are two basic types of electrode montage [COS74], [PITK04]:

- unipolar (reference)
- bipolar (differential)

Unipolar leads process the signal from more than one pair of electrodes. Electrical potential is measured between the electrode placed somewhere on the scalp and the reference electrode, which is common for all leads or group of individual leads. The advantage of this montage is the fact that the signal represents undistorted information about the shape and form of amplitude changes in the brain activity (EEG waves). On the contrary, the main problem of this method is location of electrically inactive reference electrode. If the reference electrode is placed close to the source of an electrical activity, it could generate false signals and artifacts into the original measured signal. There are several ways to create the reference electrode in the unipolar montage. The two most widely used methods are these:

- **AVR** (averaged reference) – In this method, activity from all the electrodes is measured and then the average value is computed. The resulting averaged signal is then used as the virtual reference electrode and is passed to the amplifier.

- **CR** (common reference) – This method typically uses a pair of electrodes to create the common reference. The electrodes are typically placed either over the ear-lobes (A1/A2) or over the mastoid processes (M1/M2), see Fig. 3. Then, various combinations of the reference electrodes can be used to create the reference electrode common for all channels.

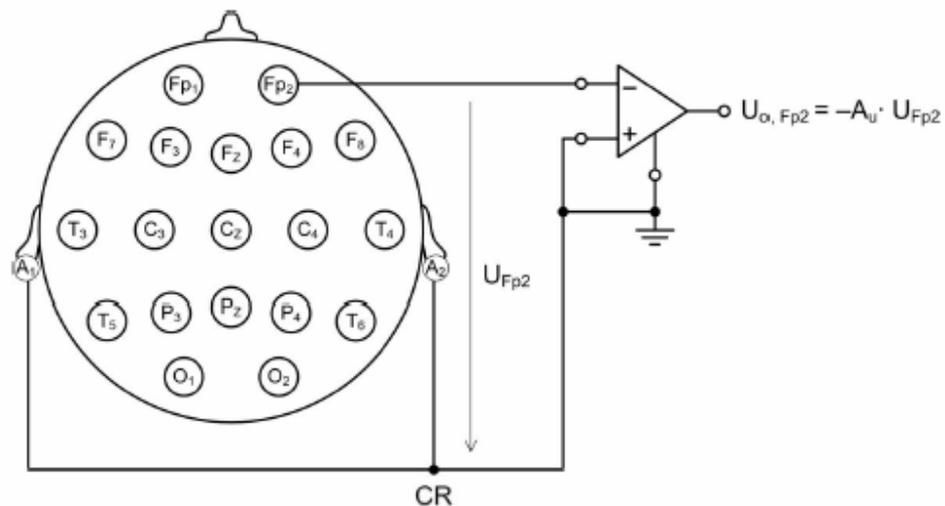


Fig. 3 Unipolar EEG montage – common reference. [PITK04]

In the case of the bipolar mode, the resulting signal is computed in the amplifier as a difference of successive pairs of electrodes. Thus, there is not any electrode common for more channels (Fig. 4). The main advantage of using a differential recording between closely spaced electrodes is more precise localization of the brain activity. It is caused by cancellation of remote sources of electrical activity that are common to both electrodes. The disadvantage of the method is deformation of the EEG wave shape. There are also several ways to arrange the bipolar mode. The best known are longitudinal and transversal montage that differ in relative combination of the electrodes [Clark98].

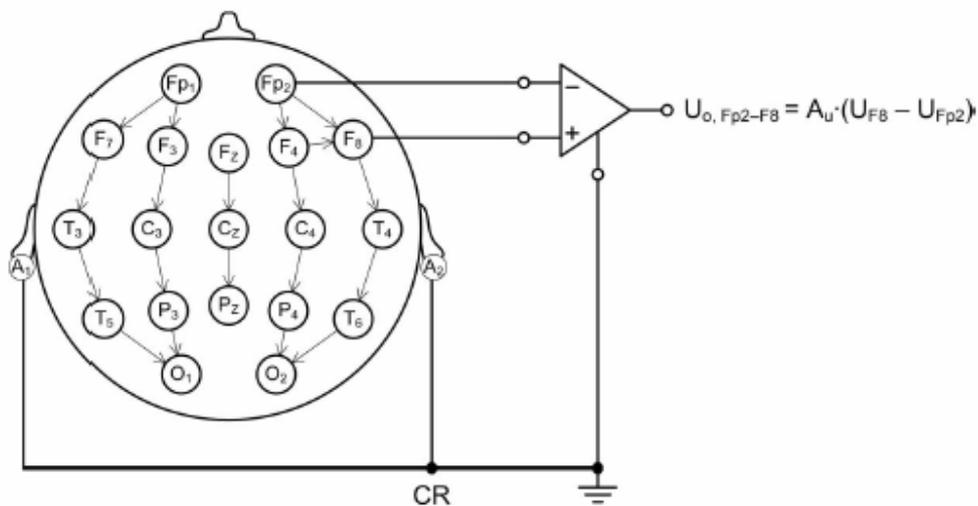


Fig. 4 Bipolar EEG montage. [PITK04]

For the need of sleep analysis, the electric activity of the brain is typically recorded from the scalp of the monitored subject. The brain activity is recorded in the form of continuous brain waves with typical amplitude of 10-400 μV . The waves with amplitude 10-30 μV are referred to as low amplitude waves, contrariwise the waves with amplitude higher than 80 μV are referred to as high amplitude waves. The frequencies of the brain waves are typically from the range [0.5-100] Hz and highly depend on the degree of brain activity. The predominant activity of the EEG signal is in the frequency range [0.5-50] Hz. The sleep medicine deals mainly with the EEG activity in the frequency range [0.5-30] Hz. In practice, this EEG spectrum can be split into several frequency bands characterizing the typical brain activities. The main EEG frequency bands are as follows:

- delta; 0.5-4.5 Hz
- theta; 4.5-8.5 Hz
- alpha; 8.5-11.5 Hz
- sigma; 11.5-15.5 Hz
- beta; 15.5-30 Hz

Delta activity: In adults, this activity is normally present in the EEG during a deep sleep in NREM III and NREM IV stages. If delta waves occur at any other time it could indicate brain dysfunction. It is also dominant rhythm in infants. The amplitude of the waves is typically over 75 μV .

Theta activity: This activity is present when the person is drowsy and falls asleep. It is also normal activity in childhood and young adulthood. In adults, it is abnormal in wakefulness. The amplitude typically reaches 25 μV but can be even higher up to 100 μV . Theta activity also reflects creativity, intuition, fantasizing, emotions, etc.

Alpha activity: Rhythmic alpha waves are characteristic of a relaxed state and are dominant when the eyes are closed. The waves are attenuated when the eyes are opened or when the person falls asleep. Alpha activity is best recorded over the occipital cortex. The amplitude of the waves is variable but is mostly below 50 μV in adults. When the alpha activity is to be characterized, it is necessary to mention inter-individual variability in the EEG alpha rhythm amplitude observed in the human population. Human subjects can be classified as either “alpha producers” or “non alpha producers”. Several authors propose more detailed categorization of alpha production. Davis and Davis [DD36] propose four types of EEG alpha records: dominant alpha (20% of healthy adults), subdominant alpha (35%), mixed alpha (20%), and rare alpha (25%). Golla *et al.* [GHW43] distinguished three alpha types: M (minimal), P (persistent), and R (responsive).

Sigma activity: Rhythmic activity with amplitude approximately 50 μV . This frequency band characterizes mainly the sleep spindles present during NREM II stage.

Beta activity: Beta activity occurs particularly during intense mental activity. It is not attenuated if the eyes are opened or closed. It is best recorded over the frontal and central areas. Beta activity seldom exceeds 30 μV . This activity can be affected by the effect of drugs. EEG is characterized as stochastic signal and therefore it can be described implicitly by the means of characteristics both in the time and frequency domain.

1.3.2 Electrooculography

Electrooculography is a diagnostic method monitoring the electrical activity of the eye – in the concrete the resting potential of the retina. EOG is based on the fact that the cornea has a positive electric potential compared to the negative potential of the retina. The eye-bulb can be then represented as steady electric dipole (corneal-retinal potential). When it is supposed that the corneal-retinal potential is constant, the resulting potential of the dipole can be used to determine the actual position of the eye. The dipole is oriented along the anterior-posterior axis and its direction veers a little bit from optic axis of the eye. The orientation of the dipole

changes when the eye-bulb moves. Electrooculogram is the resulting signal (potential) and characterizes the position of the eye.

The electrooculograph is a machine used to measure and register the potential difference with the surface electrodes placed close to the eyes. The typical electrode placement corresponds to the locations shown in the Fig. 5. Electrooculography using this electrode placement allows monitoring of both horizontal and vertical component of the EOG signal. To determine the horizontal component of the EOG, potential difference monitored by the means of the electrodes placed on the left and on the right from the eye (electrodes 1 and 2) is analyzed. The vertical EOG component is monitored with electrodes placed above and below the eye (electrodes 3 and 4). Sometimes, there is need to monitor the potential difference against the reference electrode – unipolar monitoring. The reference electrode is then typically placed above the nose (electrode 5) or in an electrically inactive area, e.g. ear-lobe. In this case, the horizontal component is monitored between the reference electrode and the electrodes 1 and 2. The vertical movements are then monitored between the reference electrode and the electrodes 3 and 4 [FF06].

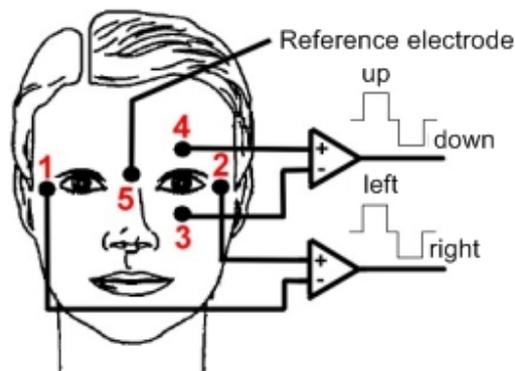


Fig. 5 EOG - electrode placement.

The signal registered by the EOG machine depends on the actual eye position (orientation of optic eye axis). If the person looks straight ahead the steady dipole is oriented symmetrically between the electrodes and consequently the resulting EOG signal is zero. When the eye moves from the center position to the left, the positive potential of the cornea moves closer to the left electrode and makes the electrode electrically more positive. By analogy, when the gaze is shifted to the right, the right electrode becomes to be more positive. The relationship

between the horizontal angle of the optic axis and the EOG output is almost linear in the range of $\pm 30^\circ$ of arc. The typical resolution is $1-2^\circ$ of arc, thus it is difficult to record small eye movements (less than 2°). The bandwidth of the EOG signal is approximately tens of hertz. The monitored signal can be confounded by the artifacts generated mainly by the EEG, EMG and the recording equipment [Clark98].

EOG signal reflects the activity and movements of the eyes and also the actual state of the person. Frequency content of the EOG signal mainly ranges from 0.5 to 15 Hz. The EOG has relatively high DC component compared to the other biopotentials. The amplitude of the EOG signal is typically lower than 2 mV; it ranges from 50-3500 μ V. The movement of the eye of about 1° of arc evokes the amplitude change approximately 20 μ V [BBML99].

Slow (rolling) eye movements are in the EOG displayed as long moderate waves. Rapid jerking movements are displayed as sharply contoured fast waves. Blinking of the eyes is presented as rapid vertical movements. An eye blink typically lasts only up to 200 ms.

1.3.3 Electromyography

Electromyography is a diagnostic method monitoring the bioelectrical signals generated by the activity of the skeletal muscles. The resulting recording of the muscle activity is called electromyogram (EMG).

Skeletal muscles can be described as compact structures compound of the muscle fibers. Contraction of the muscles is controlled by the Central nervous system (CNS). The activation of the muscle appears from the CNS and the impulse (action potential) moves through the spinal cord and then through the motor neuron to the muscle. The area where the nerve contacts the muscle is called the neuromuscular junction. The action potential then activates all the muscle fibers corresponding to the motor neuron. One motor neuron (motoneuron) can activate (innervate) a number of muscle fibers. But on the contrary, each muscle fiber can be activated by only one motor neuron. The elementary function unit of the muscle apparatus is the motor unit. Motor unit represents one motoneuron and all the skeletal muscle fibers that it innervates. The number of muscle fibers activated by one motoneuron can vary from 10 (the smallest muscles) up to about 2000 in the case of a large muscle. The motor unit represents the smallest unit of the muscle apparatus that can be activated by a volitional effort. Then all the corresponding muscle fibers are activated synchronously [RHM06], [PITK04], [Clark98].

There are two main types of electrodes that can be used to acquire the muscle signal: invasive electrodes and non-invasive electrodes. Invasive measurement is characterized by the use of wire or needle electrodes that allow a precise localization of the signal source. This method is indicated if the individual muscle fiber action potentials shall be measured.

At the sleep analysis, the non-invasive measurement is typically used. The EMG signal is acquired by the electrodes placed directly on the skin. The method is called surface electromyography (sEMG). Non-invasive measurement allows measuring of the action potentials generated by all the muscle fibers occurring in the muscles under the skin where the surface electrode is placed. The EMG signal acquired by the surface electrode is characterized as overlap of the potentials generated by the number of motor units. These action potentials are independent and therefore they can occur at random intervals. Thus, in the tissue under the electrode occur a lot of various time delayed signals. The resulting EMG signal is not purely determined as the simple summation of these signals. The EMG signal is also modified by the interference of the single action potentials in the volume conductor composed of the muscles, subcutaneous fat, skin, surface electrodes etc. [KO72], [KOS90], [SSA94], [Rodova00]. At the sleep analysis, the surface electrodes are typically placed on the chin or at the jaw of the subject.

Amplitude of the electric impulses in the single muscle fibers is low (μV). Each motor unit contains several muscle fibers, and that is why the resulting signal is high enough to be recorded by the surface electrode placed on the skin. Amplitude of the EMG signal acquired with the surface electrodes ranges from the low μV to the low mV range. Huge amount of the tissue between the electrodes and muscle fibers as well as the electrode-skin interface limits the frequency range of the EMG signal up to 500 Hz. The signal components over this limit can not be discerned from the noise. The maximal amount of the surface EMG signal power is spread in the frequency band [50-150] Hz [Day02]. For the need of sleep analysis, the information content over 10Hz is typically used and analyzed.

1.4 Sleep/wake stages

Analogous to the brain activity, also muscular activity and eye movements are not homogenous during the whole night sleep. The way to discern single phases of the night sleep is based on detailed analysis of changes in the main physiological signals (EEG, EOG and

EMG) during the whole night recording. The criteria for description and classification of sleep/wake stages are defined in the manual elaborated by the team of authors co-chaired by Rechtschaffen and Kales [RK68]. According to the only worldwide accepted and applied standard can be the human sleep characterized by six stages that are repeated through the whole night. The sleep/wake stages are as follows:

- awake state (wakefulness)
- NREM sleep
 - *NREM I*
 - *NREM II*
 - *NREM III & IV*
- REM sleep (Paradoxical Sleep)

From the list of the sleep/wake stages presented above is evident that the whole night sleep is essentially formed by three main states. The first state is a state referred to as like awake state or wakefulness. The whole night sleep can be then characterized as periodic alternation of two main types of sleep – NREM sleep and REM sleep. These types of sleep represent two different sleep mechanisms characterized by different manifestations of brain activity as well as different activity of eyes and muscles. Normal sleep cycle characterized by alternation of the NREM and REM sleep phases was firstly described in 1957 [DK57]. Depending on the aim of the analysis, the Rechtschaffen and Kales manual defines one more class that could be scored in the whole night sleep recording. A movement time can be scored, if more than half of an epoch is unrecognizable or masked by muscle artifact. In general, this class does not represent any specific state of the vigilance or sleep. It reflects presence of artifacts in the monitored signals. These artifacts are especially caused by body movement. All the epochs scored as movement time are generally excluded from the recording and are not analyzed any more. All the sleep/wake stages are characterized in the next part of the thesis. Each stage is characterized by the predominant brain activity (EEG), typical eye movements (EOG) and muscular activity (EMG).

1.4.1 Awake state

In general, at the beginning of the polysomnographic recording there is a few epochs belonging to the awake stage. Short, only a few seconds lasting intervals of awake stage can be also detected during the whole night recording. Especially at the beginning of the night

(before fall asleep) is this stage formed by two linked phases. The first phase is so-called active vigilance. This phase represents the real beginning of the recording, when the subject is restful and lies still with opened eyes. EEG signal is characterized by dominant activity of fast beta waves with typical amplitude in range 10-30 μ V. The first phase of awake stage then gradually passes to the second phase, so-called relaxed vigilance state. In this phase, eyes are already closed and the brain activity becomes to be slower. Thus, beta waves are replaced by the slower alpha waves activity. The awake state can also appear for a short interval later during the night.

In the first phase, the EOG can show the eye blinking and rapid eye movement corresponding to the visual scanning. Later in the relaxed phase the EOG signal becomes to be characterized by slow, rolling eye movements.

During the active vigilance phase, the EMG signal characterizes the high-frequency muscle contraction and movement artifact that are rather frequent. In the relaxed phase, the muscle activity becomes to be less prominent nevertheless the EMG tonic activity is still elevated.

1.4.2 NREM I

Phase of transition from wakefulness to sleep is classified as NREM I stage (NREM sleep stage 1). This stage can be called as transition stage and is referred to as drowsiness. The most significant feature of NREM I stage, especially to discern it from wakefulness, is the portion of alpha wave activity in the EEG signal in the actual epoch. Beginning of the sleep is directly linked to gradual reduction of alpha activity, so the brain activity slows down to the lower frequencies. Thus, NREM I stage is scored, if the total amount of the EEG alpha activity is less than 50% of the actual epoch. The rest of the epoch is characterized by mixed frequency content. By analogy to this description, the Awake stage is classified if the alpha activity takes over 50% of the epoch. Transition from wakefulness to NREM I stage is broad and gradual and it of course brings serious complication for manual classification as well as for design of the automatic analysis. Interpretation of the activity portion at manual classification is really subjective task and that is why the classification performed by various experts can show differences.

The reduced EEG alpha activity is mainly replaced by increasing theta wave brain activity. So, the background EEG activity is characterized as low voltage mixed frequency activity with

the highest amplitude in the frequency range [2-7] Hz. In the NREM I stage can be also present the vertex sharp waves; their amplitude is about 100-150 μV . NREM I stage lasts only a short time and represents only about 5% of the total sleep time.

The EOG signal is still characterized by slow eye movements (SEMs). Rapid eye movements are not present during NREM I stage.

The activity of chin muscles is decreased compared to the wakefulness but the amplitude of the signal is still moderately high. Reduction of muscular activity is still gradual.

1.4.3 NREM II

The “true” sleep begins with NREM II stage (NREM sleep stage 2). This stage is dominant in the whole sleep architecture and occupies about 45-55 % of the total night sleep. At the beginning, it is characterized mainly by the presence of the slow theta waves and the alpha activity that becomes already minimal. The slow wave delta activity begins to appear, but it takes less than 20% of the epoch duration. The theta activity does not significantly overtop the other brain activities. The background EEG is represented by moderately low voltage mixed frequency activity that is interspersed with two special transient phenomena typically characterizing this stage. K-complexes and sleep spindles can appear in the EEG signal.

K-complexes are characterized as slow biphasic high-amplitude waves often followed by a sleep spindle [CBDK+74]. They are characterized as low-frequency activity with frequency approximately 1-4 Hz and with total duration of at least 0.5 sec. In general, there is not a special minimal amplitude criterion for K-complex identification; however these complexes clearly stand out from the EEG background. The amplitude is at least 75 μV or approximately double of the background EEG amplitude [CRS02], [HCD01]. There are several types of K-complexes that can be discerned. K-complexes can differ either in their origin (spontaneous, evoked) [SJ68], their form and morphology [JK68], [PR91] or in their relation to the sleep spindles [EEMSN81].

The second relevant phenomena characterizing NREM II stage are the sleep spindles. Sleep spindles are short and rhythmical oscillations with the frequency 12-14 Hz lasting at least 0.5 sec. This frequency band activity is referred to as sigma waves. Typical amplitude criterion for the sleep spindle identification used during visual and automatic analysis is 15 μV [Nied98]. The name of this phenomenon, spindle, has been derived from its typical spindle

shape. Their appearance in the EEG signal trace represents the first sign of beginning of the sleep [Berger33], [LHH38b]. Sleep spindles frequently occur close to the K-complexes [Jansen90]. Presence of K-complexes and/or sleep spindles in the EEG signal is not an absolute indicator for NREM II stage classification. NREM II stage is classified, if the interval between two succeeding K-complexes or sleep spindles is shorter than 3 minutes. If the interval is longer than 3 minutes, the actual interval of the sleep recording is scored as NREM I stage.

The EEG activity in the NREM II stage becomes to be more synchronized compared to the previous stages of sleep. The NREM sleep is characterized as synchronized sleep. It is caused by the fact that during the whole NREM sleep the waves generated in different brain lobes are mutually synchronized.

There is no specific characteristic for EOG and EMG signal in the stage NREM II. Eye movements are rare and muscular activity is weak and is represented by the EMG signal with a low amplitude.

1.4.4 NREM III & IV

For the purpose of detailed analysis of the human sleep, two more NREM sleep stages (NREM III and NREM IV) can be discerned. Brain activity during both the stages is characterized by a dominant delta wave activity. Mainly the waves with frequency below 2 Hz are present. The brainwaves in both the stages are very slow and that is why these stages are usually referred as Slow wave sleep (SWS) and form a unique stage. This stage (SWS) represents a deep sleep of the sleeping subject, where the reactivity threshold to the external stimuli is high. In the other words, it is very difficult to wake someone from the slow wave sleep. The amplitude of the EEG signal is typically higher than $75\mu\text{V}$.

The only one real difference between NREM III and NREM IV stages is the portion of delta wave activity in the epoch. The epoch is scored as NREM III stage if 20-50% of the epoch contains delta waves. The rest is occupied by the background theta activity. If the slow delta activity appears in more than 50% of the epoch, it is scored as NREM IV stage. The Sleep spindles and K-complexes may or may not be present.

There are no specific criteria for EOG and EMG signal. Tonic chin muscle activity is usually present during Slow wave sleep. The activity of eyes is almost totally inhibited and the

activity recorded in the EOG channel mostly represents the EEG activity transmitted from the frontal and anterior temporal regions of the brain.

1.4.5 REM sleep

The brain activity typical for the REM sleep differs from the characteristic activity of almost whole NREM sleep (mainly the Slow wave sleep). REM sleep EEG signal shows relatively low voltage amplitude with mixed frequency content. The brainwave activity is desynchronized [Siegel00]. In the EEG signal can occur the saw-tooth waves characterized as signal with moderately high amplitude, frequency content about 2-5 Hz and triangular shaped waves. The saw-tooth waves are referred as phasic manifestation of REM sleep.

The brain activity of REM sleep seems to be similar to the NREM I stage and partially to the wakefulness stage. It makes the classification based only on the EEG sometimes insufficient for correct discrimination of these stages – wakefulness, NREM I stage and REM sleep. Because some of the REM sleep waves or manifestations are similar to the wakefulness stage, the REM sleep stage is also called Paradoxical Sleep (PS).

The REM sleep is in polysomnography also defined by two criteria reflecting important phenomena in the electrooculogram and electromyogram. The EOG signal shows evident high amplitude rapid eye movements (REMs). These typical movements are not present during the whole REM sleep. The REM sleep stage can be theoretically divided into two types of sleep – tonic REM sleep and phasic REM sleep. Rapid eye movements are present during the phasic REM sleep in contrast to the tonic REM sleep phase.

Tonic EMG activity of chin muscles is in the REM sleep very low or even totally absent [JM59], [JMC59]. Muscular activity is monotonic; almost all voluntary muscle groups are inhibited or paralyzed. Phasic activity, represented by short eruptions of muscular activity, is in the EMG prominent and irregularly present.

1.5 Sleep cycle

As mentioned above, the whole night sleep can be characterized as cyclic alternation of two fundamental phases of sleep. The sleep structure consists of NREM sleep phase and REM sleep phase. Combination of one NREM sleep phase and one successive REM sleep phase is defined as the sleep cycle. When we fall asleep, first NREM sleep phase begins and lasts

typically about 70 to 90 minutes. Then the first REM sleep phase occurs. REM sleep phase lasts at the beginning of the sleep for about 5 to 12 minutes. Thus, one sleep cycle lasts for 90 to 100 minutes on average. Through the night, the REM sleep phase becomes longer in comparison to the proportion of the NREM sleep phase (mainly the Slow wave sleep) that decreases. At the end of the night, the SWS can be even totally absent. The sleep cycle (combination of NREM sleep and REM sleep phases) repeats 3-6 times during the whole night sleep. This structure of the sleep characterizes the typical sleep where the pathological symptoms are not present.

1.6 Automatic classification of sleep

Large expansion of computer technology in the last few decades influenced positively also the medical science. Nowadays, modern computers evidently expand into the field of medical diagnosis. This chapter focuses on automatization of sleep analysis, in the concrete sleep staging.

There are many tasks in the sleep analysis where the computer science can be engaged. Four main tasks could be mentioned. Firstly, the computers are used as useful machines for visualization of the recording and for extraction of various parameters from them. It is the first step, how the computer technology can facilitate the work of physicians. These systems are already widespread in the medical practice. The last three tasks are still in progress. There is large research in the fields of artifact detection and minimization, identification of characteristic phenomena and/or waveforms in the signals, and last but not least in the development of automatic classifiers. The current research in automatic processing of artifacts is summarized in the Chapter 2 of this thesis. Identification of characteristic waveforms in the signal is a task relatively close to the detection of artifacts or noise. As the most typical waveforms identified in the polysomnographic signals can be mentioned sleep spindles and K-complexes in the EEG signal [Laing02], [HCD01], [RL98], and rapid eye movements in the EOG signal [TSISN00], [Wallner96].

The main interest in the field of sleep analysis focuses on development of suitable automatic sleep stage classifier. The field of artificial intelligence provides a broad range of methods and algorithms that have been tested in the last years in order to propose reliable automatic system of sleep/wake stages classification. Some of the favorable attempts are described in this section.

The principle of the automatic classification is the following: at first, the polysomnographic signals recorded during an epoch are processed using signal processing techniques. This first step transforms the raw signals into a set of characteristics describing the signals shape during the epoch. These characteristics are grouped into a vector called the feature vector. Then, in a second step, the feature vector is used as an input for a classifier. Most researches publish the use of new techniques to process polysomnographic signals to create new features or focus on the design and results obtained by some specific classifier.

One of the most popular classifiers used in the literature is the neural network, and more precisely the multi-layer perceptron. Robert *et al.* [RGL98] present the overview of neural network applications in the sleep research at the end of the 20th century. Authors of the paper briefly characterize some of the important attempts in automatic sleep analysis. Some of them are briefly characterized below. Schaltenbrand *et al.* propose in their two projects [SLM93], [SLTL+96] systems focused on scoring of human sleep into seven stages (movement, wake, NREM I – IV and REM sleep). The systems use information extracted from the EEG, EOG and EMG signals. A set of 17 features used to characterize the 30-sec epochs of the sleep was prepared as an input for the multilayer perceptron network trained with the classical backpropagation algorithm. In the first study [SLM93], a set of 11 whole night recordings was scored with a global agreement of about 80.6%. In the second study [SLTL+96], 60 recordings were scored (20 healthy subjects, 20 depressive patients and 20 insomniac patients). Agreement for the healthy subjects' recordings was 84.5%, for the depressive subjects 81.5% and 81% for the insomniac ones. In some projects, the two basic types of sleep (NREM and REM) are analyzed. Grözinger *et al.* [GRK95] proposed an automatic system for detection of REM sleep in the human sleep. The system is based also on the neural networks and uses data extracted only from one EEG channel. The signal was digitally filtered into six different frequency bands by Fourier transformation, rectangular windowing and retransformation. The root mean square value of each filtered signal was computed for each 20-sec epoch of the EEG signal. So, a set of six values (features) was used as input of the neural network classifier. The fully connected network was also trained with the classical backpropagation algorithm. A set of 13 polysomnographic recording from healthy subjects was used to evaluate the accuracy of the proposed system. Accuracy of the system reached 89% when the NREM sleep and REM sleep were discerned. In the later research, Grözinger *et al.* [GFR01] evaluated importance of some nonlinear and nonconventional stochastic EEG

parameters for classification of REM sleep. They investigated nonlinear features like highest Lyapunov exponent and correlation dimension, and stochastic parameters like spectral entropy and entropy of amplitudes. No improvement in classification was achieved when these new features have been added to the traditional spectral features used earlier. But, when only the new features (nonlinear and stochastic) have been used, the classification accuracy decreased by about 10%. The overview of neural network applications also refers to the sleep analysis performed on animals which is much desired in the medical science. The need for automatic sleep analysis performed on animals is mainly due to the fact that almost any pharmacological and/or medical experiments and methods have to be firstly tested and evaluated on animals. Sleep analysis in rats is processed in the work of Robert *et al.* [RKNL96]. The system was proposed to discern three stages of vigilance - wake, NREM and REM sleep. Five features were extracted from each 8-sec epoch of the EEG signal and then processed by the neural network. Six 24-hour recordings were scored during the tests with final classification agreement over 94%.

As presented above, many various algorithms have been already used to classify polysomnographic data. Becq *et al.* [BCCB+05] have evaluated and compared performances of five common classifiers. The classifiers used in the research can be regrouped into two distinct categories. Classifiers in the first group can be characterized as probabilistic classifiers based upon Bayes's rules (linear classifier, quadratic classifier, k-nearest neighbor classifier and Parzen estimator). A multilayer perceptron (MLP) is used to represent the classifiers that compute frontiers in the representation space directly from the data. This research also evaluates influence of proper data pre-processing; in the concrete data transformation towards normal distribution. Performance of all classifiers is compared both for raw data and transformed data. When the raw data have been used, the lowest classification error was reached for the MLP classifier. The classification error was about 29% on the validation sets. Classification error of the other classifier has been significantly higher (over 40%). Then, when the transformed data were used, evident decrease of classification error for all classifiers except MLP classifier was observed. MLP classifier obtained about the same classification error as before when raw data have been used. Highest improvement has been observed in the performance of k-nearest neighbor classifier and Parzen estimator which increased their classification error of about 20% and could be compared to the performance of the MLP classifier. The study has been realized over 11

recordings scored by an expert into the six different stages: wake and movement, NREM I, NREM II, NREM III, NREM IV, REM sleep. Eight features have been extracted from the polysomnographic recording and then used as input for the automatic classifiers. The features are: relative spectral powers in the six EEG frequency bands, standard deviation of the EEG and standard deviation of the EMG. This study demonstrates that proper data pre-processing as well as selection of classification algorithm are important for effective sleep analysis.

Various techniques of feature extraction performing both in the time and frequency domain have been used in the researches presented above. In the frequency domain, the Fourier transformation is the most frequently used technique. Another approach was tested in the work of Oropesa *et al.* [OCJ99]. The system combines the wavelet analysis of the signal and neural networks (multi-layer perceptron) used as automatic classifiers. Each 30-sec epoch of the EEG signal is processed by the wavelet packet transformation and decomposed into eight levels. The mean quadratic values of specially selected wavelet coefficient arrays were computed to determine 13 features characterizing the actual epoch. During the tests, testing set of 590 30-sec epochs was classified with global accuracy of 77.6%. But only four stages (wake, NREM I, NREM II and REM sleep) have been scored during this research.

There are also other techniques used in development of automatic sleep classification. Flexer *et al.* [FGD05] propose a probabilistic continuous sleep stager using only single EEG signal. The system uses the technique of Hidden Markov models that are based on the probabilistic principle. In the concrete, the Gaussian observation Hidden Markov model (GOHMM) is used. The proposed model deals with continuous probability traces defined for the three fundamental vigilance states (wake, deep sleep, REM). Then, six sleep/wake stages (wake, NREM I, NREM II, NREM III, deep sleep and REM) are scored with time resolution of 1-sec. The proposed automatic system is tested on two sets of data. The first testing set contains 20 whole night recordings. The classification accuracy of wake and deep sleep is about 80%. Classification of epochs scored by R&K scoring manual as REM sleep stage is quite lower, about 68%. The other NREM stages are characterized by low classification accuracy that does not exceed 40%. The second testing set contains 14 whole night recordings. In this case, the REM sleep and deep sleep stages kept their accuracies, but the classification accuracy of wake stage fell to 25%. There are also other attempts in the area of contextual analysis of sleep/wake stages [Shen02].

There is one more research project that should be surely mentioned in the overview of current research in automatic sleep staging. In the SIESTA project, a group of researchers developed and subsequently optimized an automatic classification system called “Somnolyzer 24 x 7”. The final system processes one central EEG, two EOG channels and one chin EMG channel. An expert system is used to perform the sleep/wake stage classification itself. The system scores each 30-sec epoch using a set of features extracted from the monitored signals. The features characterize two types of information contained in the actual epoch. Firstly, the quantitative parameters characterizing the background activity are extracted from the epochs. The second group of features results from the identification of special waveforms characterizing the actual sleep/wake stage. Presence of the special waveforms is characterized in the term of their density, intensity, amplitude etc. The results of the system published in the paper [AGPW+05] indicate the overall classification accuracy about 80% obtained when 270,100 30-sec epochs were automatically scored. Agreement in classification of the wake and NREM IV stages is about 80%. Classification accuracy of NREM stage II and REM sleep exceed 86%. Only the NREM I and NREM III stages are scored with a low agreement (about 50%) with the scoring of a human expert. The SIESTA project research group made also practical research in the fields of artifact detection and identification of sleep related waveforms.

The survey of the research presented above shows, that the main interest of the current research focuses on the sleep stage classification and artifact processing. Various techniques and algorithms have been already performed and evaluated in order to propose proper automatic classifier. As it will be seen later in the chapter 2, there have been also some attempts to propose effective artifact processing strategy. It could be said that both the areas of research are already quite well explored. So, this thesis focuses neither on the development of some specific classification algorithm nor on the proposition of a new artifact detection technique. The aim of this thesis is to propose a classification system that would effectively combine the results obtained by:

- artifact identification methods, so as to develop an automatic system that takes into account and overcomes the problem of pollution of the signals by artifacts

with the results obtained by:

- feature selection methods, so as to feed the classifier taking the decision of classification into sleep/wake stages with the most relevant characteristics extracted from the monitored signals.

Indeed, the study of the bibliography showed that almost no projects had been dealing with the selection of relevant features from the analyzed signals. Major part of the projects simply uses empirically determined features as inputs for the classifiers and does not perform any sophisticated selection over available features computed from the signals. It is caused by the fact, that polysomnographic recording can contain a lot of various signals and until now there is not any worldwide accepted set of optimal features.

To be able to perform a reliable selection of relevant features and to evaluate the results obtained by an automatic classification system, it is necessary to analyze a sufficiently large and representative database of polysomnographic recordings. Analysis of only a small number of recordings can not provide any useful information that could be consequently applicable for analysis of another data. Next section of this chapter describes the database of polysomnographic recordings analyzed during this thesis.

1.7 Presentation of the polysomnographic database used in this thesis

In this thesis, a large database of polysomnographic recordings has been used for the experiments. The full database contains 47 night-time polysomnographic recordings obtained from 13 healthy adult subjects (19–47 years old). Recordings were made continuously during the night sleep (typically 8 hours between 22:00h and 06:00h). Each polysomnographic recording contains four EEG channels (C3-A2, P3-A2, C4-A1, and P4-A1), one transversal electrooculogram, one chin electromyogram and one electrocardiogram. The analog signals were then digitized with an 8-bit A/D converter at a sampling frequency $f_s = 128$ Hz. Only the EEG (C3-A2 channel), EOG and EMG signals were analyzed in this thesis. The EEG leads were attached onto the scalp according to the International 10-20 EEG System of Electrodes Placement [Jasper58]. Concrete protocol of the investigation is described in the papers [CPCBB03], [BMPN95].

All the 47 PSG recordings were visually scored by two independent sleep physicians. Visual sleep/wake stage scoring was performed with constant epoch duration of 20 sec according to

the conventional rules of the R&K manual [RK68]. Each epoch was thus classified into one of six different sleep/wake stages: wakefulness, NREM sleep stage I, NREM sleep stage II, NREM sleep stage III, NREM sleep stage IV, and REM sleep. When the signals were confused, the class labeled as “undefined” was scored. For the need of the successive analysis realized in this thesis are the single classifications performed by the two experts labeled as “EXPERT 1” and “EXPERT 2”. The total number of epochs extracted from all 47 recordings is 77,649. The Tab. 1 summarizes the classification of all recordings and confronts the classifications of both experts. From the table it can be seen, that the inter-expert agreement complicates the automatic sleep analysis. As presented in the international research the epoch by epoch inter-rater expert agreement typically varies from 75 to 90% [KKHMK92], [SLTL+96], [NPSWR00], [DKGK+04], [AGPW+05]. The relatively low inter-rater expert agreement can be caused by many negative factors. As the main factors could be mentioned ambiguity of the sleep staging rules, broad transitions between the consecutive stages, long length of the epoch (20s or 30s), difference in the medical equipment, the experience of the physician etc.

<i>Number of epochs</i>	Awake	NREM I	NREM II	NREM III	NREM IV	REM	Undefined
EXPERT 1	8,275	2,913	36,744	3,894	9,194	16,567	62
EXPERT 2	5,643	5,231	35,924	7,862	5,440	16,847	702

Tab. 1 Comparison of expert classification - whole PSG database.

The total database of 77,649 epochs was in the next step reduced in order to avoid introduction of the expert ambiguity into the automatic classification. Three constraint conditions were defined to make the database more accurate. The stages NREM III and NREM IV were joined to form a SWS stage. Then, all the epochs which were scored by at least one expert as “undefined” were removed. The last condition results from the inter-expert agreement test. Only the epochs scored by both experts in the same stage were considered in this thesis. As the result of the limitation, 750 epochs were removed because of scoring as “undefined” class and 9,513 more because of expert disagreement. Thus, the total number of epochs used in the analysis is 67,386 and it represents 87% of the whole data. The reduced

database (*Both experts database*) is characterized in the Tab. 2 that presents number of epochs in the sleep/wake stages used for automatic classification.

<i>Number of epochs</i>	Awake	NREM I	NREM II	SWS	REM
<i>Both experts</i>	5,376	1,998	33,100	11,498	15,414

Tab. 2 Number of epochs in the sleep/wake stages – Both experts database.

Specialized software is used to visualize and analyze the polysomnographic recordings. The PRANA (Polygraphic Recording ANalyser) software package is developed by the PhiTools[®]. The software is suitable for analysis of polygraphic recordings (EEG, EOG, EMG, etc.) and topographic EEG recordings. It contains many tools specialized on conventional and advanced signal analysis and signal processing methods. PRANA is based on the MATLAB environment and allows the user to implement some original algorithms that can be integrated as user plugins into the PRANA software. More information about the PRANA software can be found in the PRANA User Guide [*PRANA05*].

1.8 Chapter conclusion

Sleep analysis consists mainly in classification of the polysomnographic recording into various sleep/wake stages. The typical polysomnographic recording contains three essential physiologic signals – electroencephalogram, electrooculogram and electromyogram. All the three signals seem to be important and helpful for correct classification of the sleep/wake stages. The general terminology used in the polysomnography defines six stages representing different states of vigilance and sleep (wakefulness, NREM sleep stages I-IV, REM sleep). For a need of practical applications, these six stages can be reduced to a set of five stages, when the NREM sleep stages III and IV are joined together. In this project, these two stages have been joined and then form a single stage marked as Slow wave sleep (SWS).

Study of the state of the art in the sleep/wake stage classification has been used as a background for proposition of a two-step classification system. The classification system will combine the results of an artifact identification procedure performed in a first phase with some classification realized in a second phase. The classification is achieved using features selected as the most relevant by a feature selection procedure. To be able to propose a reliable

automatic system, its development as well as its evaluation must be done with a use of a large base of polysomnographic recordings. The polysomnographic database has been presented in detail at the end of this chapter.

Chapter 2

Analysis of artifacts

Exact definition of the terminology and characteristic of different sleep/wake stages eminently helps to improve the quality and accuracy of the sleep analysis. However, quality of the signals contained in the polysomnographic recording also affects the results of sleep analysis. Scoring of the polysomnographic recording (electroencephalogram, electrooculogram and electromyogram) that contains a lot of various artifacts can be easily misled during the sleep analysis. Existence of artifacts and their influence on sleep analysis have been slightly mentioned in the presentation of different sleep/wake stages. For example, movement time is defined as a special state, where the signals in the epoch are defaced with the presence of artifacts.

The second chapter of the thesis will focus on artifacts that are typical for polysomnographic recordings. In the first part, the various artifacts will be characterized and categorized. Then, the general artifact processing techniques will be discussed and some concrete applications characterizing the current research in the field of artifact processing will be presented. There are two main strategies that could be used to process artifacts – artifact identification and artifact minimization. The concrete strategy employed in this thesis is based on the artifact identification performed and is performed on short segments of analyzed signals. Detailed description of the artifact processing strategy employed in the proposed two-step automatic classifier form the base of this chapter. In the last section of this chapter, the results of artifact identification performed on the available polysomnographic recordings are presented and discussed.

2.1 General characteristics of artifacts

In general, artifact is a phenomenon that has not any physiological background in the monitored organ. The potential difference marked as an artifact originates in other source than in the monitored organ. In the other words, an artifact can be characterized as a defect that can appear in the expected course of the monitored signal. So that, for example, as an artifact in the EEG can be marked any potential difference (symptom) that is not generated directly by the brain activity. The artifacts in the other signals can be defined by analogy. There are several moments in the whole process of the sleep analysis (monitoring and recording of the physiological signals, data processing) that can introduce an undesirable noise (artifact) into the original signal.

There are many criteria that can be used to categorize the artifacts or to group different types of artifacts together. One of the frequent methods used to split the artifacts is a method based on the difference in the origin of the artifacts. According to this criterion, two types of artifacts can be discerned – biological (physiological origin) and technical (non-physiological origin).

2.1.1 Technical artifacts

The artifacts caused by the non-physiological source can be split into two groups:

- Artifacts caused by the external source or by the equipment
- Electrode artifacts

The artifacts of the first group are mainly caused by the existence of external sources of electrostatic and/or electromagnetic fields in the room where the examination takes place. Existence of the external sources close to the measuring device or patient can contaminate the measured signal. As the typical example can be mentioned 50/60 Hz mains interference (power line artifact) or other diagnostic or therapeutic devices placed in the exam room. The measurement can be also obscured by the presence of persons and devices that could be a source of electrostatic field. To avoid this artifact, utmost care should be focused on placement of the patient and also on proper shielding of the medical devices.

The second group of technical artifacts contains the artifacts caused by the electrodes or by the leads. There are several causes of these artifacts, but the main cause can be characterized

as movement of the electrodes placed on the skin of the monitored person. In the concrete, the motion artifacts can origin from movement in the electrode-electrolyte interface or from skin-stretch. The movement of the electrode (relative to the electrolyte) causes change in the distribution of the equilibrium charge at the electrode-electrolyte interface. This mechanical disturbance of the charge leads to a momentary change of the half-cell potential until the equilibrium state is reestablished. If a pair of electrodes (with electrolyte) is used and one of them moves, a potential difference appears between these two electrodes. This potential is referred as motion artifact and is common for polarizable electrodes [Neuman98]. These artifacts can be reduced using modern Ag-AgCl recessed electrodes. The skin-stretch can be reduced by the use of electrodes that puncture the skin or by abrading the skin before the electrodes are placed. The electrode-skin interface is not the only weak point resulting in a motion artifact. When the leads are moved or handled, an artifact can be electrostatically induced. The motion artifact can be characterized as slow-wave and high-amplitude phenomenon. Frequency range of the motion artifacts can reach 20 Hz, but the predominant frequency range is [1-10] Hz. Very typical is also so called electrode pop artifact (contact noise artifact) that originates at the electrode-skin interface. This artifact rises from loss of contact between the electrode and the skin which is caused by the electrode movement relative to the skin. In the recording it is manifested as a sharp rise of the amplitude followed by an exponential decay.

During a long-time measurement, the electrode may detach totally. This event is very common in the polysomnography because the measurement lasts about 8 hours and the person moves during the night. There is another risk of long-time monitoring. The electric parameters of the electrodes can change during the time. It is mainly problem of the electrode impedance increase during the measurement. Thus, also the electrode attachment and conductive gel should be checked.

There is no way to totally avoid occurrence of technical artifacts. But we can try to reduce chance of their occurrence and reduce their undesirable effects. Using of high-quality material and equipment (electrodes, leads, regular test of electrode parameters, etc), optimized recording techniques and training of high-qualified medical stuff can lead to minimization of technical artifacts.

Electrodermal artifacts represent another noise that can contaminate the signal. Typically, the source of their origin is due to the person's sweating. Sweat can disturb the electrical property of both the skin and the electrode (e.g. melting of the electrolyte gel). This artifacts manifest in the recording as extremely slow waves. Their frequency is lower than 1 Hz, typically [0.25-0.5] Hz.

2.1.2 Biological artifacts

Biological artifacts are caused by the sources inside the body of the person. Moreover, biological artifacts typically originate from the normal activity of the organism and therefore they are common in medical practice. It is very difficult to avoid their occurrence; in some cases it is even impossible. Their occurrence can be partially suppressed if the examination takes place in the comfortable environment where the person can be relaxed and without fear or anxiety.

The typical signals monitored in polysomnography are electromyogram, electrooculogram and electroencephalogram. It is evident that not all physiological phenomena are referred as artifact in all these signals. For example, ocular manifestations can not be detected as artifact in the EOG signal but are undesirable in the EEG signal. Great majority of all the possible artifacts will be characterized in this section together.

Ocular artifacts

Ocular artifacts in polysomnographic recordings originate in movement of the eye-bulb or from eye-blinking. The physiological background characterizing ocular activity has been described in the chapter 1. Ocular artifacts contaminate especially the EEG signal. It is mainly due to the fact, that according to the 10-20 system are the Frontal (F) and Frontopolar (Fp) electrodes placed close to the eyes. Occurrence of the ocular artifacts decreases in dependence on the distance from the eyes [ZBDHR02]. The primary frequency range of the ocular artifacts can be defined as [0.5-4] Hz. Thus, these artifacts confound mainly the delta EEG frequency band. The low theta frequency band can be also slightly contaminated by these artifacts. Nevertheless, the ocular artifacts caused by eye-blinking can have frequency components up to 20 Hz. Artifacts caused by eye movements and blinking are of relatively high amplitude when recorded in the EEG recording.

Muscle artifacts

There are several manifestations that can be marked as a muscle artifact. They are typically caused by muscle tension (facial muscles) or by the muscle activity (movement of the head, body or limbs). Involuntary movements are present when the person is not relaxed (anxiety, fear or uncomfortable environment). Large disturbances can appear when the person executes some movements that activate the muscles on the head (e.g. movement of the head, chewing or swallowing). Muscle artifact can manifest as single spikes or oscillations or can be represented as continuous interference. In general, they markedly stand out from the background activity of the monitored signal; therefore they can be readily identified. The frequency range of the muscle artifact is broad. Maximum of the muscle artifact activity is over 25 Hz. In general, there are two ways to identify manifestations of the muscle artifacts. Firstly, the sudden amplitude abnormality characterizing the bursts can be detected in the signal trace. On the contrary, the second strategy of muscle artifact detection is based on the analysis in the frequency domain. It is based on the evaluation of the high-frequency activity in the spectrum of the signal.

Influence of the muscle artifacts on the monitored signal (EEG) is well described in the work of Bruner *et al.* [BVDM+96]. According to them, muscle artifacts contaminate the entire frequency band [0.25-32] Hz. The EEG signal is substantially contaminated from the frequency of 15Hz. Contribution of muscle artifacts can cover from 20 to 70% of power density of the artifacted epochs. Significant effect of muscle artifacts is also observed in the low delta frequency band and in the frequencies over 6 Hz.

ECG and pulse artifacts

Activity of the heart can generate two different types of artifacts. The first type originates directly from the electrical field generated by the heart. Total electrical activity of the heart can be characterized as an electrical dipole. The dipole is represented by the vector that is oriented from the negative charge to the positive charge. Orientation of the dipole depends on the actual phase of the heart cycle, thus it changes in the time. This artifact is well readable when the monitored signal has low amplitude. In the case of the EEG monitoring, the electrical dipole can contaminate several leads of the EEG recording when the referential montage is used. ECG artifacts are rhythmic and are synchronous with the QRS complex of the electrocardiogram. Contamination of the recording by the ECG artifact is more frequent when obese or short-neck subjects are monitored [COS84].

Pulse artifacts may originate when the electrode is placed over a surface artery. The pulsation of the artery periodically moves the electrode and in the signal it is manifested as slow waves. The waves are also connected to the heart cycle; they are slightly delayed behind the QRS complex. The pulse artifacts contaminate only leads that are adherent to electrode placed over the artery.

Respiration artifacts

Respiration is inseparably accompanied by the rhythmic movement of the chest, neck and head. Movement of the head can cause small movement of the electrodes used to monitor the polysomnographic signals. The respiration thus introduces some slow wave artifacts. The artifacts are synchronous with inhalation and exhalation.

2.2 Theory of artifact processing

Some of the artifacts mentioned in the previous part of the thesis can be avoided. Using of high-quality equipment in combination with high-qualified medical staff can be considered as an initial way to deal with (avoid) artifacts. Unfortunately, some of the artifacts are characterized as unavoidable. It means that their source of the origin can not be completely suppressed. These artifacts must be processed using an optimal method so as to they do not distort the information used in the subsequent sleep analysis. There are two basic strategies to deal with unavoidable artifacts [ARSG+99]:

- Artifact identification
- Artifact minimization

Artifact identification strategy leads to irreversible and complete loss of artifacted segments. On the contrary, the artifact minimization algorithm is implemented so as to clean up the segments of the artifacts and to allow analysis of the cleaned epochs. Detailed characteristic of both the strategies will be presented in the next two sections of the thesis.

2.2.1 Artifact identification and rejection

Artifact identification strategy is based on identification of the artifacted intervals in the analyzed recording. So, the whole recording is scanned segment by segment in order to identify possible artifacts. When an artifact is identified in a segment of the signal, the artifacted segment is then excluded from the recording. It is evident that such an artifacted

segment is then excluded from any subsequent analysis. Such a procedure based on rejection of contaminated epochs can lead to enormous reduction of the available data in the analyzed database. This effect is evident especially in the tasks, where the segments of recording to be analyzed are too long. In such a case, presence of only a brief artifact leads to unreasonable removing of the whole segment of the recording. So, adequate length of analyzed segments should be used. In some tasks, the artifacted segments do not have to be necessarily excluded. It can be kept in the recording and a supplementary parameter indicating presence of an artifact is only assigned to the segment of the recording.

The basic idea of artifact identification is based on application of a model for the artifact that should be detected. This method uses characteristic parameters of the signal (amplitude, frequency, energy, correlation coefficient, etc.) that represent the artifact in the best way and allow discerning artifact-free and artifacted segments of the signal. The parameters extracted from the signals should be as discriminative as possible. Once the parameters that describe the artifact best have been chosen, a detection procedure can be applied. Most often, it consists in comparing the value of the extracted parameter to a threshold value. If the parameter value is above (or below) a given value, the segment is artifact free. Otherwise, it is artifacted. The most complicated task is then to tune the threshold value. The process of threshold setting is mainly based on the experimental knowledge and/or on a trial and error method. There are two types of thresholds used in artifact identification. They can be either absolute or adaptive. The absolute threshold value is set at the beginning of the analysis and stays constant during the whole analysis. On the contrary, in the case of the adaptive threshold strategy the threshold value is periodically updated during the analysis. To update the threshold value, a so called moving window is used. The moving window moves step by step along the whole recording and at each step it delimits the interval of the signal that is then used to compute the local threshold value.

The value of the absolute threshold represents the extreme (maximal or minimal value) of the analyzed characteristic parameter. An artifact is thus characterized by a value that is out of the range characterizing artifact-free segments. Detection algorithms using adaptive thresholds are especially used to detect artifacts that manifest as a sharp and sudden change in the signal trace. The artifact should stand out from the local area demarcated by the moving window. Artifact identification strategy is wide-spread in artifact processing and can be characterized as general methodological approach. Various types of artifacts or noise can be identified by

the automatic detector using the proper parameters extracted from the signal combined with the suitable threshold value.

One of the examples of the absolute threshold application is presented in the work of Schlögl *et al.* [SKPK+99]. This work focuses on detection of overflow artifacts and represents a typical example of absolute threshold application. Overflow artifact can be characterized as a saturation of the amplifier and/or the analog-to-digital converter caused by its limited dynamic range. The limit value of the device then can be used to determine the absolute threshold value. The threshold value then can be compared with the (absolute) amplitude values of the signal in the epochs or in shorter sub-epochs. In the work of Durka *et al.* [DKBSN03] are proposed methods for detection of several types of artifacts. The authors present two types of artifact detection using absolute threshold. The first part of the artifact detectors deals with the constant threshold value that can be used if the parameters extracted from the signal are insensitive to the calibration or to another setting of the recording. If the extracted parameters are sensitive to the recording setting or can vary between the persons or recordings, then the threshold value is set relatively to the statistics of the actual recording to be processed. The statistical properties of the extracted parameter are estimated over the whole signal. In general, mean value or median value is computed from all values of the parameter calculated on the signal contained in the actual recording. Value of the statistical parameter multiplied by a certain factor is then used to determine the statistical absolute threshold. So, the constant threshold is set by an expert and is the same for all recordings, whereas the statistical absolute threshold varies for individual recordings. Van de Velde *et al.* [VEC98] compares constant and statistical absolute thresholds for detection of muscle artifacts. The authors use five parameters extracted from the EEG signal of 21 volunteer subjects. The parameters are computed both in the time and frequency domain. The parameters are as follows: maximum slope, maximum and minimum amplitude, absolute and relative high beta power, and spectral edge frequency. The research also focuses on selection of adequate length of the analyzed segment of signal. The authors conclude that the performance is significantly higher when the constant threshold is used. When absolute high beta power or slope parameter values have been computed from 1-sec segments of the signal, the highest sensitivity and specificity were reached. Performances of these two parameters combined with constant thresholds are near the expert's performance (sensitivity 81% and specificity 92%). The sensitivity for absolute high beta power parameter is about 80% with a

specificity of about 90%. When the statistical thresholds have been used, no one parameter got near the expert's performance.

Artifact detection using an adaptive threshold allows local modification (update) of the threshold value during detection of the artifacts in the whole signal. To update the threshold value, local background information defined by the moving window is used. So, the threshold value reflects much more the local course and the activity of the analyzed signal. The way to define the adaptive threshold is similar to the previous method. The only difference is that the values of the characteristic parameter defining the threshold must be periodically updated in concordance with the actual interval defined by the moving window. The adaptive threshold method is powerful if the artifacts to be detected manifest as temporary phenomena that stand out from the local background activity and whose occurrence is not frequent or permanent. If the artifacts are frequent, a soever long moving window can be used, but the background activity still will not differ from the characteristic of the actually processed artifacted interval. Application of the adaptive threshold detection is well described in the work of Bruner *et al.* [BVDM+96]. The aim of this work is to prepare a detector of muscle artifacts. The proposed method is based on the fact that the muscle artifacts characterizing bursts of myogenic activity can be characterized as relatively high-frequency phenomena. To characterize the artifacts, spectral power density in the frequency range [26.25-32] Hz was computed and used as the parameter. The parameter was computed for a 4-sec epochs in the entire recording. A 3-min symmetric moving window was used to define the local background high-frequency activity for each 4-sec epoch. The adaptive threshold was then determined as a median of the 45 values of the parameter in the actual 3-min window. Then, a 4-sec epoch is marked as artifacted, if its high-frequency activity exceeds local threshold value (local activity) by the factor of 4.

Another method to discern artifact-free and artifacted intervals employs the model of artifact-free data. Compare to the previous method, now in this case the aim is to define the model of a signal that is not contaminated by any artifact or noise. However, this method does not detect the single artifact types.

Schaltenbrand *et al.* [SLM93] prepared an unsupervised neural network (NeoART) that could be used to identify the artifact-free data. Their network is learned on the learning sets that contain only artifact-free data. At the end of the learning process, the learning sets are

described by a union of hyperspheres characterizing the individual prototypes. Outputs of the NeoART network correspond to the prototypes. Then new observations can be classified. If at least one output cell of the NeoART network fires, the observation is supposed to be artifact-free. Otherwise, a new prototype would be generated by the unsupervised network and the observation is then supposed to be artifacted. So, the unsupervised network could be used to exclude artifacted epochs from the subsequent analysis.

2.2.2 Artifact minimization

While at artifact identification the artifacted segments are totally rejected from the signal, the aim of the artifact minimization strategy is to extract or attenuate only the contribution of an artifact and leave the corrected segments of the signal to be processed. The advantage, as compared to the artifact identification, is the fact that artifact minimization does not lead to the loss of available data since it does not reject the artifacted segments. The idea of the method is to clear the signal of the artifacts and noise. Artifact minimization can be performed when the original source of the artifact is available and can be thus used to clean the artifacted signal.

It is supposed that the recorded signal ($SIG_{rec}(i)$) can be characterized as a linear combination of the original (true) signal ($SIG_{orig}(i)$) and a source of artifacts ($AF_{orig}(i)$). The source of the artifacts can be either directly recorded (monitoring of an additional signal) or reconstructed (e.g. reconstruction from other monitored signals). So, if both the recorded signal and the source of the artifacts are available, the propagation coefficients (transmission coefficient or scaling factor) θ must be determined in order to remove the artifact from the recorded signal. The propagation coefficients determine the proportion of the artifact in the recorded signal $SIG_{rec}(i)$. Then, the adequate portion of the artifact source signal ($AF_{orig}(i)$) can be subtracted and the original true signal ($SIG_{orig}(i)$) can be finally obtained.

$$SIG_{rec}(i) = \theta \cdot AF_{orig}(i) + SIG_{orig}(i) \quad (1)$$

There are two main problems to be solved so as to perform reliable artifact minimization. Firstly, the precision of the propagation coefficients θ affects the accuracy of this method. There are several methods to determine the propagation coefficients. As the first method, the visual analysis performed by the physician should be mentioned. This method is very subjective, time consuming and also inaccurate. There are also much more sophisticated

methods used to determine the interference of the artifacts in the monitored signal. These methods typically use a regression analysis – both in time or frequency domain. Their typical application is to remove ocular artifacts from the EEG signal. Some of the applications can be found in [SASP86], [GSM86], [KMVS91]. The propagation coefficients determined using a frequency domain approach vary with frequency in comparison to those determined by the time domain approach [Ille01]. The second problem of the artifact minimization consists in the fact that this method supposes that the source of the artifact is not contaminated by another source of artifacts. But it is evident that the source of the artifacts can be also contaminated by some other artifacts or that the original activity of the monitored organ can intrude the artifact source signal. This fact is crucial for this method of artifact minimization.

Moreover, in some analysis, the source of the artifacts is not available. In this case, reconstruction of the artifact source must be done. These methods can be referred as spatial filters. The spatial filters methods are based on the modeling and presence of the topographic data – topographies of the original signal and artifact. Modeling of both the topographies enables a distortion-free artifact removal. As the two main techniques should be mentioned these: Multiple source approach and Independent component analysis (ICA). These techniques differ in the way how both the topographies are estimated. The Multiple source approach is mainly used to the correction of ocular artifacts. Then, the concrete method published by P. Berg and M. Scherg [BS91a], [BS91b], [BS94] is called Multiple Source Eye Correction (MSEC). MSEC technique consists of two phases. In the first phase, the artifact topographies are determined using the principal component analysis (PCA). Then, in the second phase, the original signal topographies can be estimated by the spatio-temporal dipole source analysis [SC85], [Scherg90].

If the ICA technique is used, both the topographies are estimated together in a one step. From the nature of the method, ICA decomposes the recorded data (set of m channels) into m statistically independent processes and corresponding topographies. So, if the original signal activity and the artifact activity are independent (in general, this presumption is fulfilled), they can be separated into different components. The weakness of this method is that the independent artifact components then have to be detected manually. Some of the ICA artifact processing applications can be found in [MBS96], [Vigario97]. The two techniques slightly presented here can be considered as the introduction to the spatial analysis used to artifact removal.

There is another strategy that can be characterized as artifact minimization. Application of an appropriate digital filtration is one of the best known methods of artifact minimization. Application of this method is mainly limited by the relative location of the artifact frequency range compared to the frequency range of the original signal. If both the frequency bands are not intermingled, problem of artifact minimization is transformed to the design of a suitable digital filter (low-pass or high-pass filter). For example, the electrodermal or respiration artifacts (characterized by very low frequency range, typically less than 0.5 Hz) can be attenuated by the use of high-pass filter. Design of the digital filter then consists in the analysis of the filter type, structure, cut-off frequency or the order. Design of the digital filter should also pay attention to the linear phase characteristic. This requirement is necessary so as to ensure that the time proportions in the signals stay unchanged. It can be, for example, required when the signal differences are computed [Gotman83].

2.3 Methods used to process artifacts

When the polysomnographic recording is already recorded, the whole recording should be tested for artifacts before whatever analysis of the monitored signals begins. Presence of the artifacts can markedly confuse the quantitative analysis performed as the initial phase of the sleep classification process. Although the development of artifact detection methods is not the main goal of this thesis, the effect of proper artifact detection strategy on sleep/wake stage classification is also explored.

The artifact detection strategy employed in this thesis goes from the artifact identification strategy presented earlier in this chapter. This method excludes the segments of signal where an artifact is identified. It could lead to excessive and undesirable reduction of the available data when the analyzed segments are too long. This unwanted effect has been notably eliminated by decrease of the epoch length. Increase of the signal time resolution is also useful for the artifact detection algorithms. Since most of the artifacts are present only for a few seconds and do not contaminate the entire epoch of the recording (20 sec), employment of the short segments during artifact identification leads to precise localization of the artifacts. So, detection algorithms dealing with shorter intervals can be thus more effective, powerful and at last but not least thrifty of the data.

The practical tests and experiments realized during this thesis use a set of polysomnographic recordings scored by the sleep experts. The recordings are scored epoch by epoch with

constant epoch duration of 20-sec. The 20-sec interval is long too much for its complete rejection from the recording by the reason of possible artifact presence. Each whole night recording has been for the need of artifact analysis split into shorter intervals. To perform precise and also sensitive artifact identification the segments with duration of 2-sec have been used. So, during the artifact identification process, each 2-sec segment of the polysomnographic recording has been checked for possible occurrence of an artifact in the monitored signals. For the sleep/wake stage classification itself, the link between the hypnogram representing scoring of the polysomnographic recordings and results of artifact detection must be kept because proposed automatic classification will be done with a time resolution of 20-sec epochs. So, each original 20-sec epoch has been actually split into succession of ten consecutive 2-sec segments.

A lucid strategy is then employed so as to decide if the entire 20-sec epoch will be marked as artifacted or not. If more than 20% of the epoch duration contains any kind of artifact then the entire 20-sec epoch is said to be artifacted. The threshold value of 20% of epoch duration corresponds to two segments with a length of 2 sec. All the 20-sec epochs marked as artifacted are then excluded from the subsequent analysis – sleep/wake stage scoring. On the contrary, if number of artifacted segments is less or equal to two, the corresponding 20-sec epoch is said to be artifact-free and can be used in subsequent analysis. But, all the 2-sec segments contaminated with an artifact are cut off from the epoch trace. This artifact strategy avoids undesirable loss of available data and on the other hand provides an adequate rejection of artifacted segments (brief artifacts) or entire epochs (large, long-lasting artifacts). The criterion defined to distinguish artifact-free and artifacted epochs is based on portion of segments contaminated with an artifact. The concrete value of the threshold (20% of epoch duration) has been set in order to provide intervals of the signals long enough for quantification of the signals (extraction of the features). Tuning of the threshold value representing portion of artifacted segments is thus a trade-off between unreasonable rejections of the epochs and acquisition of sufficient and undistorted data. If more than 20% of an epoch could be contaminated with an artifact in an epoch marked as artifact-free, the information in the uncontaminated rest of the epoch could be insufficient to unambiguously characterize the actual state of the subject. Thus, it would lead to decrease in accuracy of the automatic classification.

The artifact identification strategy proposed in this work was achieved using the PRANA software which is equipped with a universal automatic detection algorithm performing both variants of artifact identification – absolute and adaptive threshold method. The general principle of the artifact identification implemented in the PRANA software can be described in three main steps. At the beginning, the signal to be analyzed can be digitally filtered in order to isolate the activity of the interest. Some of the artifacts are characterized by typical activity in a particular frequency band. In the second step, the characteristic feature (parameter of the signal) is computed from the signal. In the concrete, the feature is computed from each segment of the signal. In the last step, the computed values of the characteristic feature are compared with either absolute or adaptive threshold values. If the absolute threshold is employed in the detection algorithm, a concrete threshold value and a comparison operator (more or less) are required. When the adaptive threshold is used, local changes of the signal in the moving window characterizing background activity are being detected. To perform adaptive threshold method, length of a moving window and a multiplication factor are required. To define the actual adaptive threshold value, the median of all elementary feature values computed over the selected background window and the multiplication factor are multiplied. So, the multiplication factor indicates how much the activity of an artifact exceeds the local background activity. Concrete algorithms used in the proposed classification system to identify artifacts will be characterized in the next part of the thesis.

2.3.1 Setting of artifact identification algorithm

As presented in the first part of this chapter, various kinds of artifact can occur during monitoring of the polysomnographic signals. Some of the artifacts (e.g. electrodermal or respiration) can be simply attenuated by band-pass filtration performed during the phase of signal processing prior to feature extraction. Polysomnographic signals are filtered in order to pick up the activity that is important for the sleep analysis. Artifact detection plugin has been used to detect eight artifacts frequently present in the polysomnographic recordings. An overview of the artifacts detected in this project and general characteristics of the corresponding detection algorithms is presented below.

Since the available polysomnographic recordings were not analyzed by the experts for presence of artifacts, tuning of the artifact detectors (i.e. setting of the thresholds) could not be properly validated on the recordings with visually marked artifacts. So, setting of the

detection algorithms has been done empirically. It is evident, that proper setting of the threshold values affects both sensitivity and specificity of the artifact detectors.

Overflow detection

Overflow artifact can be typically characterized as a saturation effect caused by the limited dynamic range of the amplifier and/or analog-to-digital converter. In a case of saturation effect, the trace of the recorded signal does not represent the true signal any more. The trace typically represents only the maximal/minimal value of the quantification range. An example of an overflow in the EMG signal is presented in the Fig. 6.

Since an 8-bit quantification was used to digitize the signals, the data in the monitored signals range from -127 to 127. The overflow artifact is detected, if the absolute amplitude in the 2-sec segment is greater than or equal to 125 μV . It is a simple example of constant absolute threshold algorithm.

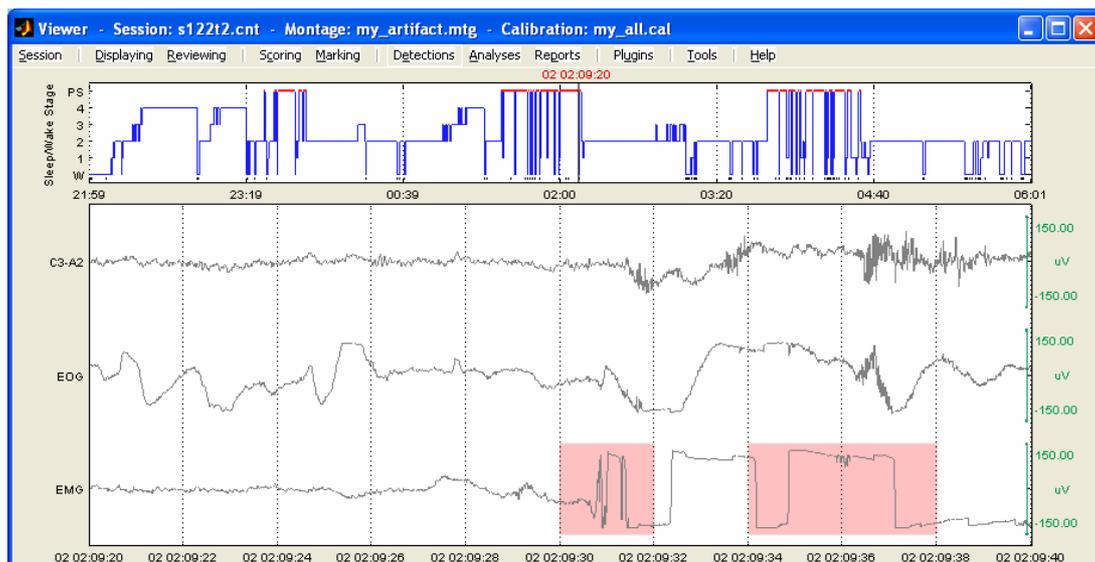


Fig. 6 Overflow in the electromyogram.

Flat-line detection

Flat-line artifact stands for a markedly low-amplitude activity present in the signal trace instead of expected moving or oscillating activity. It could be mainly caused by the saturation of the amplifier that causes insufficient amplification of the signal. So, the segments of the signal that contain flat-line artifacts do not reflect the actual activity of the monitored organ. The Fig. 7 shows an example of a flat-line artifact in the EMG signal during a wake stage.

An algorithm computing peak-to-peak amplitude (difference between the maximum positive and the maximum negative amplitudes) of the filtered signal is used to detect flat-line artifact in the signal trace. If the peak-to-peak amplitude in the segment is lower than $5 \mu\text{V}$, then the segment is marked as contaminated by the flat-line artifact.

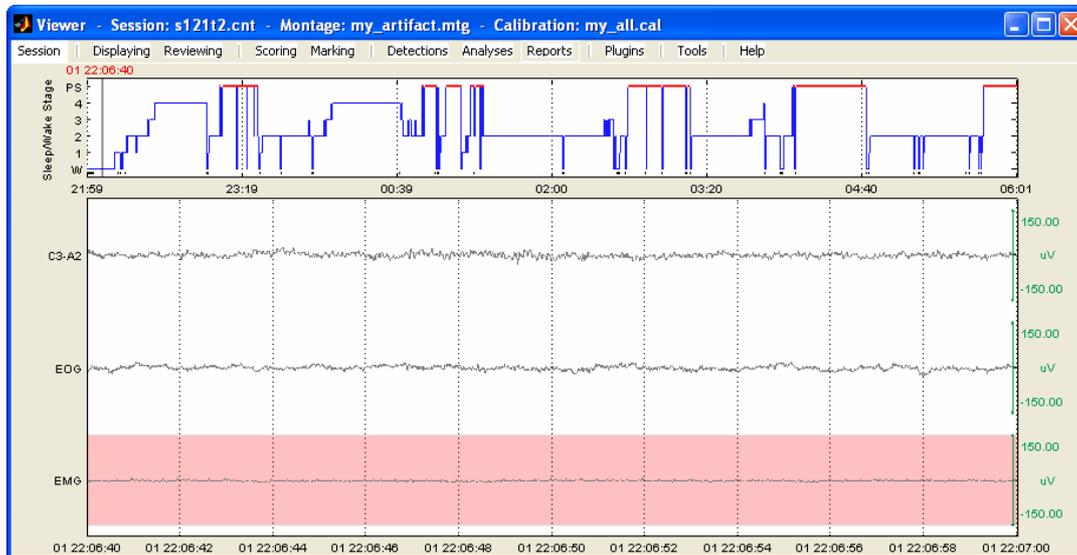


Fig. 7 A continuous flat-line artifact in the electromyogram.

Loss of signal detection

During a long-time monitoring of the physiological signals it can happen that a brief loss of the signal can appear. It can mainly correspond to detachment of an electrode. In the recording, this event can be demonstrated as constant “zero amplitude signal”. An example of this artifact can be seen in the Fig. 8.

In the proposed automatic system, a loss of signal artifact is detected whenever the amplitude of the signal is equal to zero during an interval longer than 15 samples. The length of the interval (15 samples) has been set on the base of trial and error approach.

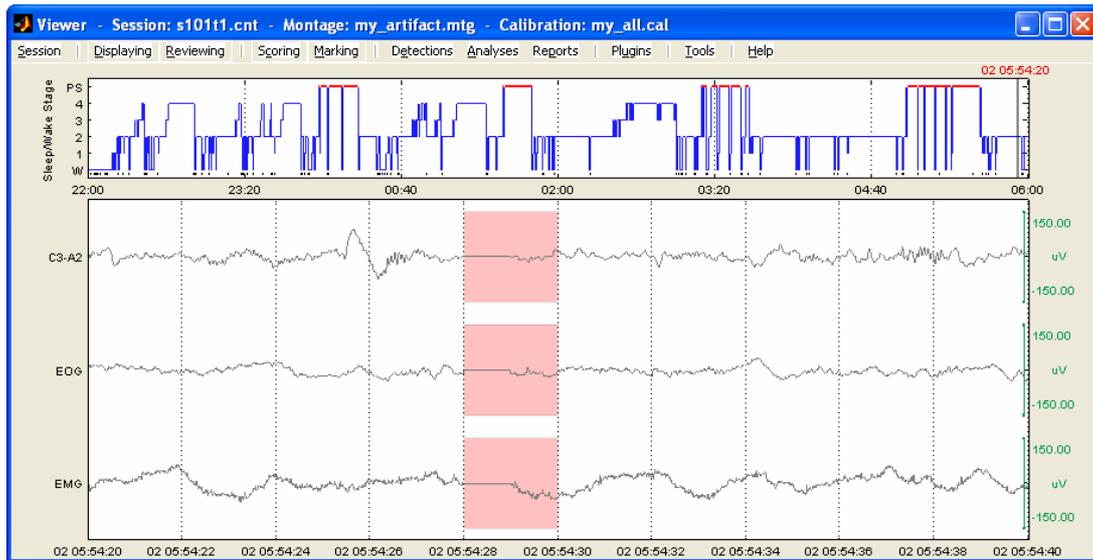


Fig. 8 A brief loss of signal in all monitored signals.

Power line artifact

Existence of the power line artifact is caused by interference of the 50/60 Hz mains into the monitored signal. In the recording, the power line artifact manifests itself as a substantial activity in the frequency range close to the 50/60 Hz. In Europe, 50 Hz mains power is used.

To detect a power line artifact, peak-to-peak amplitude is computed for each segment of the band-passed signal (45-64 Hz). If the peak-to-peak amplitude in the 2-sec segment of the filtered signal is higher than 50 μV , a power line artifact is then identified. The threshold value has been set so as to identify only the segments contaminated with high activity in the frequency range [45-64] Hz. If the activity in this frequency range is low or moderate, the segment is not marked as an artifact, because this low activity should be normally attenuated (removed) using a band-pass filtration during subsequent phase of signal processing.

High-frequency artifact

Compared to the normal activity of the polysomnographic signals, high-frequency artifact is characterized as an activity or phenomenon with substantial frequency content in a range of high frequencies. Sometimes, frequencies characterizing the artifact are even over the range of our interest. Typically, muscular activity is a prominent source of high-frequency artifacts in the polysomnographic recordings. Maximum of the activity characterizing the muscular

activity is typically over 25 Hz. So, as could be expected, the artifact is characterized as dominant high-frequency activity present in the signal.

To characterize the contribution of the high-frequency activity in the signal, the spectral edge frequency parameter is used in the detection algorithm. In the concrete, the spectral edge frequency 95 (SEF 95) indicating the highest frequency below which 95% of the total power is located is used to detect high-frequency artifacts. Since the upper frequency range (frequency range of our interest) of the polysomnographic signals usually reaches about 30 Hz, a high-frequency artifact is detected if the SEF95 computed for the 2-sec segment exceeds 30 Hz.

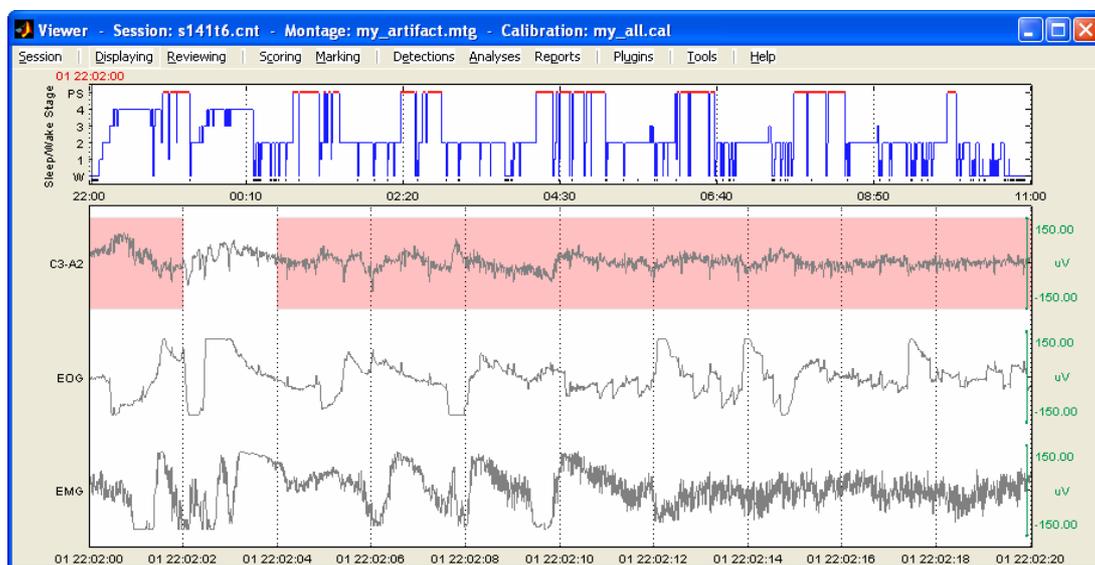


Fig. 9 A high-frequency artifact in the electroencephalogram.

ECG artifact

Disturbance of the monitored signal by the ECG signal leads to a special type of artifact. The ECG artifact manifests as a sharp peak similar to the original QRS complex of the electrocardiogram. The ECG artifact is well recognizable when the monitored signal has very low amplitude. Typical contamination of the EMG signal with ECG artifacts is presented in the Fig. 10. The proposed detector can be also used to detect other sudden and unwanted sharp peaks in the signals.

In order to identify an ECG artifact, two parameters characterizing the first derivation of the filtered signal are computed. Firstly, the peak-to-peak amplitude (pk-pk) of the signal derivation is computed. It should reflect the sharpest deflection in the signal. Then, the

interquartile range (IQR) is computed from the signal first derivation. Since the IQR computes the range of the middle 50% of the data it is not affected by outliers or extreme values typically caused by the sharp peaks (artifacts) in the signal trace. At the end, the ratio of the peak-to-peak amplitude and IQR is computed and then compared to the absolute threshold value. The algorithm is based on the fact that the sharp peaks characterizing the ECG artifact stand out from the signal background.

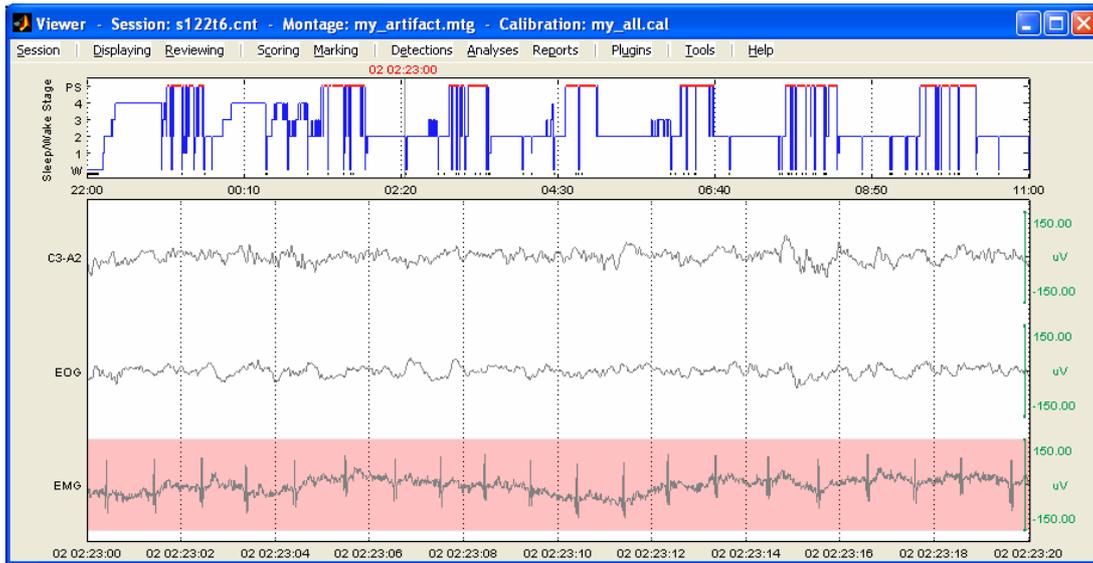


Fig. 10 Continuous contamination of the electromyogram - ECG artifact.

All the algorithms presented above use an absolute threshold value to detect the artifacted segments. The second part of the artifact detection algorithms (characterized below) uses an adaptive threshold depending on the local background activity of the signal determined by the background window. The threshold value determined for the adaptive threshold method is calculated using the median value of the characteristic parameter values computed for the elementary 2-sec segments contained in the selected moving background window. The median value is then multiplied by a certain factor. In both the algorithms, a 60-sec symmetric moving background window is used to update the threshold.

Low-frequency artifact

Some of the artifacts can manifest as a low-frequency activity. The extremely low frequencies are successfully attenuated by high-pass filtration. Nevertheless, some of the artifacts can

intermingle with the desired physiological signal and then manifest in the signal trace as slow waves.

To detect these artifacts, an algorithm characterizing activity of the signal in the low-frequency range [0-2] Hz is applied. Peak-to-peak amplitude is computed as the parameter from the filtered signal. A low-frequency artifact is detected whenever the peak-to-peak amplitude is above an adaptive threshold.

Muscular activity detection

A muscular activity artifact typically consists in a high-frequency burst of high amplitude spikes present in the signal trace. The outlying values of the artifact clearly stand out from the background signal. So, time domain features can be used to characterize the manifestation of the muscular activity. Muscular activity, especially its high frequency character can also be identified by the high-frequency artifact detector presented earlier.

The algorithm computes the variance of the filtered signal in order to identify the muscular activity artifacts. An artifact is detected whenever the variance of the signal in [5-64] Hz range is higher than an adaptive threshold. The weak point of this algorithm is that it can detect some sleep spindles and mark them as muscular activity.

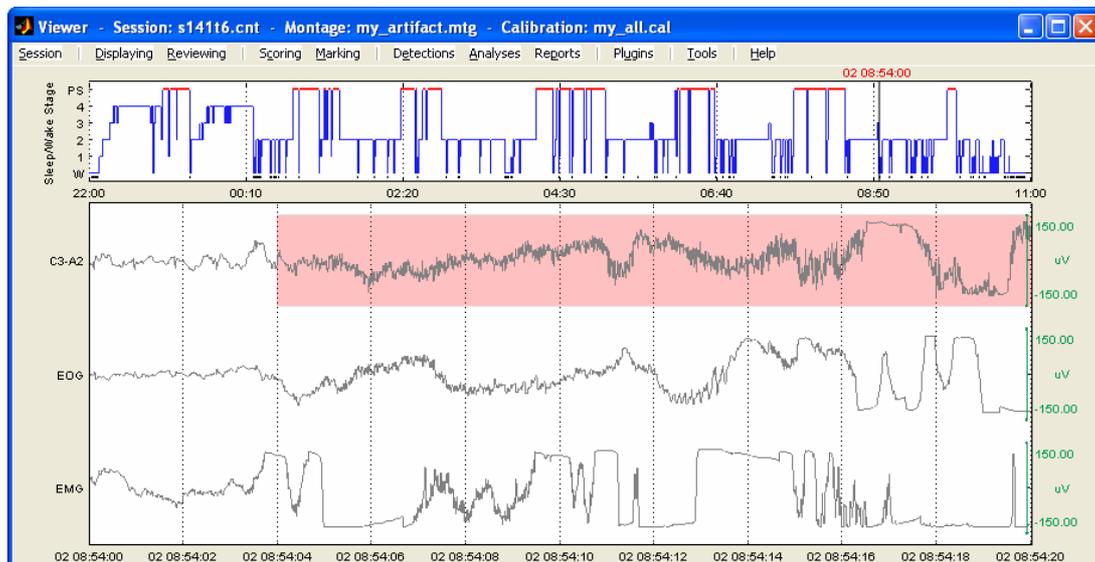


Fig. 11 A muscular activity artifact in the electroencephalogram.

Parameters of all artifact detection algorithms are summarized in the Tab. 3. The abbreviation f_N stands for the Nyquist frequency. The actual value of the Nyquist frequency is determined from the sampling frequency of the signals in the recording. The sampling frequency of the polysomnographic recordings used in this project is 128 Hz, so the Nyquist frequency is 64 Hz. It is defined as half of the sampling frequency. Last column of the table shows the length of the moving window used to define the local activity interval. Naturally, in the case of the absolute threshold method, the value is not defined.

Artifact	Filtration [Hz]	Parameter	Threshold	Background [sec]
Overflow	NO	Max absolute value	>125 μ V	-
Flat-line	$1 - f_N$	Peak to peak amplitude	<5 μ V	-
Loss of signal	NO	Length of zero	>15 samples	-
Power line	45 – 64	Peak to peak amplitude	>50 μ V	-
High-frequency	$1 - f_N$	SEF95	>30 Hz	-
ECG	3 – 32	1 st derivation (pk-pk / IQR)	>13	-
Low-frequency	0 – 2	Peak to peak amplitude	>7,5	60
Muscular activity	$5 - f_N$	Variance	>3.5	60

Tab. 3 Setting of individual artifact identification algorithms.

Identification of all the artifacts mentioned above was performed in this work. All 47 polysomnographic recordings were analyzed in order to identify and reject the artifacted segments of the signals (EEG, EOG and EMG).

2.4 Results of artifact identification

Signal analysis focused on artifact identification represents the first step in the general structure of the automatic sleep/wake stage classification. Then, automatic classification is performed using the features extracted from three signals (EEG, EOG and EMG signal).

Firstly, to present the results of artifact identification in a comprehensible form, a transparent notation must be defined. The aim of the artifact analysis is to identify the artifacts in the signal trace and remove the segments contaminated with artifacts. Artifact identification is

performed on 2-sec segments of the signals. Then, succession of ten consecutive 2-sec segments is used to evaluate the 20-sec epoch. The 20-sec epoch can be marked either as *artifact-free* or as *artifaced*. The artifact-free epochs can be subsequently used in the automatic classification. On the contrary, the artifaced epochs are excluded from the recording (signal) and are not used any more. If the 20-sec epoch does not contain any artifaced segment, it is marked as *clear* epoch. The polysomnographic signals (EEG, EOG, and EMG) were analyzed separately. The labeling of the epochs defined here (*artifact-free*, *artifaced*, *clear*) is used in the following tables, that summarizes the artifact identification analysis.

2.4.1 Preliminary analysis of the full polysomnographic database

The full database composed of 47 polysomnographic recordings has been analyzed in order to identify presence of possible artifacts. The results characterize artifact identification performed on the reduced database (*Both experts* database) described in the Tab. 2. The database contains 67,386 epochs with a constant length of 20-sec. The general summary of artifact identification performed on the three polysomnographic signals is presented in the Tab. 4. The table shows number of artifact-free, artifaced and clear epochs in the analyzed signals.

<i>Both experts</i>	EEG	EOG	EMG
artifact-free	62,674	59,247	56,263
artifaced	4,712	8,139	11,123
clear	51,727	44,049	47,144

Tab. 4 Analysis of artifact contamination in the physiological signals – Both experts database.

As it can be seen, the highest number of artifaced epochs is present in the electromyogram. The 11,123 epochs marked as artifaced represent about 16% of the whole data. This value should be regarded as high. So, detailed analysis of individual artifacts recognized in the recordings is needed in order to explain the high artifact contamination of the data.

Since the artifact identification is performed on 2-sec segments of the signals, it is necessary to present a more detailed analysis of the results. It means analysis of the artifact presence on

the level of individual 2-sec segments. This type of analysis provides estimation of presence of various types of identified artifacts. Since the epochs stored in the *Both experts* database are used, the total number of 2-sec segments is 673,860.

<i>artifact</i> \ <i>signal</i>	EEG	EOG	EMG
Overflow	5,106	14,717	44,182
Flat-line	0	1,435	8,106
Loss of signal	95	2,192	881
Power line	18	3	550
High-frequency	28,313	32,186	0
ECG artifact	91	1,801	16,328
Low-frequency	501	449	213
Muscular activity	8,687	7,423	8,142

Tab. 5 Analysis of individual artifacts in the physiological signals – Both experts database.

Tab. 5 characterizes number of occurrence determined for individual types of artifacts detected in the polysomnographic signals. The results show quite a high contamination of the analyzed signals with the overflow artifact. Especially the electromyogram is heavily contaminated with overflow. The muscular activity artifacts and high-frequency artifacts are also frequent in the polysomnographic recordings analyzed during the tests. There could be also seen high number of 2-sec segments of the EMG signal contaminated with flat-line and ECG artifacts. To explain high contamination with some concrete artifacts, special analysis of individual recordings could be useful. Results of such analysis are presented below.

The results presented in the Tab. 5 characterize the overall information about the individual artifacts. The values come from all 47 recordings together and are determined as sum over all recordings. A detailed analysis of the single recordings is also needed in order to discover possible signals that could be extremely degraded with some artifacts. If some recording contains a lot of artifacts (compared to the other recordings), it can confuse the estimate of the average artifact contamination. The inspection of the artifact detection results showed several excessively artifacted recordings. An overview of such recordings is presented in the Tab. 6. The table shows the recording identification (label), actual type of the artifact, and also the number of artifacted 2-sec segments in the concrete physiological signal.

There is a lot of recordings that have at least one of the signals markedly confused with the overflow artifact. It is mainly the case of the EMG signal. There are at least nine recordings that have extremely high portion of overflow artifacts in the EMG signal. For example, the recording 101t7 contains 4,415 2-sec segments contaminated with overflow artifacts in the EMG signal trace. It makes about 30% of the whole night recording. It can be said, that the set of the polysomnographic recordings used in this thesis is characterized by relatively high presence of overflow artifacts. This fact could be mainly explained by insufficient setting of the recording device (e.g. only 8-bit quantification).

The second case of huge artifact contamination is linked with presence of flat-line artifacts. There are 6,320 2-sec segments identified as flat-line artifact in the EMG signal of the recording with label 121t2. The flat-line artifact occupies about 45% of this whole night recording. The artifact (flat-line signal) is present during all sleep/wake stages, so it does not reflect any characteristic activity/inactivity of the person during a sleep. It is probably caused by some error occurred during monitoring and recording of the signal. There is also quite high number of artifacted 2-sec segments in the EMG signal of the recording 146t2. The recording 146t1, in the concrete the EOG signal, is also contaminated with flat-line and loss of signal artifact. In total, there are 3,517 segments contaminated with low amplitude artifacts. So, it seems that amplitude of the monitored EOG signal is in large part of the night extremely low.

The high-frequency artifacts are frequently present in the polysomnographic recordings. In general, they can reflect the muscular activity of the person and thus can also be linked with muscular activity artifacts and/or overflow. The EEG signal of the 105t1 recording is contaminated with high-frequency artifact. A detailed analysis of the recording revealed continuous high-frequency activity that intrudes the EEG signal. It could be explained as disturbance caused by some external source – medical device or other equipment. The other recordings presented in the table characterize the high-frequency interference mainly caused by the muscle activity. The analysis of the EMG signal shows both high-frequency and sharp high-amplitude muscular activity in the intervals where the artifacts are detected. Large number of high-frequency artifacts in the 124t7 recording is also caused by abnormal structure of the whole night sleep. There is extremely long interval at the beginning of the night (approximately 210 minutes) when the person is awake. During this time, muscle tension and high-frequency activity are almost permanently present in the EMG signal of the recording.

Application of the ECG artifact detector leads to identification of ECG artifacts in the signals. There are four recordings in the set of the polysomnographic recording that are highly contaminated with ECG artifacts. In the recording 146t1, there is high portion of ECG artifacts in the middle of the EOG signal. The other three recordings have ECG artifacts in the EMG signal. In the recordings 101t7 and 122t6 are the ECG artifacts uniformly distributed during the entire recording. It leads to a large number of artifacted 2-sec segments in both the recordings. The number of artifacted segments in these two recordings is 5,665 and 7,339 respectively. The recording with label 121t6 is disturbed by the ECG artifacts mainly at the end of the recording.

<i>artifact</i> \ <i>signal</i>	EEG	EOG	EMG
Overflow	-	s101t7 (1,821) s146t1 (2,120)	s101t2 (2,015) s101t7 (4,415) s105t7 (2,036) s121t6 (2,536) s123t7 (2,268) s141t1 (2,079) s141t2 (2,032) s143t2 (3,052) s144t2 (2,586)
Flat-line	-	s146t1 (1,435)	s121t2 (6,320) s146t2 (1,764)
Loss of signal	-	s146t1 (2,082)	-
High-frequency	s105t1 (8,004) s124t7 (2,985)	s121t2 (2,679) s121t6 (3,793) s121t7 (3,088) s123t6 (2,003)	-
ECG artifact	-	s146t1 (1,765)	s101t7 (5,665) s121t6 (1,106) s122t6 (7,339)

Tab. 6 Overview of extremely artifacted recordings.

The other types of artifacts do not show such extreme examples in contamination of the individual recordings. But one recording should be mentioned again. As mentioned above, the recording 146t2 is characterized by a high number of flat-line artifacts in the EMG. In addition, the EMG signal contains also 1,047 segments identified as overflow. In this signal, two other artifacts are characterized with slightly increased number of occurrence. 785 segments are identified as loss of signal and 476 segments are identified as power line artifact. As it can be seen in the Tab. 5, the recording 146t2 contains a major part of these artifacts identified in all 47 recordings. In total, the EMG signal of the recording contains 4,350

segments contaminated by different artifacts. The other artifacts are almost evenly distributed in the 47 recordings, so no recording notably exceeds the others in the number of some concrete artifact. It is also the case of muscular activity artifacts. Since the total number of contaminated segments is high, there is no recording that would have an extreme number of segments contaminated with muscular activity artifacts.

On the basis of the detailed analysis presented above, six recordings (s101t7, s105t1, s121t2, s122t6, s146t1 and s146t2) should be excluded from the analysis of artifact processing phase. These recordings contain extremely high number of artifacted segments and thus they could confuse the analysis of artifacts. So, the reduction of the database is necessary in order to provide reliable analysis of artifacts in the recordings.

2.4.2 Analysis of the modified database

When the six extremely artifacted recordings have been excluded, the total number of epochs was reduced from 67,386 to 58,968 epochs. The new database is characterized in the Tab. 7. The table presents number of epochs in the sleep/wake stages recognized by the proposed system.

<i>Number of epochs</i>	wake	NREM I	NREM II	SWS	REM
<i>Modified database</i>	4,626	1,854	28,858	9,989	13,641

Tab. 7 Description of the database used for analysis of artifact detection – Modified database.

The first results of artifact identification performed on the modified database are presented in the Fig. 12. The figure provides information about relative artifact contamination of the epochs contained in the modified database. Each histogram characterizes one of the physiological signals (EEG, EOG and EMG). In each graph, the horizontal axis indicates number of artifacted 2-sec segments in the 20-sec epoch. The vertical axis indicates number of epochs. It can be seen that the absolute majority out of the 58,968 epochs does not contain any artifacted segment. Contrariwise, the number of extremely contaminated epochs containing long-lasting artifacts is low. It is mainly due to the fact, that the extremely contaminated recordings have been excluded. So, the data in the actual database are not

biased by the presence of abnormal recordings characterized from the point of view of artifact contamination.

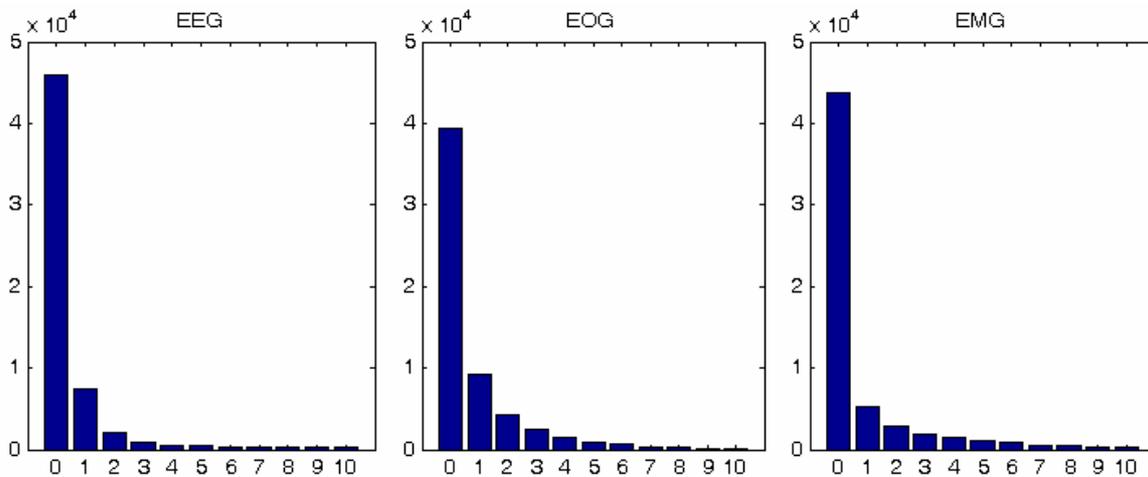


Fig. 12 Histograms characterizing degree of artifact contamination determined for analyzed epochs.

The results presented in the Fig. 12 also justify the strategy proposed to evaluate degree of contamination of the 20-sec epochs. As it can be seen, there is a lot of epochs containing only brief artifacts in the data. In this table, these epochs could be characterized by presence of only two artifacted segments at most. So, in the tasks, where the artifact identification is performed on entire 20-sec epochs, a large number of slightly contaminated epochs would be excluded unnecessarily. So, this approach would lead to a large reduction of the number of available data.

To provide overall information about artifact contamination, it is also necessary to present results of artifact analysis performed on 20-sec epochs. In the Tab. 8, the number of epochs in different sleep/wake stages depending on degree of artifact interference is presented. The results show that the wake stage is characterized by high number of artifacted 20-sec epochs. High artifact contamination can be seen for all three physiologic signals. An increase in the absolute number of artifacted epochs in the EOG and EMG signals during NREM II and REM sleep stages can be observed compared to the EEG signal. It is also reflected in the total number of artifacted epochs. In the case of the EEG, the number of artifacted epochs is the lowest. On the contrary, the numbers of epochs marked as artifacted in the EOG and EMG are significantly higher.

<i>Number of epochs</i>		wake	NREM I	NREM II	SWS	REM	total
EEG	artifact-free	1,992	1,773	28,473	9,913	13,341	55,492
	artifacted	2,634	81	385	76	300	3,476
	clear	1,101	1,415	23,087	8,713	11,661	45,977
EOG	artifact-free	2,325	1,593	27,537	9,921	11,361	52,737
	artifacted	2,301	261	1,321	68	2,280	6,231
	clear	931	1,031	21,188	9,518	6,723	39,391
EMG	artifact-free	2,811	1,569	26,126	9,060	12,359	51,925
	artifacted	1,815	285	2,732	929	1,282	7,043
	clear	1,814	1,196	22,877	7,908	9,880	43,675

Tab. 8 Analysis of artifact contamination – Modified database. Absolute contamination of the stages.

To provide a relative comparison of artifact contamination, the Tab. 9 shows the percentual evaluation of artifact-free, artifacted and clear epochs determined for individual sleep/wake stages.

%		wake	NREM I	NREM II	SWS	REM	total
EEG	artifact-free	43,1	95,6	98,7	99,2	97,8	94,1
	artifacted	56,9	4,4	1,3	0,8	2,2	5,9
	clear	23,8	76,3	80,0	87,2	85,5	78,0
EOG	artifact-free	50,3	85,9	95,4	99,3	83,3	89,4
	artifacted	49,7	14,1	4,6	0,7	16,7	10,6
	clear	20,1	55,6	73,4	95,3	49,3	66,8
EMG	artifact-free	60,8	84,6	90,5	90,7	90,6	88,1
	artifacted	39,2	15,4	9,5	9,3	9,4	11,9
	clear	39,2	64,5	79,3	79,2	72,4	74,1

Tab. 9 Analysis of artifact contamination – Modified database. Relative contamination of the stages.

As it can be seen in the Tab. 9, wake stage can be regarded as the stage with the highest portion of artifacted epochs. The relative contamination of the wake stage highly exceeds contamination of the other four stages. For the EEG and EOG signals, about 50% of all epochs scored as wake are artifacted and thus excluded from the automatic classification. In the case of the EMG, the percentage is slightly lower (about 40% of all wake epochs), but still very high. The percentage of artifact contamination observed in other stages is significantly lower (lower than 15%). The lowest relative contamination is in the SWS. In the EEG and EOG signals, only less than 1% of all SWS epochs is artifacted.

Until now, analysis of the modified database did not focus on evaluation of individual artifacts. Information about types of dominant artifacts could be important in order to analyze quality of the signals monitored. In consequence, such information could be useful to prevent or reduce presence of the dominant artifacts. Thus, the quality of the signals monitored as well as the accuracy of the sleep/wake stage classification could increase.

2.4.3 Detailed analysis of individual artifacts

Now, the detailed analysis of individual artifacts on the level of 2-sec segments created from the modified database described in the Tab. 7 will be presented. In total, 589,680 segments are contained in the 41 recordings. Number of 2-sec segments contaminated by individual types of artifacts detected in the polysomnographic signals is presented in the Tab. 10.

<i>artifact</i> \ <i>signal</i>	EEG	EOG	EMG
Overflow	4,202	10,437	36,437
Flat-line	0	0	0
Loss of signal	88	105	69
Power line	15	3	67
High-frequency	19,094	27,815	0
ECG artifact	65	25	3,140
Low-frequency	455	411	187
Muscular activity	7,390	6,385	7,669

Tab. 10 Analysis of individual artifacts in the physiological signals – Modified database.

The results presented above show that the physiologic signals are mainly contaminated by overflow, high-frequency and muscular activity artifacts. So, these three types of artifacts will

be closely analyzed in the next part. All the other artifacts are rarely present in the polysomnographic recordings. However, though their occurrence is not typically frequent, their detection is needful in order to discover some specially contaminated recordings, like those presented in the Tab. 6. The extreme value representing number of ECG artifacts in the EMG signal is mainly caused by two recordings. The recordings are labelled as 121t6 and 141t4 and contain 1,106 and 850 artifacted segments respectively. In total, these two recordings contain 1,956 segments contaminated with ECG artifact.

A detailed analysis of the identified artifacts depending on the different sleep/wake stages is presented in the next part of this chapter. For each physiological signal (EEG, EOG, EMG) a table characterizing the distribution of the individual artifacts (eight types of artifacts) in the sleep/wake stages is prepared. It is necessary to keep in mind that the number of epochs over the different sleep/wake stages is not equal in the typical whole night sleep. So, the values in all the tables should be interpreted relatively to the total number of epochs in the corresponding stage. As mentioned above, mainly the overflow, high-frequency artifacts and muscular activity artifacts will be discussed.

<i>artifact</i> \ <i>EEG</i>	wake	NREM I	NREM II	SWS	REM
Overflow	1,816	38	573	1,539	236
Flat-line	0	0	0	0	0
Loss of signal	68	0	10	3	7
Power line	15	0	0	0	0
High-frequency	14,592	642	1,323	41	2,496
ECG artifact	60	0	1	1	3
Low-frequency	181	8	209	0	57
Muscular activity	882	106	5,639	97	666
No artifact	28,646	17,746	280,825	98,209	132,945

Tab. 11 Analysis of individual artifacts in different sleep/wake stages. EEG signal.

Distribution of the artifacts in the EEG signal is presented in the Tab. 11. As it can be seen, the overflow artifact is most frequent in the wake and in the SWS stage. In the wake stage, the high-amplitude signal that can characterize the fast brain activity as well as disturbance of the EEG signal caused by abrupt body movements can lead to overflow. Electroencephalogram of the SWS stage is characterized by slow high-amplitude waves. These waves can also lead to

unwanted overflow artifact. In the other stages, the overflow artifacts are not so frequent. High-frequency artifacts frequently present during the wake stage can be explained as manifestation of muscular activity transmitted to the EEG signal. Muscular activity can also contaminate the EOG signal as shown in Fig. 13. Moreover, the recording 124t7 contains 2,966 segments contaminated with high-frequency artifacts. It forms a big part of all the artifacted segments. A large number of muscular activity artifacts in NREM II stage can be explained by transition of the high-amplitude and high-frequency activity (artifacts) generated by the muscles. These artifacts are frequently identified in the NREM II stage of the EMG signals contained in the base of recordings. Nevertheless, some of the manifestations identified as muscular activity artifacts in the NREM II stage can be characterized as false positive detections. As mentioned during the description of the detection algorithms proposed, the muscular activity detector can misclassify some of the sleep spindles present in the signal trace. It is a drawback due to the fact that the tuning of the artifact detectors has not been properly validated on the data with artifacts identified by an expert. Visual inspection of the automatically analyzed recordings revealed a low number of sleep spindles misclassified as muscular artifacts. Since the sleep spindles are characterized as brief phenomena, no more than one segment of an epoch is typically identified as an artifact. Thus, the total reduction of available epochs is not high. Moreover, the majority of the sleep spindles is still kept in the signal and thus the informational content of the epochs is not decreased.

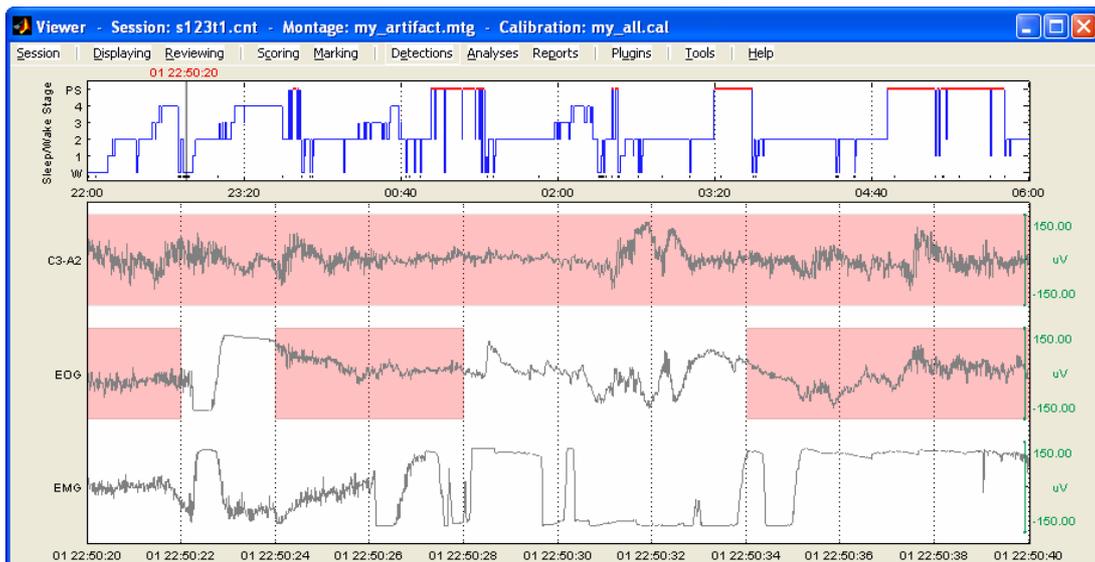


Fig. 13 Example of high-frequency contamination in the EEG and EOG.

The EOG signal is more contaminated with overflow artifacts compared to the EEG signal. The overflow is frequent in wakefulness and REM sleep stage. The characteristic movement of the eyes called REMs can be considered as the cause for the increased presence of overflow in the EOG signal. As well as in the EEG, most of the high-frequency and muscular activity artifacts corresponds to bursts of muscular activity that can be intermingled with the EOG signal. Moreover, the application of the muscular activity detector leads to the detection of some sleep spindles transmitted from the brain.

<i>artifact</i> \ <i>EOG</i>	wake	NREM I	NREM II	SWS	REM
Overflow	4,319	135	502	457	5,024
Flat-line	0	0	0	0	0
Loss of signal	61	6	20	3	15
Power line	3	0	0	0	0
High-frequency	8,606	1,637	8,215	75	9,282
ECG artifact	22	0	0	1	2
Low-frequency	37	9	69	0	296
Muscular activity	570	99	4,261	189	1,266
No artifact	32,642	16,654	275,513	99,165	120,525

Tab. 12 Analysis of individual artifacts in different sleep/wake stages. EOG signal.

EMG is mainly degraded by the frequent presence of the overflow. The high-amplitude muscular activity often leads to the overflow of the monitoring and/or recording device. Overflow is identified in 36,437 2-sec segments of the EMG signal. This fact leads to massive loss of information useful for the need of the automatic sleep classification. As can be seen in Tab. 13, the presence of the overflow is uniformly spread during the entire night sleep. Presence of ECG artifacts detected in the EMG is practically restricted to the case of two recordings presented earlier. Since the frequency range of the EMG signal is wide and the signal is typically characterized with activity in the range of high frequencies, the high-frequency artifacts have not been detected in the EMG. Thus the extreme bursts of muscles are mainly characterized by overflow and muscular activity artifacts. These bursts are frequent during wake and REM sleep stage. In REM sleep stage, it can correspond to manifestations of the phasic REM sleep.

<i>artifact</i> \ <i>EMG</i>	wake	NREM I	NREM II	SWS	REM
Overflow	8,760	1,301	14,725	5,548	6,103
Flat-line	0	0	0	0	0
Loss of signal	53	0	7	3	6
Power line	63	1	2	1	0
High-frequency	0	0	0	0	0
ECG artifact	484	101	1,921	124	510
Low-frequency	67	6	56	4	54
Muscular activity	1,929	495	2,085	336	2,824
No artifact	34,904	16,636	269,784	93,874	126,913

Tab. 13 Analysis of individual artifacts in different sleep/wake stages. EMG signal.

2.5 Chapter conclusion

Various types of artifacts or noise can be unwillingly introduced into the monitored signals and bias the results obtained by further signal processing methods. So, suitable artifact processing strategy is inevitably needed in whatever automatic system. A combination of a short time artifact identification and a subsequent decision strategy evaluating the 20-sec epoch is used in this thesis. Both absolute and adaptive threshold methods are used as the principle of the artifact identification. In the concrete, 2-sec segments of the signals are searched through in order to detect presence of possible artifacts. Each 20-sec epoch is then presented by artifact characteristics of ten corresponding 2-sec segments. Then the 20-sec epochs are marked as either artifact-free or artifacted according to the presence of artifacts in the segments. If more than 2 segments in the 20-sec epoch are intermingled with an artifact, the epoch is marked as artifacted and excluded from the future analysis. So, if an epoch is only slightly contaminated with artifacts, it does not have to be completely rejected and it can be used in the analysis. Such a decision reduces enormous loss of data that could be caused by the artifact detection.

The results on the polysomnographic recordings show a high amount of epochs degraded with overflow artifacts. This artifact is present mainly in the EMG signal. High-frequency artifacts and muscular activity artifacts are also frequent in the data. They mostly reflect the increased activity of the muscles. The analysis of the detailed results points out a few recordings (s101t7,

s105t1, s121t2, s122t6, s146t1 and s146t2) that contain one or more signals extremely contaminated and degraded with artifacts. These recordings have been excluded from the base of polysomnographic recordings for the need of analysis of identified artifacts presented in this chapter. In spite of the fact that the settings of the individual artifact detectors have not been properly validated on data with artifacts manually detected by an expert, the results confirm the importance to correctly process artifacts as a mean to increase the quality of the data to be further processed by classification systems.

Chapter 3

Feature extraction and selection of relevant features

Manual sleep/wake stage classification is based on visual inspection of polysomnographic recordings. An experienced physician is able to analyze the signal traces visually, deal with possible artifacts and then score an epoch into one of predefined sleep/wake stages. When an automatic classification is performed, a set of relevant parameters (features) computed from the signal traces should be prepared for the automatic classifier.

In this chapter, an approach proposed to determine a set of relevant features needed for automatic classification is presented. Sequential selection methods are presented as suitable tools for selection of relevant feature set out of a pool of features. The initial pool of features extracted from all the monitored signals contains various features computed in the time domain as well as in the frequency domain.

The selection methods are applied on different combinations of signals among EEG, EOG and EMG, to take into account that some signals may be missing. At the end of this chapter, the relevant feature sets obtained are presented and analyzed.

3.1 Data mining and decision systems

Many tasks try to describe and then effectively apply the knowledge hidden in the databases or in large data warehouses. Knowledge acquiring methods can be used to extract unknown and potentially effective and useful information from the data or to find relationships hidden

in the data. The principle of these methods is mainly based on the application of analytic methods. They typically use specially preprocessed data as an input and return knowledge information as an output. This branch of science is also called Data mining, Information harvesting or Knowledge discovery in databases.

All the methods are based on the main hypothesis that each single object (case) can be described with attributes (features) so that all objects belonging to the same class have similar characteristics (e.g. attribute values). That is why these methods are sometimes called Similarity based learning. Then, it is considered that each object is described by vector of N attribute values and that each such an object can be in the N -dimensional Euclidean description space represented as a single point. All the objects that belong to the same class then form a cluster of points in the N -dimensional space. The main idea of learning process is to find a suitable representation of the single clusters or to find frontiers separating the clusters in the N -dimensional space.

The whole process of data mining consists of several phases. There is a generally accepted standard that defines the single phases of the data mining process. This international standard is called Cross-Industry Standard Process for Data Mining (CRISP-DM). CRISP-DM characterizes data mining as an iteration task containing internal feedbacks in various phases of the whole process. Six phases are defined within the data mining process:

1. Business understanding – This phase consists in understanding of the project objectives and requirements and leads to task formulation.
2. Data understanding – This phase starts with an initial data collection. A knowledge engineer should appreciate data quality and data significance to the task specification.
3. Data preparation – In this phase, raw data are transformed into a data set structure that will be fed into the modeling tool. In general, the initial data set is not characterized by an acceptable format. There are also other data preparation techniques that can be realized (e.g. continuous record sampling, attribute values standardization, continuous attribute values categorization).
4. Modeling – This phase can be presented as the heart of the data mining process. In this phase, various modeling techniques can be selected and applied. The main aim is to tune their parameters.

5. Evaluation – Testing of the system on real data and results consultations. Before the model can be finally processed, it is important to evaluate the model more accurately. At the end of this phase, a decision on the use of the data mining model should be reached.
6. Deployment – Application of the system for knowledge acquiring. It is the most important phase for the customer.

During a modeling phase, new information that can lead to changes in the data preparation or to formulation of a new task can be revealed. A loop of the functions (phases) then starts again from the beginning.

The first two phases of the data mining cycle characterize the initial introduction presented in the first chapter of this thesis. The first phase consists of description of sleep analysis and polysomnography. In this phase, the sleep/wake stages and all the monitored physiological signals are presented and described in detail in order to understand the field of sleep analysis. The flow of the automatic sleep analysis is also explored. The description of the database of polysomnographic recordings and all monitored physiologic signals correspond to the second phase – data understanding. During this phase, the initial analysis of the raw data and component 20-sec epochs is performed.

The third phase begins with artifact detection presented in the chapter 2. The tables presenting the numbers of artifacted and/or artifact-free 20-sec epochs or 2-sec segments can be seen as the first results. Artifact detection represents the first modification of the raw polysomnographic recordings and leads to the increase of the data quality. The phase of data preparation contains another very important modification of the original data. The raw data must be transformed into the N -dimensional description space that can be used during the phase of automatic classifier modeling. The transformation of recordings is recommended to extract the most suitable description of the data. Various data processing techniques can be used in this task. This chapter describes processes of feature extraction, data transformation, and selection of relevant features. Then, the phases of modeling, evaluation and deployment of the automatic system are performed. Modeling phase consists in choosing and training an automatic classifier from the data. The evaluation phase is analyzed using the classification accuracies obtained with the classifiers. These phases are presented at the end of this chapter.

3.2 Extraction of features

As could be seen in section 1.6, various signal processing techniques have been already proposed in the literature and tested in order to extract useful information from the physiological signals processed. The proper extraction of relevant features from the signals is a crucial task in the development of an automatic system of sleep/wake stage classification.

Absolute and/or relative spectral powers in the EEG frequency bands are said to be the basic information extracted from the EEG signal during sleep analysis. It is given by the fact that almost each sleep/wake stage is characterized by a characteristic pattern of frequency content. Extraction of these features corresponds to the initial visual analysis performed by the sleep expert or physician who first analyzes the EEG activity. So, processing of the signal in the frequency domain is the most frequently used technique. In the concrete, Fourier transformation and wavelet transformation should be mentioned [GRK95], [OCJ99]. Then another signal processing techniques have been also used in the previous projects realized by various groups of researchers [GFR01]. Biological signal processing performed in the time domain (statistical analysis, chaos theory, etc.) is also frequently used in the area of sleep analysis.

All epochs used in the tests performed during this thesis consist of a 20 seconds recording of three signals (one EEG C3-A2 channel, one EOG and one EMG). Since the signals monitored were sampled at 128 Hz, each one of the three recorded time series contains 2,560 samples. Such a set of 2,560 samples is not suitable input information for an automatic classifier. So, various signal processing techniques have been used in order to extract several features from the three signals of each actually processed epoch.

There are eight types of features that have been extracted during this thesis from the physiological signals included in the polysomnographic recordings. To present all of them, the features can be split into two general groups. The first group contains the features that represent the frequency information computed by the means of Fourier transformation. On the contrary, the second group of features contains all the features computed in the time domain. The overview of the features completed with their short description is presented in the next sections.

To ensure that the signals can be assumed stationary during the signal processing, each epoch is split into a succession of 2-sec segments, which are short enough to fulfill the assumption

of stationarity. The same 2-sec segments were used during artifact detection performed before. So, the feature extraction algorithms can profit from the artifact identification procedure performed prior to the feature extraction. If a 20-sec epoch is marked as artifacted on the basis of artifact identification strategy (more than two 2-sec segments contain artifacts), it is not processed by feature extraction algorithms. So, the computational time requirements are reduced. In the case of epochs marked as artifact-free (at most two 2-sec segments of signal contain artifacts), all the contaminated segments are excluded from the feature extraction. Then, two different mechanisms of feature extraction are proposed for the artifact-free epochs. The first mechanism can be denoted as averaging technique. It is inspired by the averaging technique proposed by Welch [Welch67]. This mechanism is used especially to calculate the power spectrum of a signal. Each 20-sec epoch marked as artifact-free consists of ten 2-sec segments. The power spectra are calculated from all 2-sec segments that do not contain any artifacts, averaged, and assigned to the actual epoch.

The second feature extraction mechanism can be denoted as sequence technique. The segments contaminated by artifacts are simply cut off from the trace of the 20-sec epoch and the features are calculated on the remaining part. The methods of time domain analysis are not too much sensitive to the presence of the unexpected discontinuity of the processed signal trace that can appear when one or two artifacted segments are cut off from the epoch.

Before the process of feature extraction starts, the physiological signals should be filtered in order to localize the characteristic information present in the signals better. So, each signal has been separately digitally filtered using a band pass filter prior to feature extraction. The frequency ranges passed by the individual digital filters are:

- EEG; 0.5-32.5 Hz
- EOG; 0.5-15 Hz
- EMG; 8-32 Hz.

They represent the total frequency bands defined for the individual signals. So, these frequency bands are then used to characterize total spectral powers of the signals ($P(EEG, total)$, $P(EOG, total)$, $P(EMG, total)$).

3.2.1 Frequency domain features

A set of nine frequency domain features is computed from the EEG, EOG and EMG. The individual features are presented below.

- A set of five features is used to describe the spectral activity of the EEG signal in traditional frequency bands – delta, theta, alpha, sigma and beta. The features have been calculated using Fourier transformation. Relative powers in the five frequency bands have been computed by dividing absolute powers in each frequency range by the sum of powers in the EEG total frequency band.
 - $P_{rel}(EEG, \delta_{FT})$ with $\delta_{FT} = [0.5 ; 4.5]$ Hz;
 - $P_{rel}(EEG, \theta_{FT})$ with $\theta_{FT} = [4.5 ; 8.5]$ Hz;
 - $P_{rel}(EEG, \alpha_{FT})$ with $\alpha_{FT} = [8.5 ; 11.5]$ Hz;
 - $P_{rel}(EEG, \sigma_{FT})$ with $\sigma_{FT} = [11.5 ; 15.5]$ Hz;
 - $P_{rel}(EEG, \beta_{FT})$ with $\beta_{FT} = [15.5 ; 32.5]$ Hz.
- The relative power of the EMG signal in a high frequency band [12.5 ; 32] Hz has been calculated as:

$$P_{rel}(EMG, high) = \frac{P(EMG, [12.5Hz - 32Hz])}{P(EMG, total)} \quad (2)$$

- Spectral edge frequency 95 (SEF 95) is the third parameter characterizing the frequency activity of the physiologic signals. Spectral edge frequency 95 indicates the highest frequency below which 95% of the total spectral power is located. SEF 95 was computed for all physiologic signals. Spectral edge frequency function is described in the work of Rampil *et al.* ([RSSHF80]).

3.2.2 Time domain features

- The standard deviation of a random variable characterizes the spread of its values. It is defined as:

$$std_{SIG} = \left[\frac{1}{n-1} \cdot \sum_{i=1}^n (y(i) - \bar{y})^2 \right]^{\frac{1}{2}} \quad (3)$$

where n is the number of samples $y(i)$ of the measured signal y in the epoch and \bar{y} represents the mean value of the signal y .

$$\bar{y} = \frac{1}{n} \sum_{i=1}^n y(i) \quad (4)$$

- Skewness is a factor characterizing the shape of the probability distribution function of a signal. It measures degree of the asymmetry of the probability distribution function of a signal. Skewness is defined as a normalized form of the third central moment.

$$skew_{SIG} = \frac{M_3}{M_2 \sqrt{M_2}} \quad (5)$$

The k -th central moment M_k is defined as:

$$M_k = \frac{1}{n} \sum_{i=1}^n (y(i) - \bar{y})^k \quad (6)$$

- Kurtosis is also a factor characterizing the shape of the probability distribution function of a signal. In the concrete, it determines the degree of peakedness of a distribution. Kurtosis is determined as a normalized form of the fourth central moment M_4 and is defined by the equation (7).

$$kurt_{SIG} = \frac{M_4}{M_2 \cdot M_2} \quad (7)$$

- The 75th percentile defines the value below which 75% of the random variable values are located. So, the value separates lowest 75% and highest 25% of the data. It is also called upper quartile or third quartile. The 75th percentile of the signal distribution is defined as

$$card\{y(i) / y(i) < prctile75_{EEG}\} = \frac{75 \cdot n}{100} \quad (8)$$

where n is the number of samples $y(i)$ of the measured signal y in the epoch and $card$ stands for the number of elements in the set.

- The entropy has been computed from a histogram of the signal during one epoch. It is defined as:

$$entr_{SIG} = - \sum_{j=1}^N \frac{n_j}{n} \ln \frac{n_j}{n} \quad (9)$$

where n is the number of samples $y(i)$ of the measured signal y in the epoch, N is the number of bins used for the calculation of the histogram and n_j is the number of samples $y(i)$ which values are within the j^{th} bin. In this study, N is chosen as the largest integer inferior to n squared root; it is the same for each epoch. The algorithm was published in the work of Moddemeijer [Modd89].

- A set of quantitative parameters defined by Hjorth has been computed. In his works [Hjorth70], [Hjorth73] three parameters – activity, mobility and complexity were introduced and described. The parameters are defined using a standard deviation function computed for the signal amplitude and signal derivation. The symbol σ_a stands for the standard deviation of the signal amplitude, the symbol σ_d stands for the standard deviation of the signal first derivation and the symbol σ_{dd} stands for the standard deviation of the signal second derivation. The Hjorth parameters are also called normalized slope descriptors.

Activity is defined as squared standard deviation of the signal amplitude in the epoch. It is also referred to as variance or mean power.

$$Activity = \sigma_a^2 = std(y)^2 \quad (10)$$

Mobility is defined as the standard deviation of the slope (signal first derivation) with reference to the standard deviation of the signal amplitude. The ratio depends only on the curve shape and thus it measures the relative average slope. Mobility is expressed as a ratio per time unit and may be considered also as a mean frequency. For example, [MH96] shows significant correlation between Hjorth mobility parameter and mean frequency estimated by the means of the FFT.

$$Mobility = \frac{\sigma_d}{\sigma_a} = \frac{std(\frac{d(y)}{dt})}{std(y)} \quad (11)$$

Complexity is defined as the ratio of the mobility of the first derivate of the signal to the mobility of the signal amplitude. It expresses the average wave-shape in relation to the pure sin wave that is characterized by the minimum value of the complexity. Complexity can be also considered as an estimate of the bandwidth of the signal.

$$Complexity = \frac{\sigma_{dd} / \sigma_d}{\sigma_d / \sigma_a} = \frac{Mobility\left(\frac{d(y)}{dt}\right)}{Mobility(y)} \quad (12)$$

All time domain features described above have been extracted from all physiological signals (EEG, EOG, EMG) contained in the processed polysomnographic recordings. Complete list of all features extracted from each epoch of the polysomnographic recordings is presented in the table Tab. 14. On the whole, a set of 33 features is used to characterize each epoch.

EEG signal	<i>Prelδ, Prelθ, Prelα, Prelσ, Prelβ</i> <i>SEF95_{EEG}</i>
	<i>std_{EEG}, skew_{EEG}, kurt_{EEG}, prctile75_{EEG}</i> <i>entr_{EEG},</i> <i>activity_{EEG}, mobility_{EEG}, complexity_{EEG},</i>
EOG signal	<i>SEF95_{EOG}</i>
	<i>std_{EOG}, skew_{EOG}, kurt_{EOG}, prctile75_{EOG}</i> <i>entr_{EOG},</i> <i>activity_{EOG}, mobility_{EOG}, complexity_{EOG},</i>
EMG signal	<i>Prel high, SEF95_{EMG}</i>
	<i>std_{EMG}, skew_{EMG}, kurt_{EMG}, prctile75_{EMG}</i> <i>entr_{EMG},</i> <i>activity_{EMG}, mobility_{EMG}, complexity_{EMG},</i>

Tab. 14 The complete set of features used in this thesis to characterize an epoch.

3.3 Transformation of the extracted features

When dealing with a raw biological data, a widespread of the values and inhomogeneity of the data are typically observed. In order to reduce the influence of extreme values that are often observed on features extracted from physiological signals, each feature of the database was transformed using a non-linear transformation. A set of transformations towards normal

distribution was introduced by T. Gasser. In [GBM82], the transformations were used in order to normalize the EEG spectral parameters.

Each whole night polysomnographic recording was processed as follows. Firstly, several artifacts were identified in the signals monitored. Then the features were extracted from the recording using signal processing techniques and extraction mechanisms described above. In the next phase, each feature was transformed using an appropriate non-linear function. The selection of concrete transformation functions was inspired by the paper [BCCB+05]. The concrete list of transformations that were applied in this thesis to each feature is presented in the Tab. 15. After this transformation, each feature x was normalised into a new variable z , using a z-score normalisation:

$$z = \frac{x - \mu}{\sigma} \quad (13)$$

where μ is the mean value of the transformed feature x computed over the whole night recording and σ is the standard deviation of the transformed feature.

Feature	Transformation
<i>Prelδ, Prelθ, Prel_(EMG,high)</i>	$\arcsin(\sqrt{x})$
<i>Prelα, Prelσ, Prelβ,</i>	$\log\left(\frac{x}{1-x}\right)$
<i>SEF95_{EEG}, SEF95_{EOG}, SEF95_{EMG}, entr_{EEG}, entr_{EOG}, entr_{EMG}, activity_{EEG}, activity_{EOG}, activity_{EMG}, mobility_{EEG}, mobility_{EOG}, mobility_{EMG}, complexity_{EEG}, complexity_{EOG}, complexity_{EMG}, std_{EEG}, std_{EOG}, std_{EMG}, kurt_{EEG}, kurt_{EOG}, kurt_{EMG}, prctile75_{EEG}, prctile75_{EOG}, prctile75_{EMG}</i>	$\log(1+x)$
<i>skew_{EEG}, skew_{EMG}, skew_{EOG}</i>	$\tanh(x)$

Tab. 15 Transformations toward normal distribution.

3.4 Selection of relevant feature subset

From now on, each epoch is represented as a single point in the N -dimensional Euclidean description space, where $N = 33$. It corresponds to the list of all features extracted from the EEG, EOG and EMG signals showed in the Tab. 14. The extracted features were supposed to be important for the classification of sleep/wake stages. In practice, the classification can be misled or extremely slow when a lot of features are used together or when irrelevant features are contained in the feature set. So, the selection of features is needed in order to reduce the number of features used during the classification itself. It is used to reduce the number of features required for accurate representation of each epoch. It results in the selection of a feature subset from the initial set of all features already extracted. The feature selection is performed between the feature extraction process and classification. The feature selection ensures that only relevant features from the initial set of features will be used and then fed into the classifier. The irrelevant or redundant features will be removed from the set of features.

3.4.1 Sequential selection of relevant features

In this section, the methods used to select the most relevant features are presented. Sequential methods were implemented, increasing or decreasing the number of features to be used according to the value of a criterion J . Though these methods are not optimal, they were used because the results they provide are easy to analyze.

Let f_1, f_2, \dots, f_n be a set of n features to select. Let F be a subset of these n features and \bar{F} be the subset of features that are not in F :

$$\begin{aligned} F \cup \bar{F} &= \{f_1, f_2, \dots, f_n\} \\ F \cap \bar{F} &= \emptyset \end{aligned}$$

Let J be a criterion to be maximized and $J(F)$, the criterion J that is calculated with the features contained in the subset F . The sequential selection is an iterative technique which selects at each step i the subset F_i of features that maximizes the criterion J .

Sequential Forward Selection (SFS)

The method consists in increasing at each step i the number of features contained in the subset F_{i-1} by one. Let F_{i-1} be the subset of features selected at step $i-1$, that maximizes $J(F_{i-1})$. F_{i-1}

contains $i-1$ features, which were previously selected. On the contrary, the subset \bar{F}_{i-1} contains the $n-i+1$ features still to be selected. At step i , a new feature f_i is selected out of \bar{F}_{i-1} as $J(F_{i-1} \oplus f_i) = \max(J(F_{i-1} \oplus f_k))$ with $f_k \in \bar{F}_{i-1}$. The first subset is initialized as the empty set $F_0 = \{\emptyset\}$.

Sequential Backward Selection (SBS)

It consists in decreasing at each step i the number of features contained in F_{i-1} by one. Let F_{i-1} be the subset of features selected at step $i-1$, that maximizes $J(F_{i-1})$. F_{i-1} contains $n-i+1$ features, which were previously selected. On the contrary, the subset \bar{F}_{i-1} contains the $i-1$ features that were rejected. At step i , a new feature f_i is rejected out of F_{i-1} as $J(F_{i-1} - f_i) = \max(J(F_{i-1} - f_k))$ with $f_k \in F_{i-1}$. The first subset is initialized to the subset containing all the features. $F_0 = \{f_1, f_2, \dots, f_n\}$.

3.4.2 Criterion

In this work, the criterion J to be maximized is a function of the percentage of epochs correctly classified by a classifier C .

To perform the process of relevant feature selection, seven subsets, $S = \{S_1, S_2, \dots, S_7\}$ were created from the set of all artifact-free epochs. Each subset S_k contains 550 epochs. Each of the five classes to be recognized is represented in the S_k with about the same number of epochs. The way how the subsets were prepared is precisely characterized later in this chapter. A classifier C is trained on one subset S_k and validated on the other six subsets $S_{\bar{k}}$, $S_{\bar{k}} \in \bar{S}_k$, with $\bar{S}_k = S - S_k$.

An accuracy function is calculated on each of the 6 subsets $S_{\bar{k}}$ as:

$$Acc(k, \bar{k}) = \frac{\text{card}\left[\left\{epoch(i) \in S_{\bar{k}}^- / C(epoch(i)) - E(epoch(i)) = 0\right\}\right]}{\text{card}\left[S_{\bar{k}}^-\right]} \quad (14)$$

where $epoch(i)$ is an epoch belonging to $S_{\bar{k}}$, $C(epoch(i))$ is the class assigned to $epoch(i)$ by the classifier C , trained on the subset k . $E(epoch(i))$ is the class assigned by the experts to $epoch(i)$.

A circular permutation is performed on the 7 subsets S_k . The classifier is trained 7 times using the different data sets S_k . Thus, 42 values of $Acc(k, \bar{k})$ are obtained. The criterion J used to select the features is:

$$J = \frac{1}{7} \cdot \sum_{k=1}^7 \left(\frac{1}{6} \cdot \sum_{\substack{j=1 \\ j \neq k}}^7 Acc(k, j) \right) \quad (15)$$

$J(F_i)$ is the value of criterion J defined by (15) and (14) using the features contained in the feature subset F_i . In the equation (15), the term in brackets corresponds to the mean accuracy obtained on the 6 validation sets, when the classifier C is trained on one training set. J corresponds to the mean accuracy obtained on the validation sets, when the classifier C is trained 7 times with 7 different training sets. Computing J this way ensures that the accuracy obtained is insensitive to the training set used. The standard deviation of the accuracy Acc obtained using classifier C is computed by the equation (16).

$$std_{Acc} = \left[\frac{1}{41} \sum_{k=1}^7 \left(\sum_{\substack{j=1 \\ j \neq k}}^7 (Acc(k, j) - J)^2 \right) \right]^{\frac{1}{2}} \quad (16)$$

std_{Acc} is an indicator of the dispersion of the classification accuracies. It can be used to check the homogeneity of the classifications performed by seven classifiers at each individual step of feature selection or to determine whether the accuracies obtained using different features are statistically different or not.

To be able to evaluate the feature selection method in terms of a subset of relevant features, a stopping criterion should be defined for each selection method. The stopping criterion used in this thesis goes from the estimate of significant difference. At each step of the selection, a significant difference of two separate vectors containing accuracy values computed at two successive steps is evaluated. In the case of the sequential forward selection, a new feature f_i is added to the subset of selected features at step i if $J(F_i)$ is higher than $J(F_{i-1})$ and if the vectors of accuracy values computed at step $i-1$ and i are significantly different. If at least one of these conditions fails, the process of feature selection should be stopped because the relevant feature set is already reached. It characterizes the situation, when no more information added to the classifier can significantly improve the classification accuracy. On the contrary, in the case of the sequential backward selection, the relevant subset of features is

reached at the step $i-1$ if $J(F_i)$ is lower than $J(F_{i-1})$ and if the vectors of accuracy values computed at step $i-1$ and i are significantly different. It means that no more features can be removed from the subset of features without significant decrease of the classification accuracy.

To evaluate the significant difference of a pair of accuracy values vectors, statistical tests are used. In general, the tests require normal distribution of the analyzed data. Such tests are called parametric tests. On the other hand, nonparametric statistical tests do not require normal distribution of the data. The parametric tests are said to be more powerful and precise. Two tests implemented in the MATLAB environment have been used. When all the data contained in the vectors of accuracy values follow normal distribution, paired t-test were used to evaluate the significant difference. When the data do not follow normal distribution, Wilcoxon paired test were used. To test the hypothesis of the normal distribution, the Lilliefors test was used.

3.4.3 Multi-layer perceptron

The selection of a proper automatic classifier is important to select the features as well as to obtain accurate results in sleep staging. The type and structure of the automatic classifier may affect the choice of the features selected as relevant.

As showed in the first chapter, various techniques can be used to build an automatic classifier. The artificial neural networks, and more specifically the multi-layer perceptrons (MLP), are supposed to be attractive techniques for sleep staging and entire sleep analysis. In this thesis, the selection of a multi-layer perceptron as an automatic classifier was based on previous projects realized in the laboratory. Firstly, Becq *et al.* [BCCB+05] compared the classification accuracy of five automatic classifiers learned to classify sleep recordings. Zoubek *et al.* [ZCLBC07] compared three different types of automatic classifiers (multi-layer perceptron, quadratic classifier and k-nearest neighbor) using the same database of 47 polysomnographic recordings as presented in section 1.7. In both the projects, the best results were obtained with a MLP classifier. A short description of the multi-layer perceptron is presented below. More details about MLP can be found in [FS91], [Fausett94], [Patt96], [Gurney97], [HNNSP02].

Artificial neural networks (ANN) are said to be a useful and powerful tool for complex data analysis. They are inspired by the architecture and function of the human brain. Artificial neural nets consist of many various process units - neurons. Each such a process unit can be

compared to a real neuron of the human brain. All the neurons that form a neural net are interconnected and form the single layers in the structure of the ANN. Each connection of two neurons is characterized with a quantity parameter called a weight. Each neural network can be characterized by three basic parameters:

- topology
- activation function
- learning technique

Artificial neurons forming the multi-layer perceptron are interconnected and organized into individual layers. Three types of layers are defined in the terminology of artificial neural networks: input, hidden and output layer. The input layer only serves to introduce the information into the network. Since it usually does not consist of standard neurons it is not generally included in the description of the neural network. The hidden layers represent a connection between the input and output layers. The name of this layer is derived from the fact that the outputs of the neurons are fed to the neurons of upper layers and thus are hidden for the user who can only observe the input and output of the entire neural network. The complexity of the final approximation is determined by the structure (number of neurons, interconnection, etc.) as well as by the number of the hidden layers in the neural network structure. If at least one hidden layer is used, the structure is called “multilayer perceptron neural network”. Multilayer perceptrons are defined to solve nonlinear tasks (e.g. classification of nonlinear separable data). Neurons in the output layer form the final output of the whole network. The number of neurons in the input and output layers is typically determined by the actual problem which should be solved, i.e. the number of classes to be recognized. All neurons in adjacent layers are interconnected and each connection is defined as a weight and is represented with a rational number. The particularity of multi-layer perceptrons is that the information is always transmitted in one way: from the inputs to the hidden layer and then to the outputs. They are a sub-group of the so-called feed forward neural networks.

Each neuron is defined by its activation function. An activation function is a linear or nonlinear transformation that transfers the weighted sum of the inputs of the neuron to its output. Various activation functions can be used in neural networks; e.g. linear, sigmoidal or

threshold functions. The selection of the activation functions affects the behavior of the whole neural network.

Ability to learn knowledge from data is probably the most important characteristic of artificial neural networks. During the phase of learning, examples characterizing the problem to be solved are exposed to the network. These data are called the training dataset. Learning of the neural network then consists in tuning the connections between pairs of neurons, i.e. tuning the weights. Two types of learning can be defined – supervised and unsupervised learning. If supervised learning is used, the data in the training dataset contain output information characterizing the desired class. The number of target classes is thus known in advance. MLP neural networks belong to the class of supervised networks.

In this work, a multi-layer perceptron with three layers has been implemented as an automatic classifier. Its structure (number of neurons in the hidden layer and their activation function) was selected from a trial and error procedure performed using a data-subset. The number of neurons in the first layer is defined by the number of input features describing the actual epoch to be processed. So, it differs for each combination of features during feature selection. The transfer function of the neurons in the first layer is a hyperbolic tangent function. The second hidden layer of the network contains 6 neurons; the transfer function is a logarithmic sigmoid function. The output layer of the network consists of 5 neurons; the transfer function of each neuron is a hyperbolic tangent. The number of neurons in the output layer is determined by the number of target sleep/wake stages to be classified. The neural network is learned using error backpropagation gradient algorithm. The weights representing connections between the neurons were randomly initiated at the beginning of the learning phase. For each learning subset, the network was learned ten times with ten different random initialisations so as to avoid being trapped in a local minimum during the training phase and not reach the global minimum. Then the network with the highest classification accuracy calculated on the validation subsets was kept. This strategy has been employed for all seven learning subsets.

3.5 Results of feature selection

In this section, the subsets used to learn the neural network classifiers are firstly presented. They have been built so as to fairly represent all the sleep/wake stages. Then, the feature sets containing relevant features are presented and the performances obtained for the corresponding automatic classifiers are evaluated. In the last part of this section, the

individual features selected as relevant are characterized and their contribution to accurate classification is analyzed.

3.5.1 Presentation of the learning subsets

To realize the selection of relevant features characterizing the sleep/wake stages, a special database of epochs has been prepared. In order to be able to process all features extracted from the polysomnographic recording, only the epochs that have all three signals (EEG, EOG and EMG) marked as artifact-free have been used to form the database. On the basis of artifact identification (see section 2.4.1), six polysomnographic recordings were excluded from the original set of 47 recordings. When these six recordings were excluded, the initial number of epochs was reduced from 67,386 to 58,968 epochs. Then, out of these 58,968 epochs were selected only the epochs with all three signals marked as artifact-free. The database (*Artifact-free database*) is characterized in the Tab. 16. The first line of the table characterizes the database that contains only the epochs that have all three monitored signals artifact-free. The database contains 46,283 epochs in total.

	wake	NREM I	NREM II	SWS	REM
Artifact-free database	1,075	1,321	24,758	8,969	10,160
Test database	762	762	783	770	773

Tab. 16 Description of the database used for selection of relevant features.

As it can be seen, the sleep/wake stages are unevenly distributed in the database. It corresponds to the distribution of the stages during the whole night sleep (see tables Tab. 1 and Tab. 2 that characterize the complete database of epochs contained in the 47 polysomnographic recordings). The transition stage NREM I lasts for only about 2-5% of the night sleep. NREM sleep stage II is a dominant stage during the sleep and lasts about 45-60% of the night. Slow wave sleep (SWS) lasts about 20% of the night sleep. And at last, the REM sleep lasts about 20-25% of the night.

In order to avoid errors induced by difference in representation of the individual sleep/wake stages, a special test database *S* was prepared. The database is characterized in the second line

of the Tab. 16. It contains about the same number of epochs scored in every sleep/wake stage. The epochs in each stage were selected randomly from the artifact-free database.

Thus, the complete test database S used for feature selection contains 3,850 epochs. The test database S was then split into seven subsets S_k , $S = \{S_1, S_2, \dots, S_7\}$. Each subset S_k contains 550 epochs, so that each one of the five sleep/wake stages is represented with about the same number of epochs. The condition of equal distribution of the sleep/wake stages is crucial; it ensures that the method selects the features able to classify all stages with the highest classification accuracy. If the epochs were distributed unevenly, the selection algorithm (sequential selection and accuracy criterion J) would favor the stages represented with a large number of epochs in the subsets S_k and on the contrary would miss out the infrequent sleep/wake stages.

The size of the subsets S_k (550 epochs) was determined according to the results of a study [BCCB+05] whose partial goal was to analyze the effect of the number of examples on the classification error. The conclusion of the paper was that a minimal number of 500 examples (epochs) was sufficient to train and validate an automatic classifier on a sleep/wake classification problem and to get an unbiased evaluation of the classification accuracy. Increases in the number of epochs did not bring significant improvement in the classification accuracy. The structure of learning subsets S_k used in this thesis was also influenced by the number of epochs in the artifact-free database. Two stages are represented with a low number of epochs; wakefulness (1,075 epochs) and NREM I stage (1,321 epochs). These low values of epochs limit the two main parameters determining the structure of the subsets. The parameters are number of the subsets and size of each subset S_k . On the basis of a compromise between the requested number of epochs in a subset and the number of available data, seven subsets with a uniform size of 550 epochs each were randomly prepared from the artifact-free database presented above. Obviously, each subset contains about the same number of epochs in each sleep/wake stage.

3.5.2 Relevant feature sets

The EEG signal characterizes the fundamental information needed for proper sleep analysis. So, the EEG is considered as obligatory for automatic classification realized by the proposed classification system. Thus, there are four possible combinations of the monitored signals. The combinations are as follows: EEG, EEG + EOG, EEG + EMG, and EEG + EOG + EMG.

Each combination is characterized with the list of features selected as the most relevant and with classification accuracy reached during validation on the seven subsets S_k containing only artifact-free epochs. The classification accuracy is characterized by the means of two parameters.

- The minimal and maximal values, mean value (criterion J), standard deviation, and median value calculated over the 42 values of the accuracy parameter Acc (14). These general statistics computed for the four diverse sets of relevant features are summarized in the Tab. 21.
- The confusion matrix, which focuses on classification accuracy of each sleep/wake stage. The confusion matrix is a conventional tool used for more detailed analysis of a classification task. Confusion matrix combines information about the actual stages (scored by physician, expert) and stages predicted by the automatic classifier. All the rows represent the stages scored by the physician, thus an object is presented in particular row if it belongs to the stage that corresponds to the actual row. On the other hand, the columns represent the stages predicted by the automatic classifier. An object belongs to the column if it is classified to the corresponding stage. Each case (i,j) corresponds to the number of examples classified as i by both experts and j by the classifier, expressed as a percentage of the examples classified as i by the expert. A classifier that performs perfect classification is represented with confusion matrix containing zeros everywhere except a central diagonal.

Moreover, for each combination of signals, a figure presenting the improvement of the global classification accuracy at each step of the selection is displayed. In each figure, the dots represent the classification accuracy (15) obtained at each step of the feature selection. The bars express the corresponding standard deviation (16). The axis of abscissas shows the features selected at each step. The vertical line represents the limit determined by the stopping criteria. It corresponds to the situation when no more features added to the classifier can significantly improve the classification accuracy.

EEG

When only the EEG signal is used, the initial pool of features contains 14 features. Using the sequential selection method, a set of four relevant features has been selected. The relevant features are $PreI\beta$, $entr_{EEG}$, $PreI\sigma$ and $PreI\alpha$. The order of the features corresponds to the order of their selection. The overall classification accuracy is $74.70 \pm 1.19\%$.

%		classifier				
		wake	NREM I	NREM II	SWS	REM
expert	wake	79.77	11.87	3.92	0.61	3.83
	NREM I	12.34	49.61	7.35	0.61	30.09
	NREM II	1.83	5.75	85.37	6.09	0.96
	SWS	0.11	0.04	4.52	95.33	0
	REM	3.60	30.56	2.40	0.39	63.05

Tab. 17 Confusion matrix. Relevant features extracted from the EEG signal.

The classification accuracies of NREM sleep stage I and REM sleep are very low. The other stages are rather well scored on the basis of EEG features.

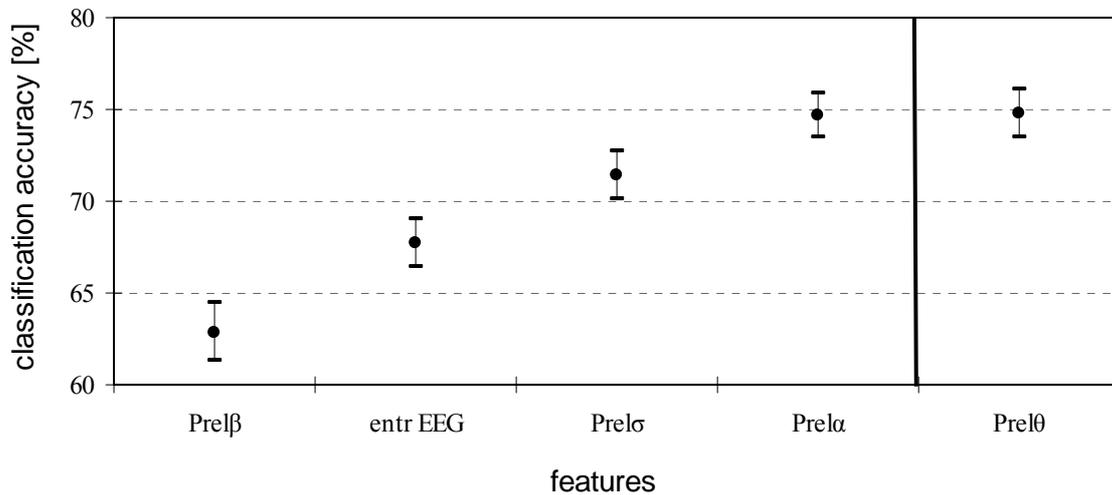


Fig. 14 Selection of relevant features when only EEG features are used.

EEG + EOG

When the EEG and EOG are available, the initial pool of features contains 23 features, 14 of them extracted from the EEG and 9 features from the EOG signal. The set of relevant features consists of $Prel\beta$, $mobility_{EOG}$, $Prel\alpha$, $entr_{EEG}$, $Prel\sigma$, $kurt_{EOG}$ and $Prel\theta$. The overall classification accuracy is $80.71 \pm 1.25\%$.

%		classifier				
		wake	NREM I	NREM II	SWS	REM
expert	wake	84.43	9.95	2.54	0.37	2.71
	NREM I	8.86	72.11	5.32	0.37	13.34
	NREM II	0.47	6.56	85.27	6.17	1.53
	SWS	0.28	0.13	4.35	95.24	0
	REM	3.53	27.90	1.79	0.37	66.41

Tab. 18 Confusion matrix. Relevant features extracted from EEG and EOG signals.

Though the EOG signal was added, the classification accuracy of REM sleep is still rather low. A high number of REM epochs are still classified by the automatic system as NREM I stage. However, the classification of NREM I is significantly improved.

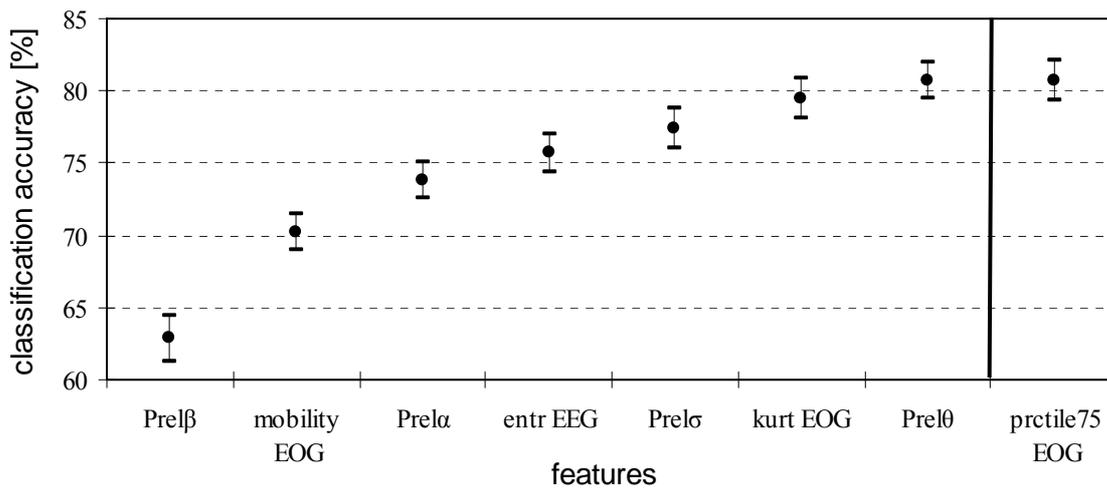


Fig. 15 Selection of relevant features when only EEG and EOG features are used.

EEG + EMG

The set of available features contains 24 features, 14 features extracted from the EEG and 10 features extracted from the EMG. The relevant set of features contains $Prel\beta$, $mobility_{EMG}$, $Prel\alpha$, $Prel\sigma$, $entr_{EEG}$ and $Prel\theta$. The overall classification accuracy is $80.34 \pm 1.02\%$.

%		Classifier				
		wake	NREM I	NREM II	SWS	REM
expert	wake	82.70	10.98	3.39	0.74	2.19
	NREM I	10.46	55.64	6.08	0.61	27.21
	NREM II	1.19	4.69	85.01	5.90	3.21
	SWS	0.09	0	4.89	95.02	0
	REM	1.66	13.34	1.64	0.39	82.97

Tab. 19 Confusion matrix. Relevant features extracted from EEG and EMG signals.

The addition of the EMG causes high improvement in classification of REM sleep. However, a lot of NREM I is misclassified as REM sleep. Wake, NREM II and SWS stages are well classified.

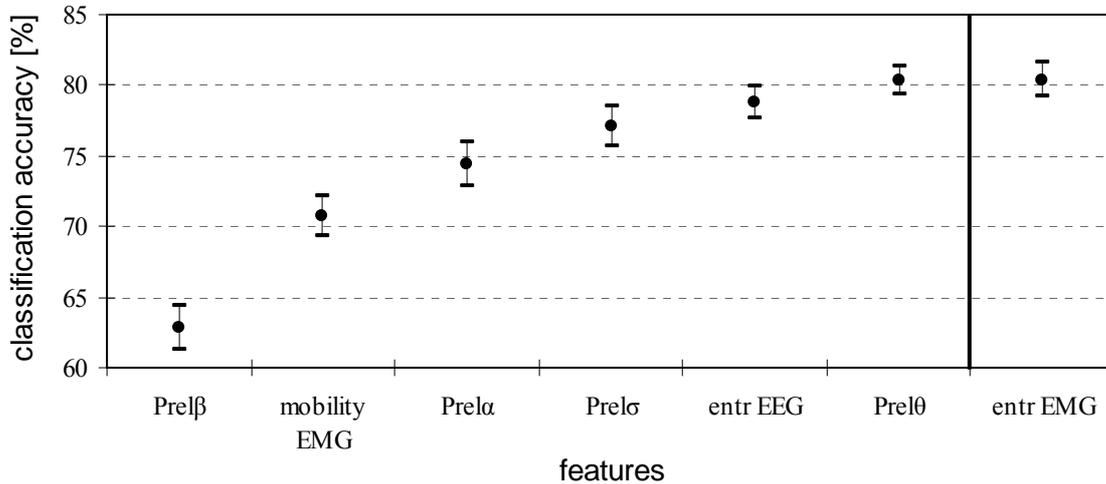


Fig. 16 Selection of relevant features when only EEG and EMG features are used.

EEG + EOG + EMG

When all three signals are used, the initial set of features contains 33 features. A set of seven relevant features has been selected. The relevant features are $Prel\beta$, $mobility_{EMG}$, $Prel\alpha$, $Prel\sigma$, $entr_{EOG}$, $entr_{EEG}$ and $kurt_{EOG}$. The overall classification accuracy is $82.52 \pm 1.21\%$.

% expert		classifier				
		wake	NREM I	NREM II	SWS	REM
wake		84.64	8.73	3.04	0.59	3.00
NREM I		9.01	69.55	5.91	0.50	15.03
NREM II		0.68	5.32	84.61	7.09	2.30
SWS		0.13	0.06	3.38	96.39	0.04
REM		2.35	18.33	1.70	0.32	77.30

Tab. 20 Confusion matrix. Relevant features extracted from all physiological signals.

No sleep/wake stage is classified with markedly low accuracy compared to the others. The lowest accuracy is reached for NREM I stage (about 70%).

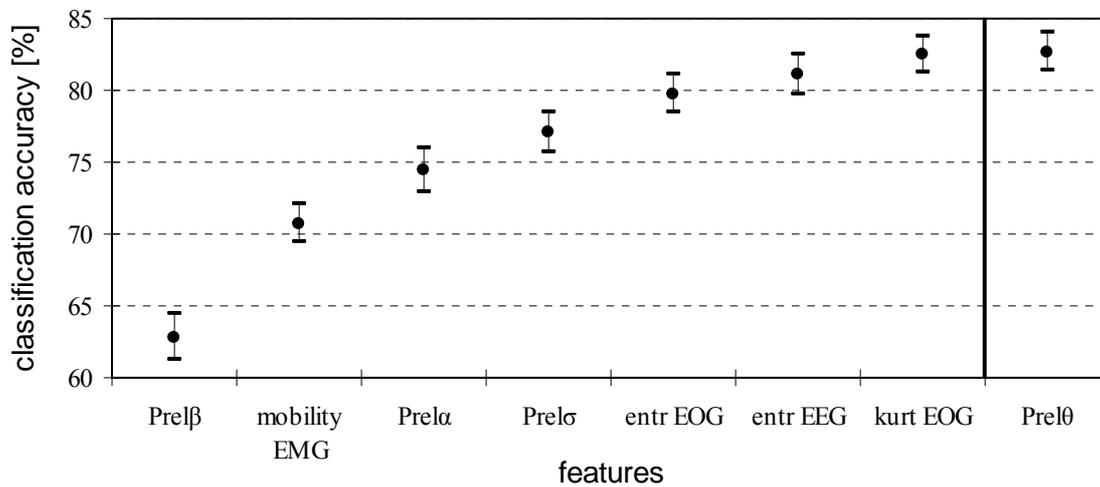


Fig. 17 Selection of relevant features when EEG, EOG and EMG features are used.

A global overview of classification accuracies is presented in the Tab. 21. As it can be seen, the lowest averaged classification accuracy (15) is obtained when only the EEG features are used to characterize the epochs. In this case, only four features were selected as relevant and

used as inputs for the neural network classifiers. The confusion matrix (Tab. 17) reveals high disagreements in scoring of NREM I and REM sleep stages. Only about 50% of NREM I epochs are correctly scored.

When the EOG signal is added (Tab. 18), the classification accuracy of the NREM I stage is increased of about 20% in average. The other stages are also slightly improved. On the contrary, when the EMG signal is added to the EEG and the EMG features are used in the classification (Tab. 19), a high improvement in classification of REM sleep arises. The classification accuracy of REM sleep is increased of about 20%. These two findings are in concordance with the hypothesis that the EOG and EMG signals are helpful for classification of these two stages, which are characterized by a similar EEG activity. In the REM sleep stage, the EOG signal is characterized by the presence of the rapid eye movements.

Improvement obtained by adding the EMG signal can be explained by the variable muscular activity (muscle tone) during the night sleep. In the REM sleep, the EMG activity is totally absent and the voluntary muscle groups are inhibited. On the contrary, in the wakefulness or NREM I stages is the muscular activity present. The EMG trace is characterized as high-frequency activity with moderately high amplitude. Thus, as could be expected, when both EOG and EMG signals are added to the single EEG signal (Tab. 20), classification accuracies of wake, NREM I and REM sleep stages are significantly increased. When the confusion matrixes for only EEG (Tab. 17) and for EEG + EOG + EMG signals (Tab. 20) are compared, it can be seen that the EOG and EMG evidently help to discern wakefulness, NREM I and REM sleep. Especially the NREM I and REM sleep are better discerned.

	mean value	standard deviation	min	max	median
EEG	74.70	1.19	71.82	76.91	74.73
EEG + EOG	80.71	1.25	78.00	83.09	80.73
EEG + EMG	80.34	1.02	78.18	82.54	80.36
EEG + EOG + EMG	82.52	1.21	80.54	84.91	82.37

Tab. 21 Statistics characterizing performances of four possible combinations of signals.

As can be seen in the Tab. 21, the values of standard deviation estimated from the values of accuracy parameters are relatively low. This fact confirms the homogeneity of the seven

classifiers learned for each combination of signals. So, the mean values can be considered as accurate estimates of the classification accuracy.

3.5.3 Importance of the relevant features

This section focuses on analysis of the relevant features in terms of improvement of classification accuracy of the sleep/wake stages. In the previous section, the four sets of relevant features have been presented in the terms of classification accuracy reached when the single classifiers are used on 7 subsets of data. Now, the individual relevant features will be characterized in detail and the gain in classification accuracy of individual sleep/wake stages will be discussed. Relevant features will also be characterized with a help of figures illustrating improvement in discrimination of sleep/wake stages. The figures represent the epochs stored in the seven subsets of data used for selection of relevant features. Moreover, four figures are placed through this section so as to show percentage of correct classification obtained for individual sleep/wake stages at each step of selection (SFS). Each figure characterizes one combination of available signals.

Features extracted from the EEG.

The detailed analysis of the sets of relevant features reveals one interesting fact. The set of four relevant features extracted from the EEG signal ($Prel\beta$, $entr_{EEG}$, $Prel\sigma$ and $Prel\alpha$) has been also selected for all the other combinations of signals (i.e. EEG + EOG, EEG + EMG, EEG + EOG + EMG). This fact is similar to the manual scoring performed by the physician. During a manual scoring, physician primarily analyzes the EEG signal trace and only when his decision is not clear focuses on the information contained in the EOG and/or EMG signals. Data mining methods selected a set of four features representing the core of the information stored in the EEG. The features selected from the other signals can be then interpreted as additional information used to precise the scoring. So, the four relevant EEG features are characterized in the next sections. Firstly, the effect of three spectral features on classification of sleep/wake stages will be discussed.

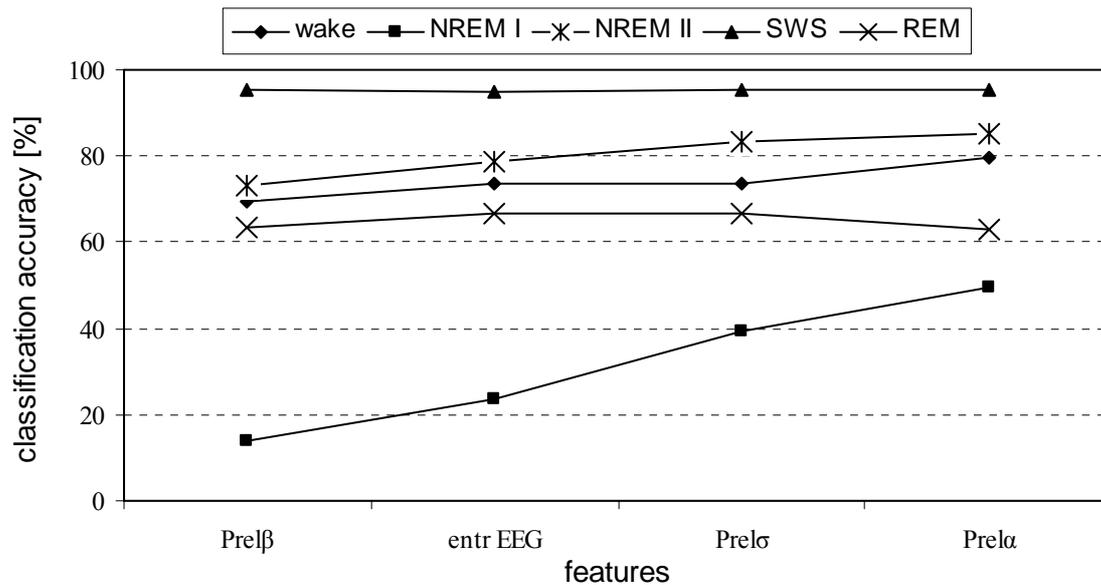


Fig. 18 Classification accuracy of sleep/wake stages obtained at each step of selection - EEG features.

Prel β

The most relevant feature is the relative power in beta frequency band; *Prel β* . It was selected by the SFS as the most relevant for all combinations of monitored signals. When using only the *Prel β* , the slow wave sleep (SWS) is scored with classification accuracy of about 95% when computed over the seven subsets. This stage is characterized by dominant slow delta activity and consequently the fast beta waves are nearly absent in the SWS stage. The lowest classification accuracy is for the NREM I stage. Only about 13% of the NREM I epochs are correctly scored on the basis of the EEG beta relative power. NREM I stage is mainly misclassified by either wakefulness (about 25% of NREM I) or REM sleep (about 50% of NREM I). The classification accuracy of the remaining stages (wakefulness, NREM II and REM sleep) is about 70%. The active vigilance – first phase of the wakefulness is typically characterized by dominant high-frequency beta activity that takes the highest part of the epoch compared to the other stages. So, a significant part of the wake can be scored on the basis of the beta activity. On the contrary, NREM II stage is characterized by only a low amount of the beta activity and thus is well discerned from the other stages, especially from the wake, NREM sleep stage I and SWS. The mean values of relative beta power computed for different sleep/wake stages are presented in the Fig. 19.

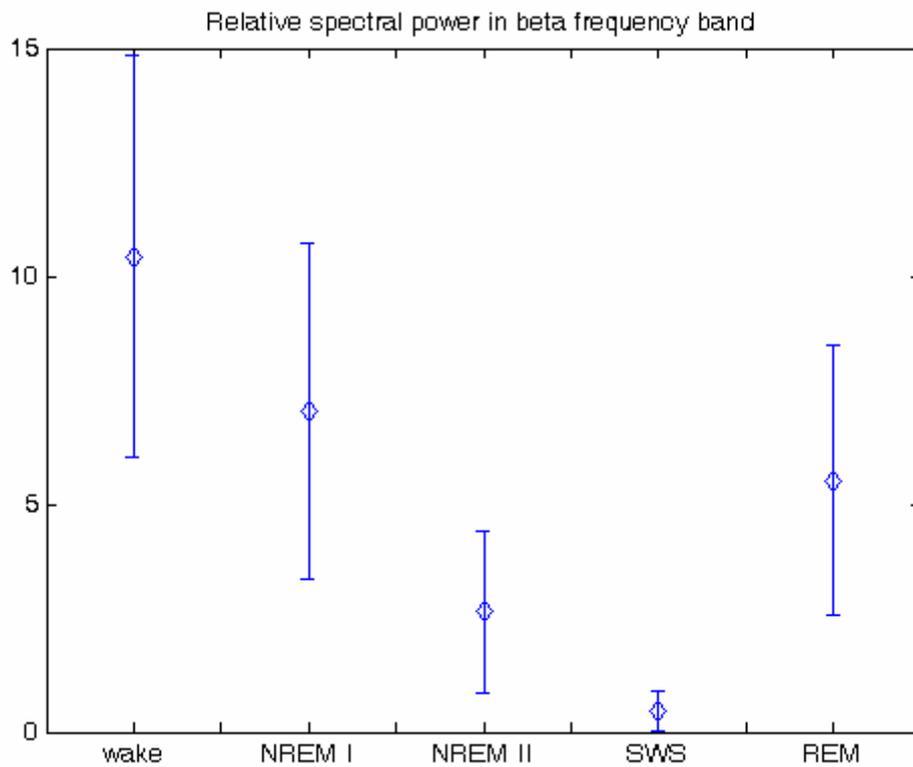


Fig. 19 Mean values and standard deviations of the beta relative power feature computed for different sleep/wake stages.

Prelo

The sigma relative power $Prelo$ is the second relevant feature characterizing the frequency content of the EEG signal. Sigma waves are mainly related to the presence of sleep spindles which are typical for NREM II stage. A detailed analysis of the confusion matrix, when the sigma relative power feature is added, confirms improvement in scoring of NREM II stage. The amount of sigma activity is also a useful parameter to distinguish NREM I and REM sleep stages from the NREM II stage. The improvement in discrimination of NREM II and REM sleep stages is characterized in Fig. 20. So, in total, classification accuracy of NREM I, NREM II and REM sleep is markedly increased. Sigma relative power does not really improve scoring of wake stage. It is caused mainly by the fact that a part of the wake stage is characterized by the transition from beta activity to alpha activity. So, the waves with frequencies corresponding to the transient sigma frequency band are present within the

wakefulness and that is why sigma activity does not really help to distinguish wakefulness and NREM II stage that is interspersed with sleep spindles.

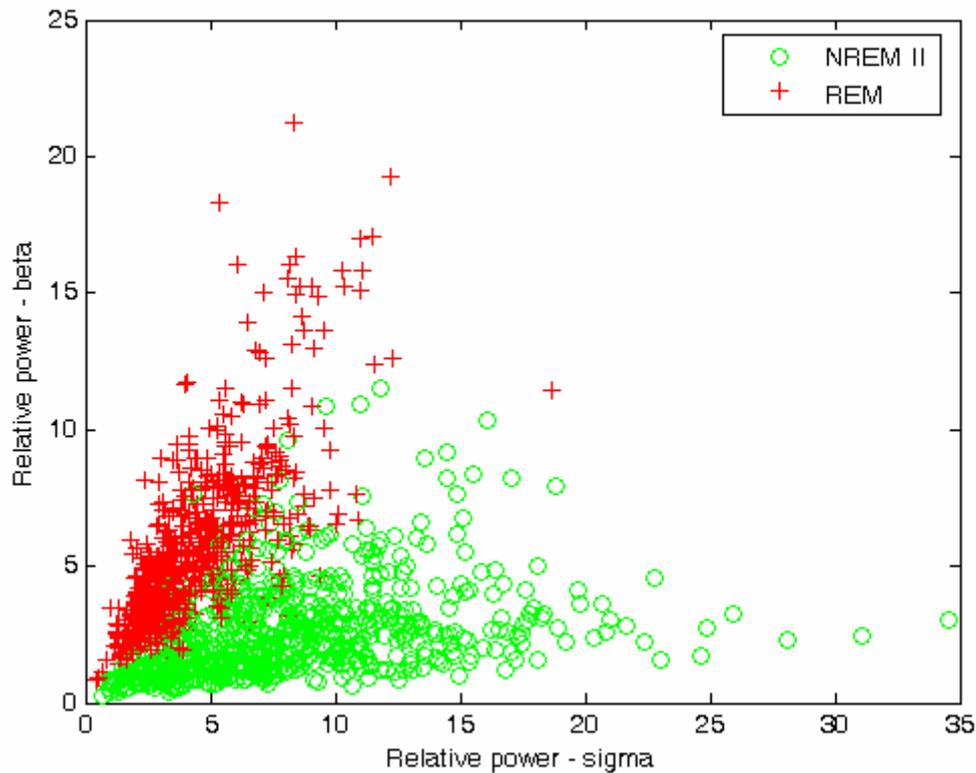


Fig. 20 Effect of the sigma relative power on discrimination of NREM II and REM sleep.

Prela

Alpha activity is dominant during the so-called relaxed vigilance state which is the second phase of the wake stage. Then, in the subsequent phases of the sleep, contribution of alpha activity is gradually reduced. The main importance of this feature is thus the improvement in discrimination of NREM I stage and REM sleep from the wakefulness (see Fig. 21). This improvement leads mainly to the increase of classification accuracy of wakefulness and NREM I stages. On the other hand, alpha activity does not significantly improve discrimination of NREM I and REM sleep stages that are characterized by similar EEG activity.

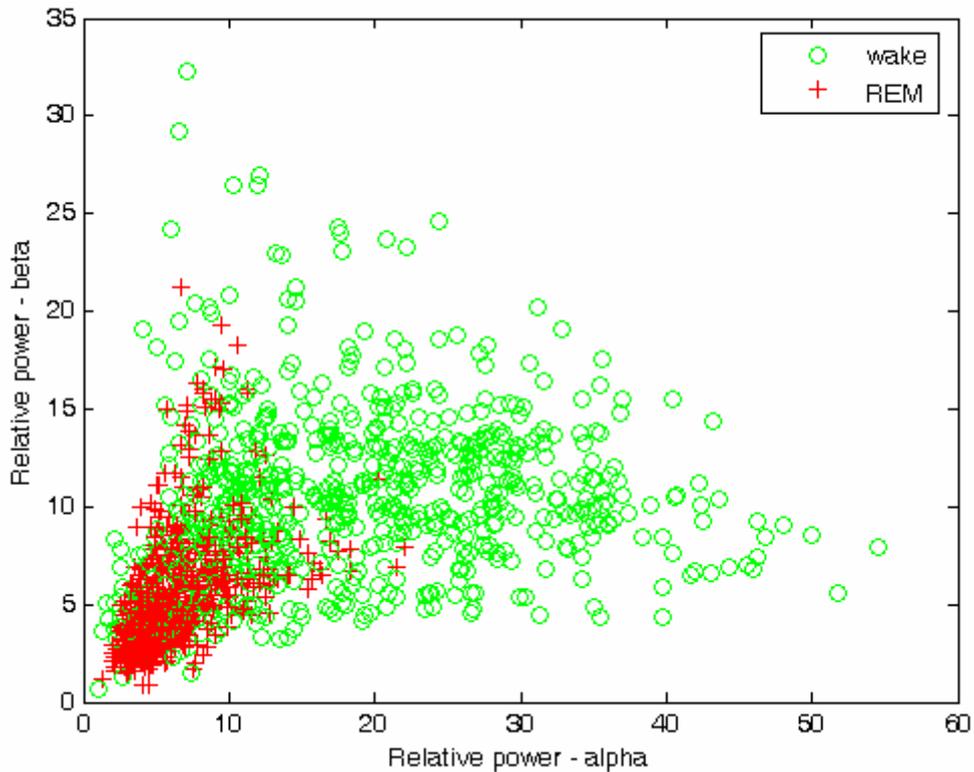


Fig. 21 Effect of the alpha relative power on discrimination of wake and REM sleep.

entr_{EEG}

Entropy is a stochastic time domain parameter which characterizes the regularity of the signal. In other words, it quantifies a degree of disorder of the signal amplitude distribution. The entropy calculation used in this thesis reflects the homogeneity of the amplitude values in the epoch of a signal. The computation also reflects the actual range (minimal and maximal values) of the values within the epoch. Entropy is a measure of the signal variability: the more variant the signal, the higher the entropy. The results of the analysis of entropy values for the different sleep/wake stages showed that the highest values of EEG entropy are computed for the SWS stage. It reflects a homogeneous distribution of the signal amplitude during SWS characterized by the slow and high-amplitude trace. An evident increase of the entropy values is observed when the person goes from NREM I to SWS through NREM II stage. Low values of entropy are computed for wake, NREM I and REM sleep stages. When the EEG entropy is added to the feature set, the classification accuracy of wake, NREM I and NREM II stages is increased. The EEG entropy helps to discern these three stages from REM sleep and leads to a

decrease in false classification of epoch into REM sleep stage. The improvement in discrimination of NREM II and REM sleep can be seen in the Fig. 22.

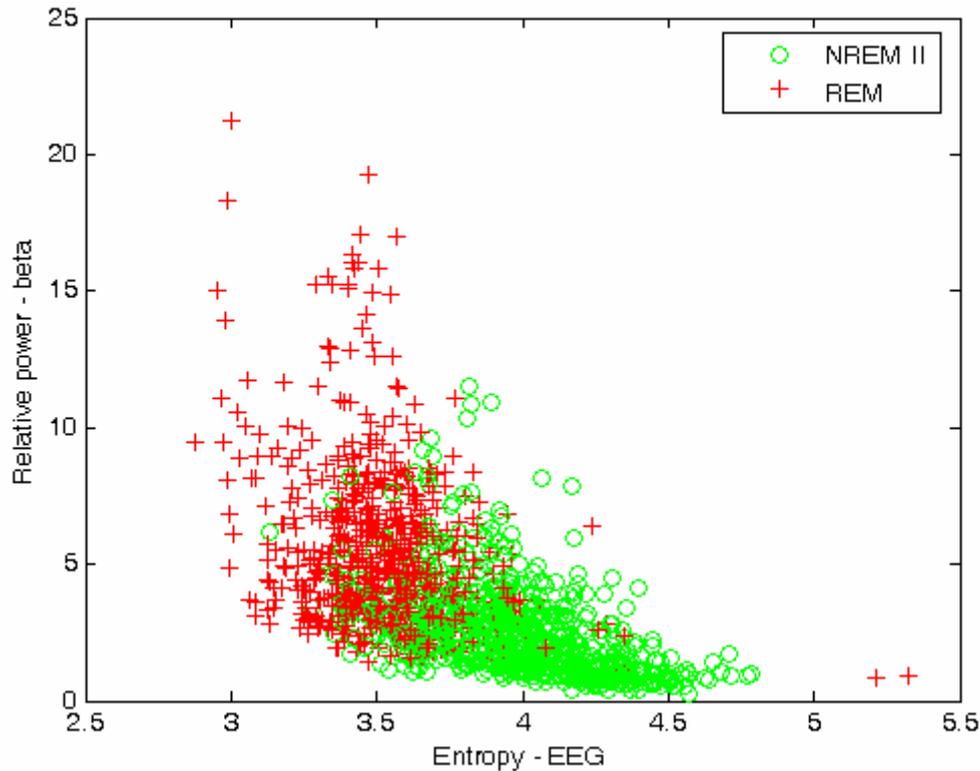


Fig. 22 Effect of the EEG entropy on discrimination of NREM II and REM sleep.

Prel θ

Theta relative power, *Prel θ* , is the last EEG feature selected by the proposed selection strategy as relevant. It has been selected only for EEG + EOG and EEG + EMG combinations of signals. When theta relative power is compared over the five sleep/wake stages, the only one stage that markedly varies from the others is the SWS stage, which has the lowest portion of theta activity. This parameter discerns only partially the NREM I and REM sleep stages from wake and NREM II stages. The stages NREM I and REM sleep contain the highest portion of theta activity compared to the other stages. Since the differences in theta activity for various sleep/wake stages are not distinctive, this feature has been selected as the last relevant one. However, importance of theta activity for sleep/wake stage classification seems to be increased when it is combined with the other features selected in the previous steps of relevant features selection (see Fig. 23 and Fig. 28). Theta relative power improves the

classification of wake, NREM I and REM sleep stages. Especially, the classification of wake stage is improved at the expense of false scoring of NREM I and conversely.

Features extracted from the EOG and EMG.

Four relevant features were selected from the EOG and EMG signals. Firstly, the features extracted from the EOG will be characterized.

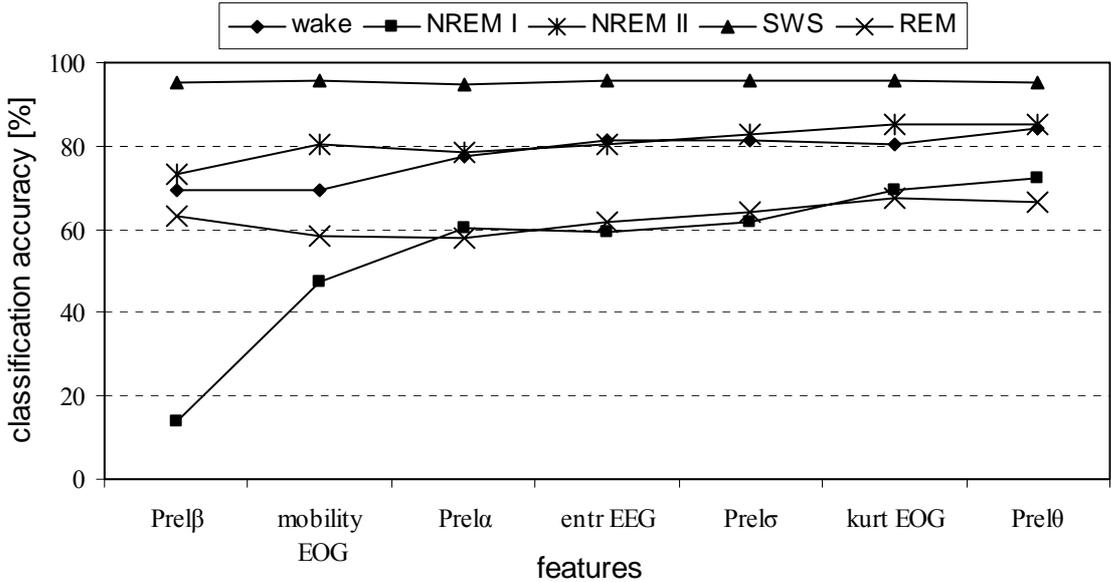


Fig. 23 Classification accuracy of sleep/wake stages obtained at each step of selection - EEG and EOG features.

entr_{EOG}

EOG entropy shows large variations of values in the wake and REM sleep stages. In the wake stage, this variation reflects the transition between active and relaxed vigilance. In the case of the REM sleep, the variation in entropy is due to the alternation of the phasic and tonic REM sleep phases. When continuous REMs (Rapid Eye Movements) are present in the epoch, the entropy value is increased. The REMs can be present during active vigilance and phasic REM sleep phase. This fact especially leads to better differentiation of wake and REM sleep stages from NREM I stage (Fig. 24), so the classification accuracy of wake and NREM I stages is mainly improved.

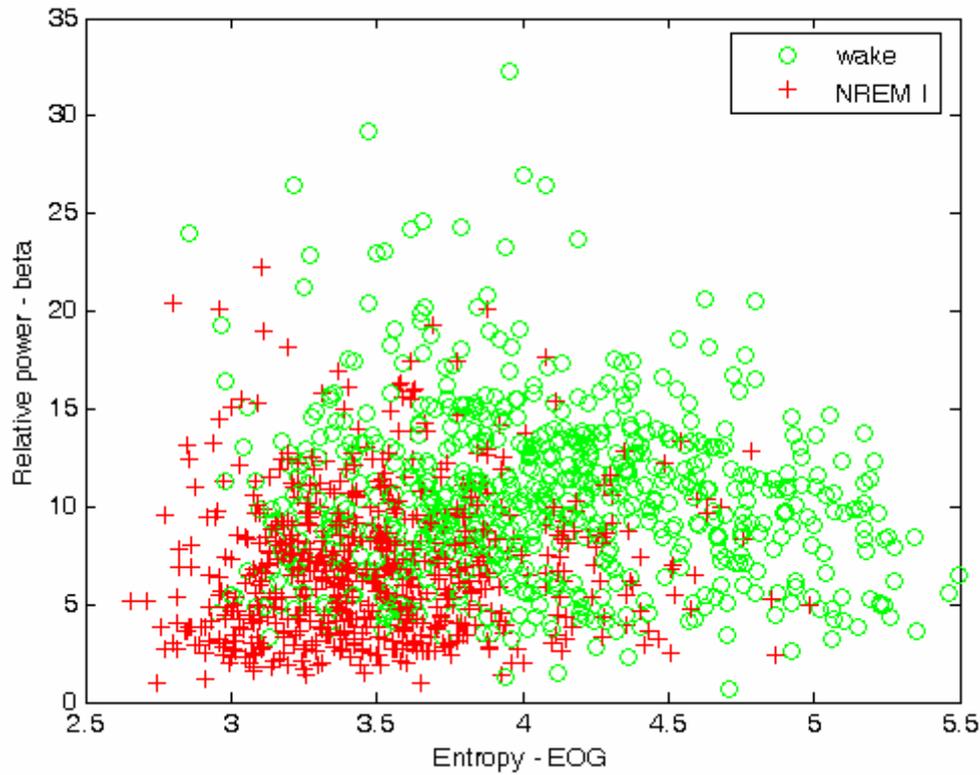


Fig. 24 Effect of the EOG entropy on discrimination of wake and NREM I stages.

$kurt_{EOG}$

Kurtosis is a measure of whether the distribution is peaked or flat relative to the normal distribution. The kurtosis of a signal measures the presence of irregular values such as transitory sharp variations in the signal. Sharp variations related to the presence of rapid eye movements (REMs) can occur in the EOG during REM sleep (phasic REM sleep) and active vigilance, and explain why EOG kurtosis is higher for some epochs of REM sleep and wakefulness. Thus, EOG kurtosis helps to increase the classification accuracy of NREM I and REM sleep stages, as presented in Fig. 25.

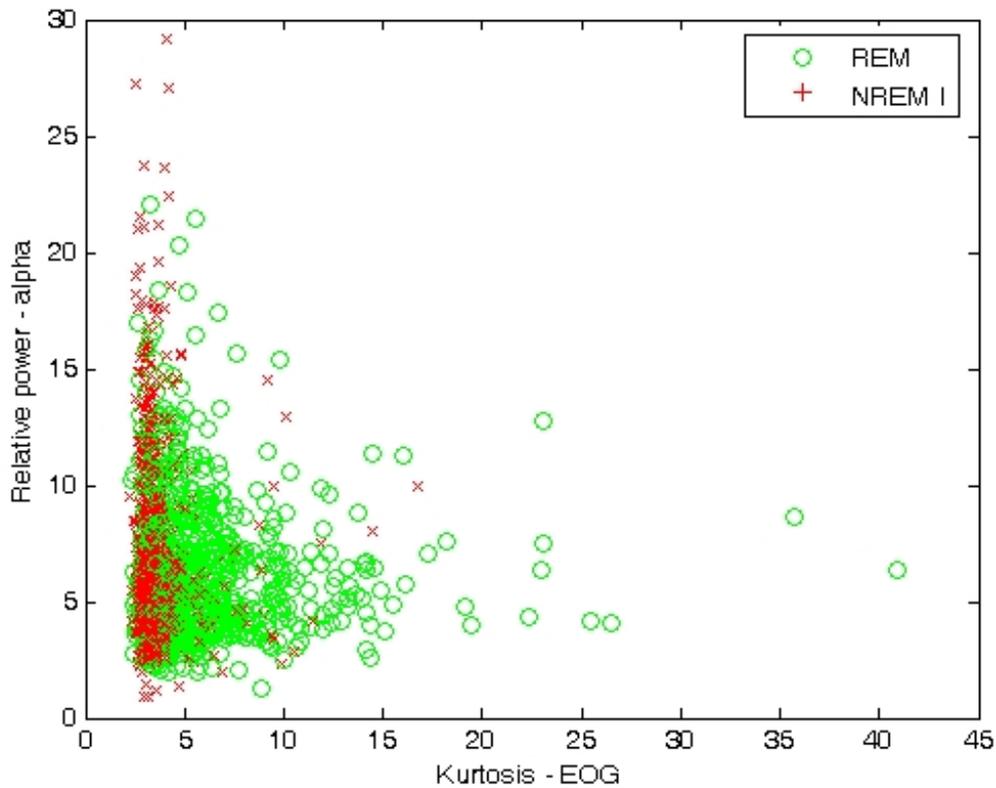


Fig. 25 Effect of the EOG kurtosis on discrimination of NREM I and REM sleep.

mobility_{EOG}

The analysis of the confusion matrix, when the mobility of EOG is added, shows increase in classification accuracies of the NREM I and NREM II stages. EOG mobility helps to discern them especially from the REM sleep stage (Fig. 26). Since the mobility of EOG is selected as the second feature (when EEG and EOG signals are used) and beta relative power has a very low classification accuracy of the NREM I stage, adding EOG mobility improves the classification of the NREM I stage of about 30%. The analysis of EOG mobility computed for individual sleep/wake stages shows that the highest values of this parameter are computed for epochs representing NREM II stage. This fact might reflect frequent presence of the sleep spindles transmitted to the EOG signal.

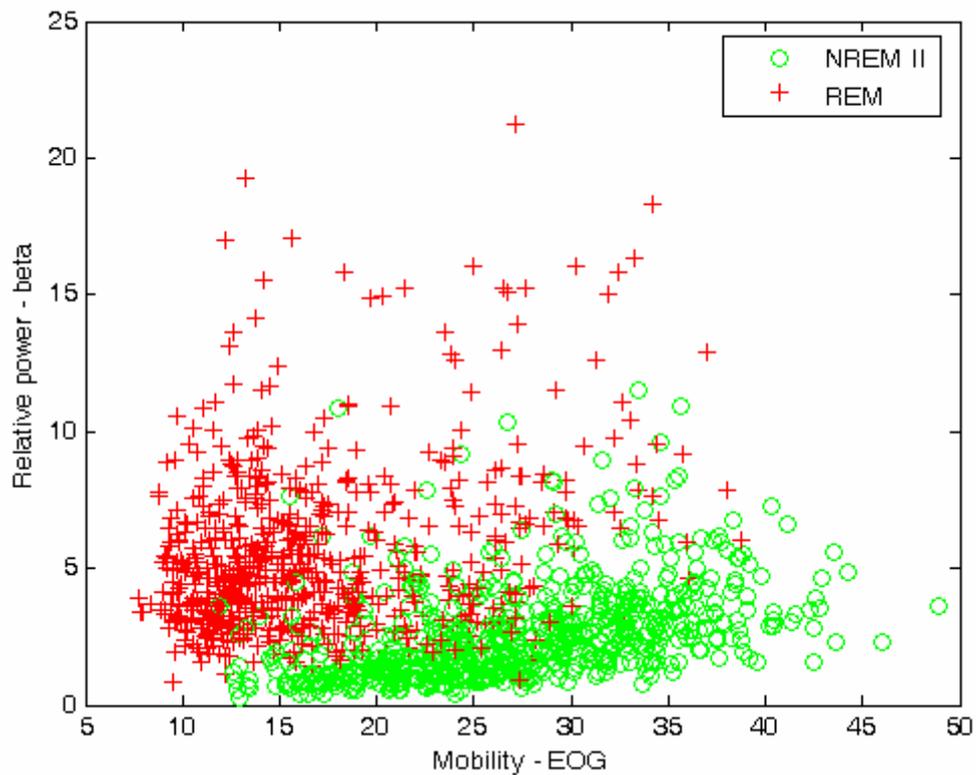


Fig. 26 Effect of the EOG mobility feature on discrimination of NREM II and REM sleep.

mobility_{EMG}

As presented in the description of the Hjorth parameters, the Hjorth mobility should reflect the mean frequency of the signal. Activity of the muscles decreases when the person goes from wake to SWS stage. During the REM sleep stage, the EMG activity is very low or even totally absent. The only activity (short eruptions of muscles) is present during the phasic REM sleep. This description of muscular activity is then reflected in the analysis of EMG mobility values over the sleep/wake stages. The highest values of the mobility represent the wakefulness. It corresponds to the high-amplitude activity especially in the phase of active vigilance. Then, the mean values of the Hjorth mobility of EMG decrease gradually. The lowest mean value characterizes the REM sleep stage, though several outliers characterizing phasic REM sleep can be observed. The EMG mobility brings improvement mainly in scoring of NREM I and REM sleep stages (Fig. 27). There is also slight improvement in classification of the wake stage.

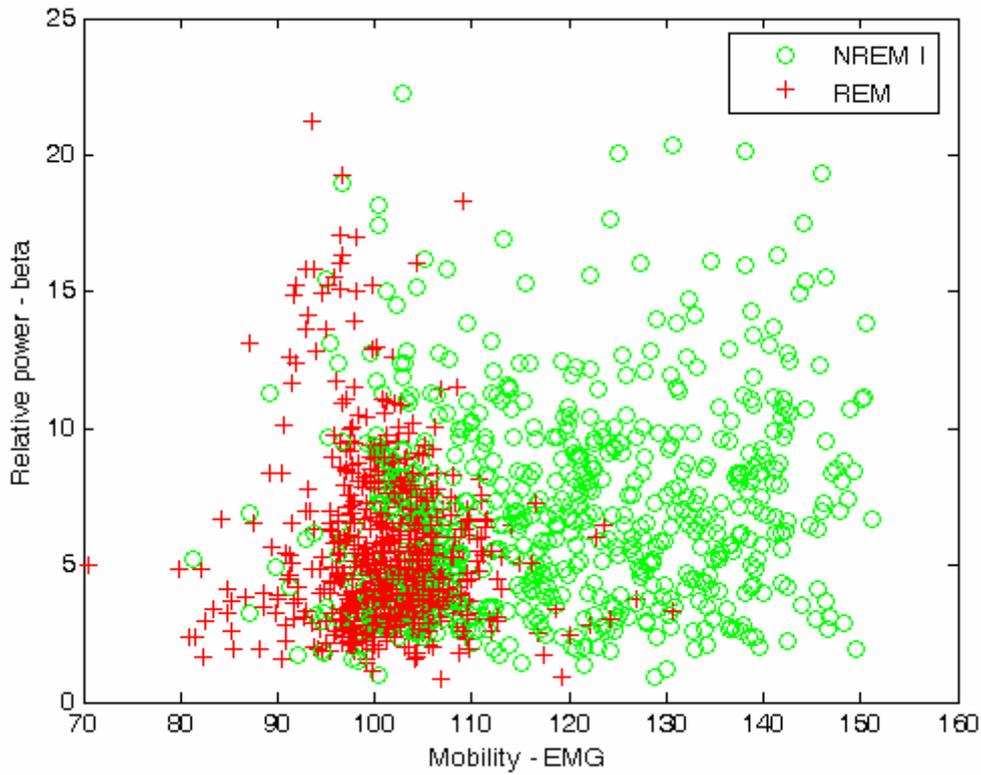


Fig. 27 Effect of the EMG mobility on discrimination of NREM I and REM sleep.

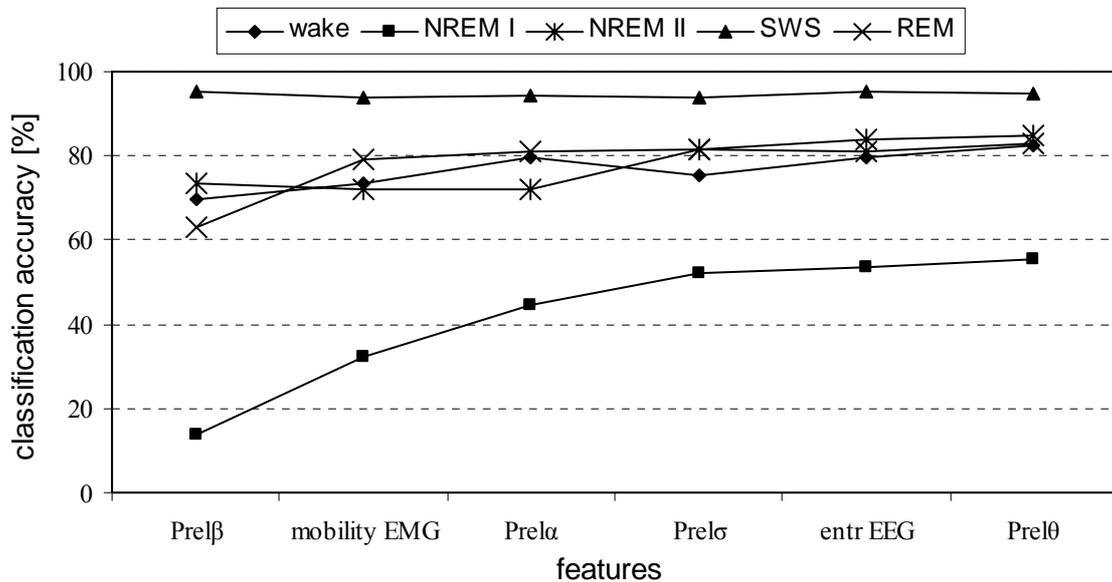


Fig. 28 Classification accuracy of sleep/wake stages obtained at each step of selection - EEG and EMG features.

Global importance of selected features.

To perform selection of relevant features, a special set of seven subsets has been prepared so as to equally represent all sleep/wake stages. This condition ensures that the accuracy functions Acc (14) and the classification criterion J (15) computed over the seven subsets represent a fair compromise between all stages scored in this thesis. Thus, the whole process of feature selection does not favor one stage to another one and the final feature set is the most relevant for accurate classification of the set of five sleep/wake stages (wakefulness, NREM I, NREM II, SWS, and REM sleep). As can be seen for example in Fig. 18 and Fig. 29, the first feature selected as relevant is the beta relative power $Prel\beta$. When only $Prel\beta$ is used, the neural network classifier is capable to correctly score about 95% of SWS epochs. There is no increase in classification accuracy of SWS when the other relevant features are added. So, the selection of relevant features focuses on improvement in classification of the remaining stages, especially NREM I stage whose classification accuracy is extremely low (only about 13%) when only $Prel\beta$ is used.

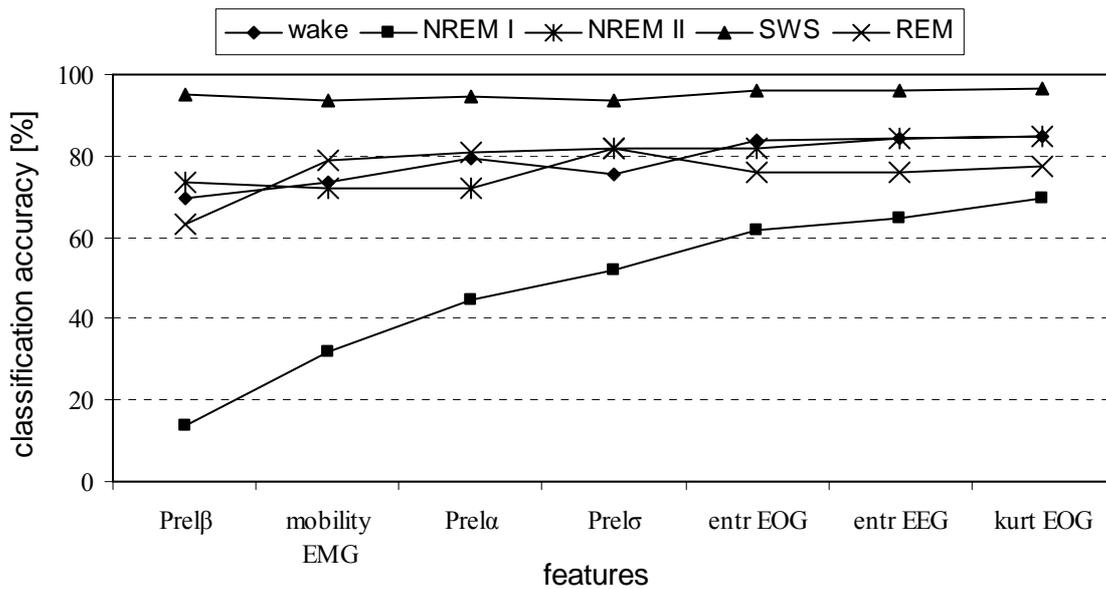


Fig. 29 Classification accuracy of sleep/wake stages obtained at each step of selection - EEG, EOG and EMG features.

The results of feature selection show that appropriate selection of the features significantly improves classification accuracy of sleep/wake stages. The features especially help to distinguish wake, NREM I and REM sleep stages and therefore lead to increase in

classification accuracy of these stages. The biggest gain in accuracy is achieved in classification of the NREM I stage. Nevertheless, in the case when the EOG signal is not used as an input for the classifier, the classification accuracy of the NREM I stage is still low. It is only slightly over 50% of agreement. But it mainly corresponds to the information contained in the EOG signal that can not be used when the EOG signal is artifacted.

The results also confirmed the hypothesis that frequency analysis of the EEG signal is essential in the sleep analysis. Activity of the EEG signal is mainly characterized by the help of the spectral powers computed in the typical EEG frequency bands. It corresponds to the description of the individual sleep/wake stages, where presence of the characteristic waves determines the actual stage. The relative powers in the beta β , sigma σ and alpha α frequency bands have been selected by the sequential selection method as relevant features that are important for proper sleep/wake stage classification.

Then, five features computed in the time domain have been selected as relevant for sleep staging. Two of them, although computed in the time domain, can give an estimate of frequency information characterizing EOG and EMG activity. These features are Hjorth mobility parameters computed from the EOG and EMG. Hjorth mobility is considered to characterize the mean frequency of the analyzed signal. This fact could indicate the need of proper frequency analysis performed also on the EOG and EMG signals. Until now, frequency analysis of only EEG signal has been considered as powerful approach in sleep analysis. There is evident advantage of the Hjorth mobility compared to the frequency analysis performed by the means of Fourier transformation. The Hjorth parameters require low calculation time since they are based on simple computations of standard deviation and signal derivation.

The last three features, $entr_{EEG}$, $entr_{EOG}$ and $kurt_{EOG}$, represent the time domain parameters that characterize the regularity of distribution of the signal. These parameters analyze the monitored signal as a random variable. Both the functions (entropy and kurtosis) come from the histogram of the random variable representing the signal.

3.6 Chapter conclusion

Application of signal processing techniques is necessary in order to extract descriptive parameters from the analyzed signals. Signal processing techniques performing both in the

time and frequency domain have been used. As presented in the Tab. 14, the original pool of features extracted from the three polysomnographic signals (EEG, EOG and EMG) contains 33 features in total. Then, a sequential selection strategy has been used so as to determine the most relevant features needed for accurate sleep classification. The selection strategy used is proposed so as to maximize the classification accuracy and do not favor one stage to another one. A multilayer perceptron is employed as an automatic classifier used during feature selection.

The process of feature selection has been realized for four various combinations of signals and in total determined nine relevant features that will be then used in the complex classification system presented in the next chapter. Four out of the nine features are present in all tested combinations. Unfortunately, only these four features have been selected as the most relevant when only the EEG signal is used for classification. The low number of features in the feature set could be the reason of the relatively low classification accuracy achieved with EEG features. But it could also indicate that the proposed signal processing techniques are not capable to extract more useful information from the EEG signal and that the information content of the EEG is limited. For the other combinations of signals, the numbers of relevant features as well as the overall classification accuracies are higher. There are six relevant features in the case of EEG + EMG and seven features selected for the combinations EEG + EOG and EEG + EOG + EMG.

The results of feature selection show that the EEG signal can be considered as indispensable for automatic sleep/wake stage classification because the majority of the relevant features is computed from the EEG signal. Moreover, frequency analysis of the EEG is especially needed. When only the EEG signal is used, three stages (wake, NREM II, and SWS) are correctly recognized. Classification accuracies of the individual stages are over 80%. However, NREM I and REM sleep are highly confused. When the EOG and EMG signals are added to the EEG, discrimination between these two stages significantly increases.

As it can be seen, the real challenge in automatic sleep analysis is the successful discrimination of NREM I and REM stages. At visual analysis, trained physicians are able to do it effectively using the three polysomnographic signals (EEG, EOG and EMG). An automatic classifier should also be able to perform accurate discrimination of NREM I and REM sleep, if correct and relevant features computed from all three signals would be used. So,

future research should focus on the extraction of these useful features. The three other stages (wake, NREM II and SWS) are already correctly classified with classification accuracies of at least 85% when EEG, EOG and EMG are used. The classification errors occur on adjacent sleep phases. It is mainly due to the periods of transitions from one sleep stage to another. Correct classification of transitions of sleep/wake stages is difficult even for human expert.

Chapter 4

Two-step system for sleep analysis

The results presented in chapter 2 and chapter 3 enable the development of an automatic classification system able to deal with artifacts in the polysomnographic signals. The structure of the proposed system is a two-step classification system presented in the Fig. 30. The main idea is to use a different classifier for each epoch to be classified, depending on the quality of the three polysomnographic signals (EEG, EOG, and EMG) during the epoch.

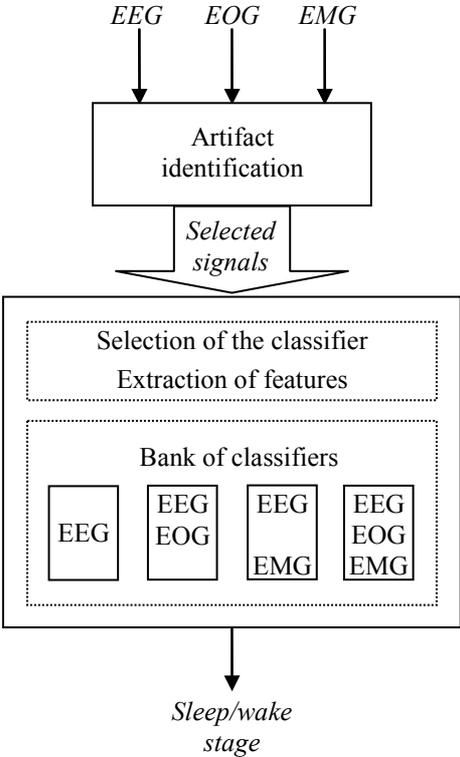


Fig. 30 Scheme of the two-step classification system.

The first step consists in checking all the three signals to determine if any artifact is present in the epoch to be classified. The concrete strategy was presented in detail in chapter 2. The output of this part is then Boolean information determined for each analyzed signal: artifacted (1) or artifact-free (0). The concatenation of Boolean information characterizing individual signals provides a diagnosis on each epoch that is used in the second part of the complex system.

The second step consists in performing the classification of the actual epoch. Each epoch can be classified in one of the five sleep/wake stages (wake, NREM I, NREM II, SWS, REM). The classification is achieved using a suitable classifier from a bank of four various classifiers. Selection of the classifier to be used is performed according to the output of the first step. Criteria for selection of a suitable classifier are summarized in the Tab. 22. The inputs needed for each classifier are described in chapter 3. It is necessary to keep in mind, that the electroencephalogram (EEG) is assumed to be crucial signal for sleep/wake classification. Thus, if the EEG is artifacted, no classification can be performed and the epoch is excluded.

EEG	EOG	EMG	Classifier / signals
0	1	1	classifier1 / (EEG)
0	0	1	classifier2 / (EEG + EOG)
0	1	0	classifier3 / (EEG + EMG)
0	0	0	classifier4 / (EEG + EOG + EMG)

Tab. 22 Criteria for selection of a classifier from a bank of classifiers. (0 = artifact-free, 1 = artifacted)

For the need of practical implementation of the proposed system, each of the four various classifiers has been learned and validated using the seven subsets of data presented in section 3.5.1. So, for each combination of input features, seven neural networks have been learned. Each neural network classifier has been learned using one of the seven subsets of data and validated on the other six subsets. In the final implementation of the two-step classification system, only one of the seven neural networks has been selected for each combination of physiological signals. In the concrete, the neural network classifier characterized with the highest classification accuracy computed on the corresponding six subsets has been chosen and stored in the bank of classifiers. This means that only 550 epochs were used to train the

classifiers, i.e. 0.8% of the data base. The proposed system is then ready to be used to score the whole night polysomnographic recordings.

The two-step system based on a bank of classifiers has been chosen so as to allow dealing with incomplete data caused by the presence of artifacts in the analyzed physiological signals. When all signals are available, the set of relevant features contains seven features in total - four features extracted from the EEG, two features extracted from the EOG and one feature computed from the EMG. So, all monitored signals are important for accurate sleep scoring. Missing values can appear when at least one signal out of the three monitored is artifacted. For example, if EMG is marked as artifacted, the set of seven relevant features needed for classification based on information extracted from all signals will contain one missing value (mobilityEMG). Such an incomplete feature set can not be processed by an ordinary automatic classifier and the corresponding epoch can not be scored. Excluding the epochs that contain at least one artifacted signal leads to a great loss of analyzed data and in consequence decreases the applicability of the classification system. The proposed bank of classifiers allows classification of the epochs containing an artifacted signal using features extracted from available artifact-free signals. So, the proposed system markedly reduces the number of epoch that must be excluded (not classified) because of artifacts confusing some of the analyzed signals.

Various techniques can be employed to deal with missing values. The best known methods are based on the principle of substitution of the missing value with a substitute. In the simplest approach, the missing values are replaced with a global value. There are various techniques to estimate the substitute value. The global substitute value can be estimated as a mean value, median, or modus computed from a corresponding row of data or can be set as zero value. Such a simple approach can mislead the subsequent classification. Several publications can be found where application of k-nearest neighbors is used to impute the missing values [TCSB01], [NWC04]. Methods based on regression analysis have also been used to estimate the missing values [ZWD03]. All the methods based on imputation of missing value are biased by the number of missing values in the concrete set of data. A statistic estimate of the substitute (mean, median, etc.) as well as a prediction of the missing value from the available data using regression methods require representative amount of available data. If the portion of missing values is high and the number of available data is low,

the estimate of the substitute can be inaccurate and in consequence can degrade the entire analysis.

Another approach used to deal with missing values modifies directly the structure of the classification system used. This approach is partially similar to the bank of classifiers proposed in this thesis. For example, P.K. Shape and R.J. Solly [SS95] use Multiple Neural Network classifiers for dealing with missing values. Multiple neural networks (MNN) represent a strongly separated architecture where each network works independently of the others. Each network is trained and specialized for its specific task and the final decision is then made on the results of the individual expert networks. There can be various techniques to implement the decision strategy. For example, it can be based on the application of a rule based decision system or another neural network can be employed to process the outputs of the expert networks. Contrary to the bank of classifiers proposed, all the individual networks are used to classify each object. In the case of a bank of classifiers proposed in this thesis, each time only one network (classifier) is used to process new set of input data. The selection of the network and input features used is based on the results of artifact identification performed on the three monitored signals in the first phase of the complex classification system.

Chapter 5

Results of practical experiments

This chapter describes the results obtained on the data presented in section 1.7 when using the two-step sleep/wake stages classification system. The performance of the system proposed is then compared with two traditional neural network classifiers using features extracted from all three signals. The first classifier employs the same artifact identification strategy as the proposed two-step system. The second one does not perform any artifact analysis. At the end of this section, the results of the experiments are compared and discussed.

The polysomnographic database has been described at the end of the first chapter. The database contains 47 whole night recordings. Since the EEG signal is considered as crucial for sleep staging, the quality of the EEG signal affects the experimental tests performed on the database. According to the results of artifact identification, the recording s105t1 has been excluded from the database used for the need of the final tests. The EEG signal of this recording is highly contaminated with continuous high-frequency artifacts. So, there are 46 polysomnographic recordings that have been analyzed. The same criteria as in the description of the initial *Both experts* database have been applied. The stages NREM III and NREM IV have been joined into SWS stage, epochs scored as “undefined” have been excluded and only the epochs with consensual scoring of both experts have been used. So, the final database (*Both experts-test*) contains 66,164 epochs. The distribution of the epochs into individual sleep/wake stages is shown in the Tab. 23.

<i>Number of epochs</i>	Awake state	NREM I	NREM II	SWS	REM
<i>Both experts-test</i>	5,298	1,981	32,462	11,210	15,213

Tab. 23 Description of the test database; Both experts-test database.

5.1 Application of the two-step system

The analysis of the results obtained with the two-step system on the 46 night recordings starts with the artifact identification performed for each epoch of the three signals monitored. Before the performance of the proposed two-step system is presented in terms of classification accuracy, the results of classification are presented by the distribution of classifiers used. Tab. 24 shows how many epochs were either scored by the diverse classifiers or excluded. The first line of the table shows the absolute numbers of epochs processed by each individual classifier. In the second line of the table, the same information is expressed using percentage values calculated on the whole base of epochs. The last line of the table presents percentage values calculated when the unclassified epochs (3,765 epochs) are not included into the calculation.

	EEG classifier 1	EEG EOG classifier 2	EEG EMG classifier 3	EEG EOG EMG classifier 4	excluded
<i>Number of epochs</i>	1,525	7,717	4,534	48,623	3,765
<i>% (all)</i>	2.3	11.7	6.8	73.5	5.7
<i>% (scored)</i>	2.4	12.4	7.3	77.9	-

Tab. 24 Analysis of the classification process.

Tab. 25 provides a detailed analysis of the epochs contained in the recordings. The table shows the absolute number of epochs processed by each individual classifier depending on individual sleep/wake stages.

	classifier 1	classifier 2	classifier 3	classifier 4	excluded
wake	445	329	535	1,162	2,827
NREM I	73	268	207	1,345	88
NREM II	358	4,131	1,587	25,931	455
SWS	56	1,295	96	9,678	85
REM	593	1,694	2,109	10,507	310

Tab. 25 Numbers of epochs analyzed by individual classifiers - distribution into sleep/wake stages.

From Tab. 24, it can be seen that 3,765 epochs (5.7%) have been excluded and thus not classified into sleep/wake stages by the system. These epochs have been excluded because the EEG signal is marked as “artifacted”. The rest of the database, 62,399 epochs (94.3%) in total, has been scored in the second block of the proposed classification system. Each epoch has been scored using one of the four classifiers stored in the bank of classifiers. As can be seen in Tab. 24, the majority of the data (48,623 epochs) has been scored using the classifier 4, which uses features computed from all three signals. This means that about 80% of the epochs classified by one of the four classifiers were classified by the classifier 4. On the contrary, only 1,525 epochs (about 2.5%) have EOG and EMG signals marked as artifacted and thus have to be scored by the classifier 1 using only EEG features.

The overall classification accuracy obtained by the two-step system, computed over the 62,399 epochs, is 85.48%. This accuracy is slightly above the performances of existing automatic classification systems. Some of them have been presented in the overview of current automatic sleep analysis presented in chapter 1. For example, the automatic system proposed by Schaltenbrand *et al.* [SLTL+96] reached classification accuracy of 84.5% when 20 recordings from healthy subjects were classified. Sleep stager proposed by the SIESTA group [AGPW+05] is characterized with global classification accuracy of about 80%. However, this automatic system does not join together stages NREM III and NREM IV. Probabilistic continuous sleep stager proposed by Flexer *et al.* [FGD05] was evaluated on 20 whole night recordings. The system was able to correctly classify only 68% of epochs scored by expert as REM sleep. Moreover, classification accuracy of stages NREM I, NREM II and NREM III was below 40%.

The detailed analysis of the results is presented in the Tab. 26 which shows the corresponding confusion matrix.

% expert		classifier				
		wake	NREM I	NREM II	SWS	REM
expert	wake	78.07	12.79	3.40	2.10	3.64
	NREM I	8.14	64.77	7.13	0.63	19.33
	NREM II	1.80	4.65	86.92	4.80	1.83
	SWS	0.15	0	5.09	94.75	0.01
	REM	2.13	16.30	1.75	0.49	79.33

Tab. 26 Confusion matrix. Performance of the complex two-step classification system.

As can be seen in the confusion matrix, the two-step system is very successful in classification of NREM sleep stage II and SWS. Classification accuracy of these stages exceeds 85% (about 87% and 95% respectively). These stages are traditionally well classified during automatic classification. The classification accuracy of wake and REM sleep stages is slightly below 80%. The lowest classification accuracy is obtained for NREM I stage and reaches only about 65%. This stage is still confused with wake and REM sleep.

In the following, the performances of each of the four classifiers (1 to 4) are evaluated separately. The presented values are obtained during application of the two-step automatic classifier on the data in the *Both experts-test* database.

Classifier 1: EEG

1,525 epochs have only the EEG signal marked as artifact-free. These epochs are thus scored by the classifier 1. This classifier reached a classification accuracy of 72.72%. This value is the lowest over the four classifiers used. It could be partially explained by the fact that these epochs have both EOG and EMG signals artifacted. Therefore, one can imagine that the quality of the EEG signal may also be slightly degraded by the presence of transmitted artifacts. Some improvements in artifact identification strategy could lead to more effective detection of such noise.

Tab. 27 shows the confusion matrix obtained. Compared to the performance obtained by the classifier on the 7 subsets S_k during feature selection (see Tab. 17), a decrease in classification

of NREM II stage and increase in classification of REM sleep can be observed. The classification accuracy of NREM I stage is low, as it was already observed in section 3.5.2.

%		classifier				
		wake	NREM I	NREM II	SWS	REM
expert	wake	80.67	9.66	4.94	4.50	0.23
	NREM I	15.07	47.94	2.74	0	34.25
	NREM II	5.31	19.27	70.39	3.07	1.96
	SWS	1.79	0	0	98.21	0
	REM	2.53	21.25	3.20	4.22	68.80

Tab. 27 Confusion matrix. Performance of the classifier 1 (EEG signal).

Classifier 2: EEG + EOG

Classifier 2 scored 7,717 epochs and correctly classified 82.62% of these epochs. The analysis of the confusion matrix (Tab. 28) shows a decrease in accuracy of wake and NREM I when compared to the Tab. 18 presenting the performance obtained on subsets S_k . The decrease of classification accuracy in NREM I stage is especially surprising, because, from the feature selection process, EOG signal was supposed to be useful for classification of this stage.

%		classifier				
		wake	NREM I	NREM II	SWS	REM
expert	wake	60.49	22.80	6.38	1.52	8.81
	NREM I	10.08	55.22	9.70	1.87	23.13
	NREM II	0.68	4.11	89.52	5.16	0.53
	SWS	0.08	0	6.41	93.51	0
	REM	3.13	27.98	2.42	0.35	66.12

Tab. 28 Confusion matrix. Performance of the classifier 2 (EEG and EOG signals).

Classifier 3: EEG + EMG

Classifier 3 scored 4,534 epochs. The classification accuracy reached 80.19%. The confusion matrix is presented in Tab. 29. The low accuracy obtained for stage NREM I is due to the absence of EOG signal as presented in Chapter 3. A decrease in classification accuracy of NREM II stage is observed compared to Tab. 19.

		classifier				
		wake	NREM I	NREM II	SWS	REM
expert	wake	82.62	9.16	1.49	4.11	2.62
	NREM I	14.98	55.07	2.90	0.48	26.57
	NREM II	3.59	10.78	77.25	2.14	6.24
	SWS	0	0	1.04	98.96	0
	REM	2.28	11.85	1.19	1.28	83.40

Tab. 29 Confusion matrix. Performance of the classifier 3 (EEG and EMG signals).

Classifier 4: EEG + EOG + EMG

48,623 epochs were classified with classifier 4. The classification accuracy is 86.82%. This classifier obtains the highest classification accuracy compared to the other classifiers contained in the bank of classifiers. The analysis of the confusion matrix (Tab. 30) obtained with this classifier does not show any significant decrease in classification accuracy. All the accuracies computed for individual sleep/wake stages are comparable to the values reached during feature selection (Tab. 20).

		classifier				
		wake	NREM I	NREM II	SWS	REM
expert	wake	79.95	12.82	2.84	0.43	3.96
	NREM I	6.32	69.07	7.51	0.45	16.65
	NREM II	1.82	4.15	87.33	4.93	1.77
	SWS	0.16	0	4.98	94.85	0.01
	REM	1.91	15.04	1.68	0.14	81.23

Tab. 30 Confusion matrix. Performance of the classifier 4 (EEG, EOG and EMG signals).

General discussion

The results show that the classification of NREM I stage is still a problem and is affected by the quality of the signals. When at least one signal is artifacted, the accuracy of NREM I stage is lower than the accuracy reached in the section 3.5.2, even when EOG is used. Only when all the signals are marked as artifact-free, the classification accuracy of NREM I stage is acceptable (69%).

The fact that some decrease in classification accuracies was observed, compare to the results obtained in chapter 3, can be explained by the concrete setting of the learning phase. All the neural network classifiers stored in the bank of classifiers have been learned on epochs where all the three signals were marked as artifact-free. Thus, the probability that undetected noise was present in the signals analyzed has been low. But, when an artifacted signal is identified in an epoch, the other signals can be contaminated by some noise transmitted from the artifacted signal. The features extracted could then be biased, which could explain the decreases in accuracy.

Although the classifiers using incomplete set of signals (classifiers 1-3) bring some slight decrease in global classification accuracy, the proposed approach dealing with missing values seems to be effective. It allows the correct classification of epochs that would be excluded because of the presence of artifacts in at least one of the monitored signals. The classification accuracy computed for these 13,776 artifacted epochs is 80.72%. This value alone is high enough to conclude on the interest of the method presented in this thesis. The classification of sleep epochs using an incomplete set of signals to overcome the presence of artifacts is worth the effort. But it is evident that artifact identification should be improved in order to better identify noise transmitted from artifacted signals.

5.2 Comparison with simple classifiers

The proposed two-step classification system is compared with two single sleep stagers composed of only one neural network instead of a bank of classifiers. The first one is equipped with the artifact identification step. It makes a decision (classification) when all the three signals are detected as artifact-free. The rest of the epochs is excluded from the classification. The second automatic sleep stager is not equipped with artifact identification step. It makes a decision whether the signals are artifacted or not. No epochs are excluded.

Simple classifier using artifact identification

This single classifier processes epochs which have all three signals (EEG, EOG and EMG) artifact-free and thus available, and excludes all the others. It performs the same artifact identification strategy as employed in the two-step classification system. This classifier corresponds to the classifier 4 used in the two-step system using bank of classifiers.

The overall classification accuracy of the stager is 86.82%. The confusion matrix is presented in Tab. 30. This automatic classifier is able to score 48,623 epochs out of the 66,164 epochs contained in the whole *Both experts-test* database. It represents only 73.5% of the data. The rest of the database, 17,541 epochs (26.5%), is excluded from the analysis and classification of these epochs is not performed.

Simple classifier without artifact identification

The second neural network classifier used to compare the proposed classification system does not perform any artifact analysis of the polysomnographic recordings. The relevant features are only computed from EEG, EOG and EMG and then used as inputs for the classifier. A complete elaboration phase was achieved to build this classifier, from the selection of relevant features to the training of the neural network. The selection of relevant features was achieved using the selection strategy presented in Chapter 3. Seven data subsets containing 550 possibly artifacted epochs were created. SFS selected seven relevant features: $Prel\beta$, $entr_{EMG}$, $Prel\alpha$, $entr_{EOG}$, $entr_{EEG}$, $Prel\alpha$ and $Prel\theta$.

The overall classification accuracy obtained on the whole database of polysomnographic recordings is 83.24%, which is slightly lower than the classification accuracy of the complex two-step system. However, this single classifier classifies the whole base of 66,164 epochs (*Both experts-test* database). The confusion matrix is presented in Tab. 31. The comparison between this matrix and the confusion matrix obtained for the two-step system (Tab. 26) shows that the classification accuracy of the REM sleep obtained with the single classifier has decreased by 10%. REM epochs were wrongly classified as NREM I stage. This increase in the number of REM sleep epochs misclassified as NREM sleep stage I is slightly counter-balanced by a decrease in the number of NREM I epochs wrongly classified in REM by 1.5%. On the whole, the two-step system using a bank of classifiers performs a better discrimination between REM sleep and NREM I stage. The system without artifact processing misclassifies 4,201 epochs of stages NREM I and REM sleep. When the two-step system is used, the number of misclassified epochs scored by both experts as NREM I and REM sleep is equal to 2,762 epochs. So, the absolute number of misclassified epochs has been reduced by 1,439. However, as presented in Tab. 25, some epochs scored by both experts as NREM I and REM sleep were excluded when the two-step classification system was used. In total, 398 epochs

scored as NREM I and REM sleep were excluded from the classification process, because of artifacts in EEG. Nevertheless, still 1,041 epochs of NREM I and REM sleep were correctly classified by the two-step system using a bank of classifiers and wrongly classified by the single classifier. Thus, the improvement in discerning NREM I and REM sleep stages is mainly due to the elimination of artifacted segments contained in the analyzed signals. Indeed, as presented in Tab. 8 and Tab. 9, the EOG and EMG signals contain a high number of artifacted epochs in NREM I and REM sleep stages.

%		classifier				
		wake	NREM I	NREM II	SWS	REM
expert	wake	80.99	14.01	1.94	1.78	1.28
	NREM I	5.71	67.64	8.58	0.25	17.82
	NREM II	1.29	4.98	86.96	4.86	1.91
	SWS	0.74	0.01	5.15	93.95	0.15
	REM	1.49	25.29	2.41	0.55	70.26

Tab. 31 Confusion matrix. Performance of the classifier without phase of artifact identification.

The confusion matrix of the simple stager without a phase of artifact identification also shows a slight increase of the classification accuracy in the wake stage. The classification accuracy of wake increased by 3% compared to the two-step system. It could be explained by the high artifact contamination of the wake stage. About half of the wake epochs are detected as artifacted (high-amplitude and high-frequency artifacts). It seems that the sleep stager, learnt on possibly artifacted data, misinterpreted these high-amplitude artifacts as a true high amplitude signal, which is typical for the wake stage. This artifact manifestation then facilitated classification of epochs into wake stage.

5.3 Comparison of the three different classifiers

Tab. 32 summarizes the accuracies reached by the three automatic classifiers, as well as the numbers of epochs classified.

Type	Accuracy	Number of epochs
Complex two-step classifier	85.48%	62,399
Classifier with artifact detection	86.82%	48,623
Classifier without artifact detection	83.24%	66,164

Tab. 32 Classification results for different classifiers compared in this chapter.

The highest value of classification accuracy is reached when a unique classifier using all three signals is used in combination with an artifact identification strategy. However, this high classification accuracy is ransomed by a high number of data that can not be classified by the unique classifier. More than 25% of the whole data are not classified because of presence of artifacts in at least one signal. This high number of excluded epochs limits the usability of the system.

When the two-step classification system is used, only a slight decrease of classification accuracy is noticed. But the number of processed epochs is much higher. Only about 6% of the whole data can not be classified by the system. So, the strategy using a bank of classifiers enables the classification of 13,776 epochs excluded when only the unique classifier is used.

When the classification is performed without artifact processing, the final classification accuracy computed over the whole database is the lowest although the classifier is fed only with features computed from all signals. The difference in classification accuracy obtained for the classifiers with and without artifact identification justifies the need of an effective artifact processing strategy for sleep/wake stage classification.

5.4 Chapter conclusion

The two-step classification system that combines results of artifact identification with a bank of classifiers has been tested in this chapter. The structure of a bank of classifiers has been selected so as to enable the analysis of epochs containing missing values caused by the

presence of artifacts in some of the signals. The results showed that, when an automatic classifier that requires a complete set of features to be computed from all three artifact-free signals is used, a high number of epochs cannot be scored because of artifacts identified in the signals. However, most of the epochs containing artifacts in EOG and/or EMG can be correctly classified using features extracted from the artifact-free signals. So, the bank of classifiers represents an effective approach for automatic sleep analysis.

The results also show that artifact identification and rejection performed prior to the classification is the cause of higher quality of features extracted from the signals. It is mainly evident in the increased ability to distinguish stages NREM I and REM sleep when the two-step automatic system is employed. As can be seen in Tab. 9, these stages contain a high portion of artifacted epochs in the EOG and EMG signals. Since these two signals are supposed to be important for discrimination of wake, NREM I and REM sleep stages, their quality as well as the quality of the features extracted from them is crucial for correct and precise automatic classification.

Chapter 6

Conclusion

This thesis proposes a complex two-step decision system for classification of human sleep recordings into sleep/wake stages. Its general idea is the following. In the first step, artifacts are detected in the analyzed signals and so called artifact-free signals are consequently determined for each epoch of the whole recording. In the second step of the analysis, relevant parameters are computed from the available artifact-free signals and processed using an adequate automatic classifier stored in a bank of classifiers. The bank of classifiers is composed of four neural networks, each of them using inputs extracted from a different combination of polysomnographic signals.

This system has been designed so as to meet two fundamental requirements:

- Effective processing of artifacts without losing too many data.
- Employment of the most relevant parameters computed from the available signals.

The results of the research presented in this work can be interpreted as the testification of the structure proposed for the two-step automatic classification system.

The analysis of the results revealed that a high portion of the epochs is contaminated briefly by very short artifacts. About 25% of the epochs stored in the database contain at least a segment of 2 seconds contaminated by an artifact. However, only less than 10% of all the analyzed epochs contain more than 4 seconds of artifacted signal. Thus, the automatic artifact identification we proposed, using a 2-sec time resolution combined with a strategy designed to evaluate the entire 20-sec epoch, is not only effective in signal denoising, but in addition it also helps to reduce the loss of available data. The epochs of the signal in which at most two

2-sec segments contain any kind of artifact are marked as artifact-free and can be then processed in the subsequent analysis. It is evident that all the 2-sec segments containing an artifact are removed from the signal trace of these epochs. In addition to this, since the artifacts are identified in each signal separately, the quality of the individual signals contained in the sleep recording can be indeed evaluated independently (artifact-free or artifacted). Therefore, presence of artifacts in whatever signal monitored does not have to lead to the automatic rejection of the whole epoch of the recording.

The artifact analysis designed and performed this way allows the classification of sleep recordings using a structure based on a bank of classifiers. The bank of classifiers contains four neural network classifiers. The relevant parameters selected for diverse combinations of signals contained in the sleep recordings are used as inputs for the individual automatic classifiers. The artifact identification strategy proposed predetermines the general structure of the complex automatic classification system. This is an effective way to deal with artifacts, without losing a large amount of data. The originality of this proposition lays in the fact that each epoch can be classified by a different classifier which uses different features as input, depending on the quality of the three signals monitored. The different sets of features used by individual classifiers were selected as the most relevant by an appropriate selection of features.

In the second part of the research, a sequential method was proposed to determine the most relevant parameters which describe the various sleep/wake stages in the best way. The proposed method of feature selection used an adequately selected data subset as well as an appropriate selecting criterion combined with a statistical test to end the selection. The method was designed so as not to favor one sleep/wake stage to another and to be insensitive to the training data used. The relevant feature sets have been selected out of 33 features computed from the EEG, EOG and EMG signals. The results of the feature selection lead to propose alternative methods to process the signal in the time domain. As instance, the entropy or the kurtosis of signals were preferred by the selection method to the more traditional standard deviation. The results also confirmed the importance of the EEG signal in sleep analysis, with the consequence that only four combinations of signals monitored (EEG, EEG + EOG, EEG + EMG, EEG + EOG + EMG) could be used in the bank of classifiers.

Moreover, the results showed that a correct classification of wake, NREM II and SWS stages could be achieved using EEG only, with an accuracy above 80% for each stage. However,

information contained in the EEG signal is insufficient to correctly discriminate NREM I from REM, which are highly confused. The classification accuracy of these two stages is significantly improved when the EEG signal is analyzed together with the EOG and EMG signals.

The performance of the two-step classification system was evaluated on a large base of polysomnographic recordings containing 66,164 epochs. The classification system proposed reached 85.5% of global accuracy with 94% of the 20-sec epochs actually classified. Only about 6% of the data (i.e. 3,765 epochs) were rejected because of artifacts in EEG signal. Moreover, the results showed that the two-step classification system enables a successful classification of the epochs containing artifacts in EOG or EMG (about 81 % of global accuracy was reached on these epochs). These epochs, which represent 20% of the complete database, would be rejected by a traditional system. The effectiveness of the two-step classification system is evident both in the global classification accuracy reached as well as in the total number of epochs that can be actually scored.

Future researches in the field of automatic sleep analysis should focus both on improving the artifact processing strategy and on the extraction of new relevant parameters computed from the physiological signals analyzed. As presented in chapter 2, the actual settings of the artifact detection algorithms were not properly evaluated. The performances of the automatic classification system could be improved by optimizing the artifact detection algorithms, which could lead to a more accurate identification of artifacts. Moreover, other types of artifacts, such as ocular artifact for instance, should be identified by an automatic classification system. Indeed, effective artifact processing strategy is necessary to extract more reliable information from polysomnographic signals.

A key issue in automatic classification of sleep stages is the discrimination of NREM I from REM stages. New parameters able to discriminate these two stages should be proposed, using advanced signal processing techniques.

Finally, automatic classification techniques able to include contextual information could be useful. Until now, polysomnographic recordings are processed epoch by epoch and classification is typically performed using only information extracted from the epoch to be scored. Information contained in the epochs preceding the current one is not taken into

account. Moreover, smoothing rules could be implemented so as to avoid sudden and incorrect shifts in the hypnogram.

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Automatic classification of human sleep recordings combining artifact identification and relevant features selection

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Keywords: decision making, diagnosis, medical applications, pattern recognition, signal processing

This thesis engages in automatic analysis of human sleep. It mainly focuses on the development of an automatic system for classification of polysomnographic recordings, composed of three signals: EEG, EOG and EMG. This thesis proposes a complex classification system, which is capable to deal with various artifacts possibly present in the physiological signals and which uses the most relevant parameters computed from the analyzed signals.

The first part of this thesis presents a procedure to automatically identify eight common artifacts in 2-sec segments of the analyzed signals. Then, a strategy is applied in order to evaluate quality of the signals characterizing each 20-sec epoch of the recording.

In the second part of this thesis, an iterative feature selection method is proposed and applied on a large database of polysomnographic recordings, so as to select the most relevant parameters that will serve as inputs for the automatic classifier.

Then, as a result of the two first parts, a complex two-step sleep/wake stages automatic classification system is proposed. In a first step, an artifact detection system selects the artifact-free polysomnographic signals in the epoch to be scored. In the second step, the features selected as the most relevant are extracted from the artifact-free signals and classified using a neural network classifier chosen among a bank of four classifiers, which differs one from the others by the signals used. Thus, the final classification system allows classification using relevant features computed from artifact-free signals, without losing many.

Classification automatique d'enregistrements de sommeil humain combinant l'identification d'artéfacts et la sélection de caractéristiques pertinentes

Les mots clés: décision, diagnostic, application médicales, reconnaissance de formes, traitement du signal

Cette thèse porte sur la classification automatique de sommeil humain et plus précisément le développement d'un système automatique de classification d'enregistrements polysomnographiques composés de trois signaux: EEG, EOG et EMG. Le système développé est conçu pour prendre en compte l'occurrence d'artéfacts polluant ces signaux en utilisant les caractéristiques les plus discriminantes issus de ces signaux.

La première partie de la thèse présente une procédure permettant l'identification automatique, sur des plages de signaux de 2 secondes, de 8 types d'artéfacts parmi les plus courants ainsi qu'une stratégie permettant d'évaluer la qualité globale d'un signal sur une période de 20 secondes.

Dans une deuxième partie, une méthode de sélection de caractéristiques est proposée puis appliquée sur une base de signaux, afin de sélectionner les caractéristiques qui serviront d'entrées au classifieur.

Enfin, en conséquence des deux premières parties, un système de classification automatique à deux étapes est proposé. Dans une première étape, un système de détection d'artéfacts permet de sélectionner les signaux ne présentant pas d'artéfacts au cours de l'epoch à classer. Dans la deuxième étape, les caractéristiques les plus discriminantes sont extraites et classées à l'aide d'un réseau de neurones sélectionné parmi un ensemble de quatre classifieurs, chaque classifieur utilisant des caractéristiques d'entrées extraites de combinaisons de signaux différentes. Le système proposé permet la classification des enregistrements de nuits de sommeil à partir de caractéristiques extraites de signaux non pollués par des artefacts, sans perdre un trop grand nombre d'epochs.