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ANALÝZA SPÁNKOVÉHO SIGNÁLU EEG

ANALYSIS OF SLEEP EEG SIGNAL

DIPLOMOVÁ PRÁCE
MASTER'S THESIS

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Diplomová práce

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Ročník: 2 ***Akademický rok:*** 2007/08

NÁZEV TÉMATU:

Analýza spánkového signálu EEG

POKYNY PRO VYPRACOVÁNÍ:

Seznamte se s možnostmi aplikace polysomnografických záznamů vybíraných pro analýzu signálu EEG snímaného ve spánku. Navrhněte a ověřte nejvhodnější algoritmus pro analýzu mikrospánkových fází : FFT, waveletová transformace, zpracování v časově frekvenční oblasti. Při analýze využívejte programové prostředí Matlab. Klinickou interpretaci dosažených výsledků konsultujte na specializovaném pracovišti, které dodá i nezbytná data.
Práce musí obsahovat : Teoretický rozbor problematiky a zdůvodnění zvolené metody analýzy, dokumentaci k programu, komentář k dosaženým výsledkům.

DOPORUČENÁ LITERATURA:

[1] Nevšímalová S., Šonka K. a kol.: Poruchy spánku a bdění. Maxdorf, Praha, 1997
[2] Pacheco O., Vaz F.: Integrated system for analysis and automatic classification of sleep EEG. Engineering in Medicine and Biology Society, 1998, part 4, pp.2062-2065

Termín zadání: 30.10.2007 ***Termín odevzdání:*** 30.5.2008

Vedoucí projektu: doc. Ing. Jiří Rozman, CSc.

prof. Ing. Jiří Jan, CSc.
předseda oborové rady

UPOZORNĚNÍ:

ANOTACE

Cílem této práce byl vývoj programu pro automatickou detekci arousalu v signálu spánkového EEG s použitím metod časově-frekvenční analýzy. Předmětem studie bylo 13 celonočních polysomnografických nahrávek (čtyři svody EEG, EMG, EKG a EOG), tj. celkově více než 100 hodin záznamu. Jednalo se o část dat z dřívějších výzkumných prací expertní lékařky v problematice spánku Dr. Emilie Sforzy, Ženeva, Švýcarsko, která rovněž poskytla základní hodnocení těchto dat. V záznamech bylo celkem označeno 1551 arousal událostí. Pro usnadnění výběru konkrétní metody časově-frekvenční analýzy byla následně vytvořena sada nástrojů pro vizualizaci jednotlivých signálů a jejich různých časově-frekvenčních vyjádření. S ohledem na závěry vizuální analýzy, charakter signálu EEG a efektivitu výpočetních metod byla pro analýzu vybrána waveletová transformace s mateřskou vlnkou Daubechies řádu 6. Jednotlivé svody EEG byly dekomponovány do šesti frekvenčních pásem. Z takto odvozených signálů a signálu EMG byly následně stanoveny ukazatele možné přítomnosti události arousalu. Tyto ukazatele byly dále váhovány lineárním klasifikátorem, jehož hodnoty vah byly optimalizovány pomocí genetického algoritmu. Na základě hodnoty lineárního klasifikátoru bylo rozhodnuto o přítomnosti události arousalu v daném svodě EEG – arousal byl detekován, jestliže hodnota klasifikátoru překročila danou mez na dobu více než 3 a méně než 30 vteřin. V celém záznamu pak byl arousal označen, byl-li detekován alespoň v jednom ze svodů EEG. Následně byly odvozeny míry senzitivity a selektivity detekce, jež byly rovněž základem pro stanovení fitness funkce genetického algoritmu. Pro učení genetického algoritmu byly vybrány první čtyři záznamy. Na základě takto optimalizovaných vah vznikl program pro automatickou detekci, který na celém souboru 13 záznamů dosáhl ve srovnání s expertním hodnocením míry senzitivity 76,09%, selektivity 53,26% a specificity 97,66%.

Klíčová slova: spánek, probuzení, arousal, microarousal, polysomnografie, EEG, analýza signálu, automatická detekce, FFT, STFT, waveletová transformace

Bibliografická citace: JEŽEK, M. Analýza spánkového signálu EEG. Brno: Vysoké učení technické v Brně, Fakulta elektrotechniky a komunikačních technologií, 2009. 48 s. Vedoucí diplomové práce doc. Ing. Jiří Rozman, CSc.

ABSTRACT

The aim of this study was to develop an automatic detection program for scoring the sleep EEG arousals, based on one of time-frequency analysis methods. The subject of the study was 13 overnight polysomnographic recordings (four leads of EEG, EMG, ECG and EOG), i.e over 100 hours in total. It was a subset of data used in former studies by sleep expert Dr. Emilia Sforza, Geneva, Switzerland, who also provided baseline arousal scoring. Total number of 1551 arousal events were marked in the recordings. Next, several tools for recordings' visualization were developed to facilitate the decision on methods of analysis. Following the conclusions made after extensive visualization of input recordings in different time-frequency representations and regarding the character of EEG as neuroelectric waveforms and computing efficiency, discrete wavelet decomposition with Daubechies order 6 mother wavelet was chosen. The EEG signals were decomposed into six frequency bands. The results together with EMG recordings were used to evaluate a set of indices describing EEG and EMG changes accompanying arousals. These indices were weighted to form linear classifier of microarousal suspicion in each EEG lead – a microarousal was marked as present when it remained suspect in period of 3 to 30 seconds. Outputs of four EEG channels were then integrated to report final outcome. Based on sensitivity and selectivity measures the algorithm was optimized by genetic algorithm. The subject of tuning were the linear classifier parameters and first four of 13 recordings were selected as training data. A microarousal detection program emerged on basis of the tuned algorithm and resulted in average sensitivity of 76,09 %, selectivity of 53,26 % and 97,66 % specificity over all 13 recordings compared to expert visual scorings.

Keywords: sleep, arousal, microarousal, polysomnography, EEG, signal analysis, automated detection, FFT, STFT, wavelet transform

Prohlášení

Prohlašuji, že svou diplomovou práci na téma Analýza spánkového signálu EEG jsem vypracoval samostatně pod vedením vedoucího diplomové práce a s použitím odborné literatury a dalších informačních zdrojů, které jsou všechny citovány v práci a uvedeny v seznamu literatury na konci práce.

Jako autor uvedené diplomové práce dále prohlašuji, že v souvislosti s vytvořením této diplomové práce jsem neporušil autorská práva třetích osob, zejména jsem nezasáhl nedovoleným způsobem do cizích autorských práv osobnostních a jsem si plně vědom následků porušení ustanovení § 11 a následujících autorského zákona č. 121/2000 Sb., včetně možných trestněprávních důsledků vyplývajících z ustanovení § 152 trestního zákona č. 140/1961 Sb.

V Brně dne 29. května 2009 ....

podpis autora

Poděkování

Děkuji vedoucímu diplomové práce Doc. Ing. Jiřímu Rozmanovi, CSc. za účinnou metodickou, pedagogickou a odbornou pomoc a další cenné rady při zpracování mé diplomové práce a dále pak Dr. Sylvie Charbonnier a Dr. Suzanne Lesecq za odborné vedení výzkumné stáže v Grenoblu.

V Brně dne 29. května 2009 ....

podpis autora

Content

Introduction

An interest in unraveling the brain and how we think has characterized much of human history. Basically the functional aspects of the brain are studied using electrical signals, magnetic signals, or indirect measurements based on injected materials such as radionuclides. The underlying basis of all these measurements is the neuron as the fundamental unit of central nervous system. The neuron represent an excitable cell capable to switch rapidly from one polarity, across the membrane of the cell, to another. The pulse of electrical energy, called the action potential, carry the information around the nervous system.

Only the neurons are electrically active and represent the source of the signals referred to the electroencephalograph (EEG). Electrical recordings between any two electrodes from the outer surface of the head reveals the continuous electrical activity of the nerve cells within the brain. The patterns of the amplitude of electrical activity vary noticeably among such states as coma, sleep and wakefulness. Sleep is not a passive state, but rather a dynamic process characterized by specific psychophysiological changes.

Currently, the research of the sleep EEG is highly popular as the exact analysis may help in the area of sleep disorders like sleep apnoea, narcolepsy, or insomnia. The research focuses on the visual analysis of polysomnographic recordings which means the parallel recordings of electroencephalogram, electrooculogram and electromyogram. The scoring system of such recordings is basically aimed on sleep microstructures and performed by sleep experts according to scoring rules. The frequent lack of explicit experts concordance and the time-consuming process of personal visual scoring led to many researches of automatic detection and scoring systems.

The most examined methods of automatic detection are based on combinations of signal analysis, such as spectral analysis, short-time Fourier transform or wavelet transform with machine learning based classification/modeling, such as neural networks, discriminant analysis, support vector machines or k-means clustering, and/or optimization methods, such as genetic algorithms.

The aim of this study is to develop an automatic detection program for scoring the EEG arousals using one of time-frequency analysis methods.

1 Brief history of the sleep research

The beginning of contemporary studies of the sleep dates back to the mid-19th century. Before the understanding of the central nervous system there was a couple of interesting theories about the cause of sleep. One of such theories considered the lack of blood, congestion or pressure of blood in the brain as the cause of sleep. Another theory provided an idea of the accumulation of toxic substances during the day which simply caused sleep. Also the lack of oxygen was considered as a regular cause of everynight sleep.

Even after recognition of neurons and their electrical activity there was a long period of persuasion that neurons are paralyzed and activity is somehow switched off. In 1868, Wilhelm Griesinger described eyes movements during the sleep and referred them to as a part of dreaming and Sigmung Freud, in 1895, noticed the decrease of the myotonus.

At the beginning of the 20th century Henri Piéron wrote a book entitled Le problème physiologique du sommeil [1], in which sleep is characterized physiologically in a modern scientific approach. More systematic research was applied when the Austrian neurologist Constantin von Economo postulated the existence of an active sleep-regulating center in the brain and localized it. He described excessive sleepiness in patients with lesion in the back of the hypothalamus and insomnia in patients with lesion in the preoptic area and in the front of the hypothalamus. The identification of such centers was based on clinical and pathoanatomical observations of patients with specific viral encephalitis, the lethargic encephalitis [2], in 1917 - 1920. His findings were later confirmed by Walter Rudolph Hess and Steven Walter Ranson. In 1920 Nathaniel Kleitman´s research focused on how sleep and wakefulness relate to circadian rhythms and the effects of sleep deprivation. He decided on the cerebral cortex to be the site of wakefulness. Later in 1929 he proposed the theory that the inactivity and fatigue of the central nervous system and the loss of surrounding stimulation caused sleep [3].

The modern sleep research is connected with the invention of the electroencephalograph (EEG) by German scientist Hans Berger in 1929. EEG is an instrument that measures and records brain wave patterns. In 1937, based on 30 wholenight EEG measurements, the research group of Alfred Loomis discovered cycle repeating patterns and classified sleep into five different stages [4].

In 1953 Nathaniel Kleitman and his student Eugene Aserinsky reported their findings about periods of eye movements during the sleep. They called that „Rapid eye movement sleep“ (REM). Eye movements were rapid and binocularly symmetrical, EEG pattern was similar to one discovered in wakefulness and respiratory and heart rates were increased in contrast to other sleep periods. If the person was awoke during the period of REM sleep, he described highly vivid dreams, but if awoke during nonREM (NREM) period he did not recall dreams [5]. Nathaniel Kleitman and William C. Dement decided on cyclic nature of sleep in 1955 and in the subsequent research recorded this cyclic pattern of REM and NREM sleep using the EEG and electrooculogram (EOG). From 4 to 5 cycles REM-NREM occur during the night while one cycle lasts around 90-100 minutes. Kleitman and Aserinsky then divided NREM sleep into four stages ranging from the lightest sleep in stage 1 to the deepest sleep of stage 4.

Worldwide, many researches were focused on study of sleep disorders. One of the most cited author is Czech clinician Bedřich Roth, who helped to establish the first European sleep laboratory and directed the study at narcolepsy and hypersomnia [2].

Allan Rechtschaffen and Anthony Kales focused their work on standardization of scoring EEG recordings, so in 1968 their Manual of Standardized Terminology, Techniques and Scoring System for Sleep Stages of Human Subjects was published by the United States Government Printing Office [6]. Authors defined parameters, techniques and wave patterns of polysomnographic recordings, which means recordings of electroencephalogram (EEG), electrooculogram (EOG) and electromyogram (EMG) recorded at the same time.

Another manual was published later in 1982 by Christian Guilleminault and it was specifically oriented to detect sleep pathophysiologies associated with specific sleep disorders. Guidelines contained standards of scoring breathing, leg movements, abnormal EEG, nocturnal tumescence, and other sleep phenomena [7].

In 1992, the American Sleep Disorders Association (ASDA) formalized the rules for scoring central nervous system arousals and published the manual in the journal Sleep [8]. For scoring rules see Table 2. Many researches are still based on this scoring manual in spite of the publication of the new one in 2007 by the American Academy of Sleep Medicine (AASM). This new scoring manual invented by researchers of AASM contains guidelines of changed scoring rules. The Manual was published in a single volume entitled the AASM Manual for the Scoring of Sleep and Associated Events: Rules, Terminology and Technical Specifications [9] and represents a giant step towards standardization of clinical polysomnography. Even as scoring rules were evolving with changing methodology, no official guidelines emerged concerning computerized polysomnography.

2 Polysomnographic measurement, macrostructure and microstructure of sleep

2.1 Polysomnographic measurement

The polysomnography (PSG) is considered as an essential method in sleep research, using electrophysiological techniques. It consists of measuring electroencephalogram (EEG), electrooculogram (EOG) and electromyogram (EMG). Still at the time, according to Rechtschaffen and Kales´s Manual of Standardized Terminology, Techniques and Scoring System for Sleep Stages of Human Subjects [6], the most frequently used recordings are of one channel of EEG, two channels of EOG and one channel of EMG. The electrocardiogram (ECG), sleeping position, respiration (flow), oxygen saturation and leg movements are usually also monitored, in addition to basic three techniques. If video recording is present, the method is widely referred to as videopolysomnography.

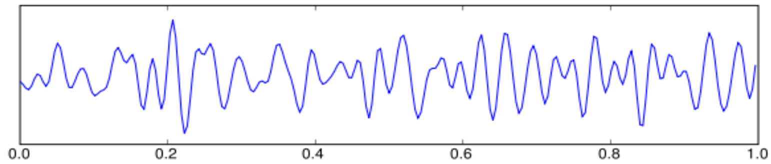
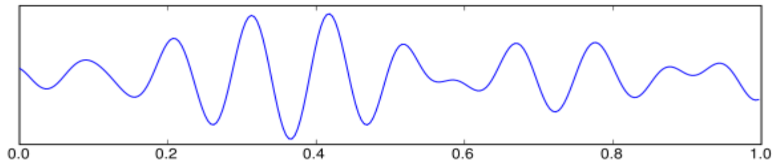
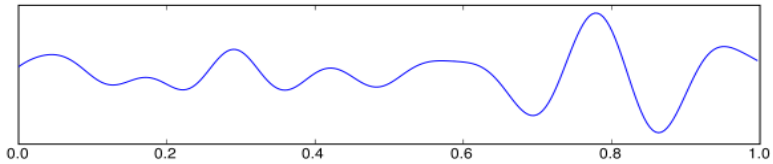
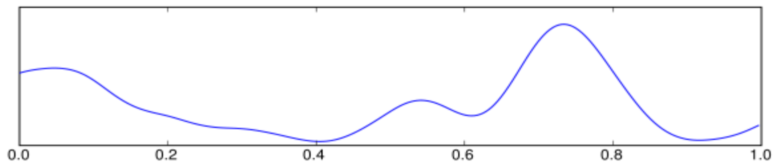
2.1.1 Electroencephalogram (EEG)

The EEG is considered to be the main measure of PSG recordings. Two electrodes are attached to the surface of the human scalp and connected to an amplifier, the output of the amplifier reveals variation in voltage over time. The most important characteristics of EEG are amplitude and frequency. The amplitude of the normal EEG can vary between approximately -100 and +100 μV, and its frequency ranges up to about 40 Hz. Hans Berger, by his measurements of electroencephalogram (EEG), proved the sleep is not a passive unitary state. Changes in EEG frequency and amplitude were consistently correlated with vigilance, drowsiness and sleep periods.

The background activity, measured by EEG, is varying and forms 4 basic waves: beta, alpha, theta and delta. Beta activity is typical while the subject is awake. Alpha is predominant in relaxed state with eyes closed. Theta waves are typical in normal wake state in children but in adulthood this activity appears only in small amount in drowsiness. Delta waves are present in deep sleep and, if the subject is healthy, do not exist in wake state.

Each wave is characterized by the amplitude (For delta, theta and alpha bands these values are following: 10 – 30 μV for low-voltage, 30 – 70 μV for middle-voltage and above 70 μV for high-voltage EEG. For beta band the values are lower: below 10 μV low-voltage, 10 – 25 μV middle-voltage and above 25 μV high-voltage EEG) and frequency (beta = 12 Hz and higher, alpha = 8 – 12 Hz, theta = 4 – 8 Hz and delta = 0,1 – 4 Hz) (see Table 1). Extended definition of EEG activity includes another asymmetric wave form called sigma, specific for stages of spindles. The frequency of sigma varies approximately from 12 to 16 Hz.

Table 1: Four basic waves of EEG [10]

Type of EEG Wave	Frequency	Graphic representation
Beta	12 Hz and higher	
Alfa	8 – 12 Hz	
Theta	4 – 8 Hz	
Delta	0,1 – 4 Hz	

Mostly described system of electrode placement is the 10-20 electrode placement system for EEG measurement. In this system, the location of an electrode is specified in terms of its proximity to particular regions of the cortex (F-frontal, C-central, P-parietal and O-occipital) and of its bilateral location (odd numbers for left side, even numbers for the right side and 'z' for midline). Thus, 'Pz' defines a midline electrode location over the parietal lobe, while 'F3' defines a left frontal site (see Fig. 1) [11].

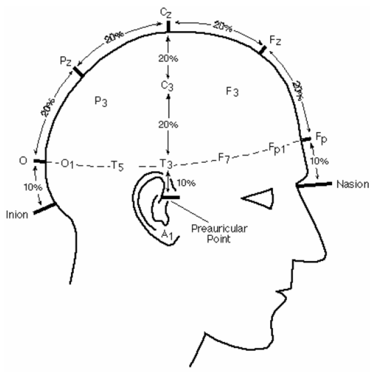


Fig. 1: The 10-20 system of electrode placement [11]

2.1.2 Electrooculogram (EOG)

Yet, Aerinsky and Klietman in 1953 [5] showed that polygraph devices could measure electrical changes around the eyes associated with spontaneous eye movement activity together with the EEG electrical changes on the scalp associated with sleep. Authors found that during sleeping EEG states, sudden eye movement activity occurred periodically throughout the night. Once awakened from these periods, subjects reported dreams more frequently than from periods without eye movement activity. This form of sleep is now known as Rapid Eye Movement (REM) sleep. The potentials for eyes movements recording are usually measured from 1 cm below and lateral to the outer canthus of the eye (Point A1 resp. A2) and 1 cm above and slightly lateral to the outer canthus of the other eye (Point B2) and/or the same eye (Point B1). The reference electrodes for both eyes are placed on the same ear lobe or mastoid (Point C) (see Fig. 2).

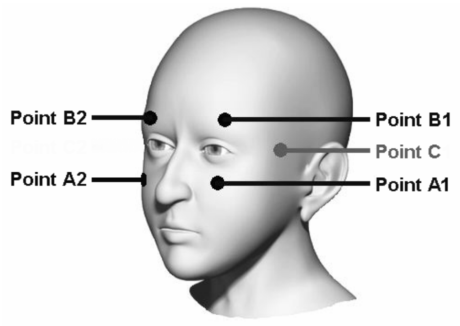


Fig. 2: Placement of electrodes of EOG

2.1.3 Electromyogram (EMG)

Michel Jouvet in 1967, in the research based on study of animals showed that bilateral electrical lesions to the pontine tegmentum area of the brainstem of cats produced a unique consequence during sleep, which was called “Oneiric Behaviour” or “REM Sleep Without Atonia” (REM-A) [12]. During EEG and EOG defined REM sleep, cats with such lesions showed behaviors such as locomotion, jumping, attacking and grooming. Later on, researchers suggested these animals were possibly acting out their dreams. In humans, excessive movement during sleep or REM sleep behavior disorder are thought to be related to the functioning of the region of brainstem. In the standard sleep polysomnography, external electrodes are placed at the region of chin (points A1, resp. points A2) and/or submental region (points B1, resp. points B2) and measure the electrical activity of jaw muscles (see Fig. 3). This measurement aids in the detection of REM sleep, as net muscle activity or muscle tone normally decreases during REM atonia.

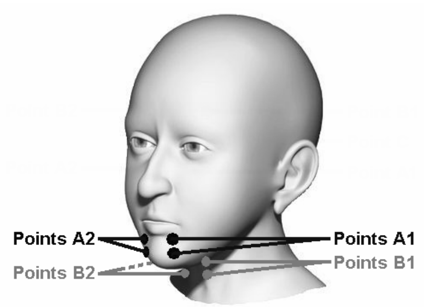


Fig .3: Placement of electrodes of EMG

2.2 Macrostructure of sleep: sleep stages

American Sleep Disorders Association considered wakefulness, REM sleep and NREM sleep as main stages of vigilance. After an extensive research based on polygraphical description of sleep, the NREM sleep was divided into four specific stages. These stages are i.a. representation of sleep depth. The slightest one is the “Stage 1” and the deepest one is the “Stage 4”. The deeper stages 3 and 4 are also referred to as “Slow wave sleep” (SWS) and the connectivity of brain neurons in this period is lowered [2].

During the night, the frequency of sleep stages alters. SWS dominates in the early hours of sleep while REM sleep usually occurs mainly in the second half of sleep. The five stages of sleep (see Fig. 4), including their repetition, occur cyclically. Healthy human sleep begins in stage 1 sleep and progresses through stages 2, 3, and 4 NREM sleep before entering the REM sleep [13] (see Fig. 5). The first cycle, which ends after the completion of the first REM stage, usually lasts for 100 minutes. Each subsequent cycle lasts longer, as its respective REM stage extends. So a person may complete five cycles in a typical night's sleep.

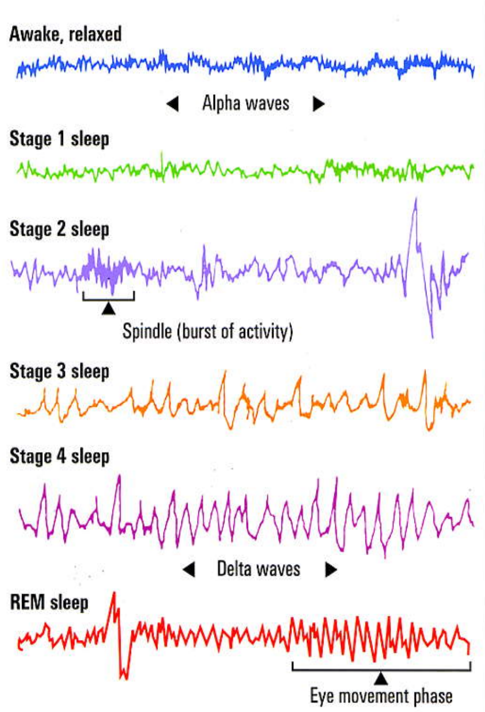


Fig. 4: Wave pattern of different sleep stages [13]

2.2.1 The waking stage (Stage W)

The waking stage is referred to as relaxed wakefulness as it means the body prepares for sleep. All people fall asleep with tense muscles and their eyes moving erratically. Then, normally, as a person becomes sleepier, the body begins to slow down. Muscles start to relax, and eye movement slows. After closing eyes and relaxing, the EEG typically shows a regular pattern of 8 – 12 Hz, known as alpha waves. The stage may be also specific by the relatively high tonic EMG and followed by the short period of movement time.

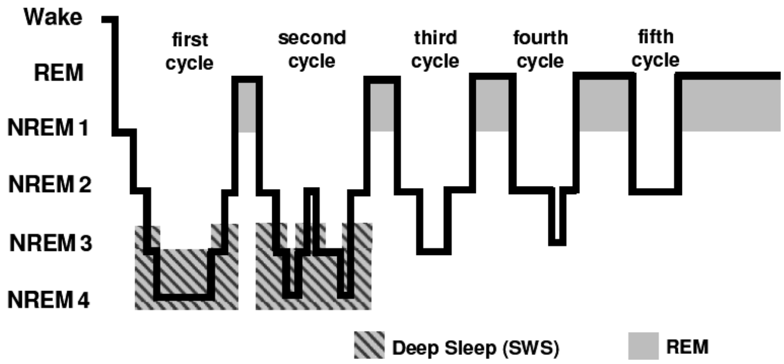


Fig. 5: The sleep cycle of a normal healthy adult: the sequence of states and stages of sleep [13]

2.2.2 Stage 1

Individual drifts into "Stage 1" sleep and the EEG becomes slower (2 – 7 Hz) and less regular. EEG is reduced in amplitude with little or no alpha (less than 50%). Slow eye movement can be present. EMG level is lower than in the previous stage of waking.

2.2.3 Stage 2

"Stage 2" is characterized by the appearance of spindles and K-complexes. Spindles are short runs of rhythmical EEG waves of 12 – 16 Hz. Typical K-complexes are EEG waveforms lasting about 0.5 second with a well-delineated negative sharp wave of 12 – 14 Hz, which is immediately followed by a positive component. Should the duration between two succeeding occurrences of sleep spindles or K-complexes be lower than 3 minutes, this period could be scored as „Stage 2", even if there are movement artifacts or increased tonic activity.

2.2.4 Stage 3

"Stages 3" is characterized by slow EEG waves of 1 – 2 Hz known as delta waves, which appears in 20%-50% of the period. Also in this stage, sleep spindles and K-complexes may occur.

2.2.5 Stage 4

Same as the "Stage 3", the "Stage 4" is characterized by slow waves up to 2 Hz which appears in more than 50% of the period.

2.2.6 REM sleep

REM sleep is characterized by an EEG pattern similar to "Stage 1", but the rapid eye movements appear on the EEG record and EMG recordings are of lowest amplitude. The heart rate and respiration speed up and become erratic, while the face, fingers, and legs may twitch. Intense dreaming occurs during REM sleep as a result of heightened cerebral activity, but paralysis occurs simultaneously in the major voluntary muscle groups, including the submental muscles.

2.2.7 The period of movement time (MT)

Rechtschaffen and Kales described the period of movement time (MT) as the period in between the normal sleep stages that, for more than half of its length, inhibits the possibility of determining the sleep stage [6].

2.3 Microstructure of sleep

The alternation of the above defined sleep stages represents the macro-dynamics of brain. In the concrete sleep stage the level of arousal is assumed to be stable, but some stages are characterized by specific fluctuation of arousal. This fluctuation represents microdynamics of brain.

The theory of microstruture of sleep is divided into two main concepts. The first concept describes the Cyclic alternating pattern (CAP). The second concept, referred to as an arousal paradigm, provides description of special arousal types. Besides ASDA´s arousals, according to the ASDA definition [8], called microarousals (MA) and phases of transitory activation (PAT) sleep contains also K-complex bursts (K-burst) and delta bursts (D-bursts) [14] which, in spite of their sleep-like features, are endowed with activating effects on autonomic functions.

2.3.1 Cyclic alternating pattern (CAP)

The cyclic alternating pattern (CAP) is functionally connected with fluctuation of arousal and offers a global framework for characterizing and measuring arousal instability [15]. CAP represent the periodic EEG activity of NREM sleep, characterized by sequences of different transient electrocortical events [16].

CAP sequences occur in all four stages (1, 2, 3 and 4) with usually 4 sleep onsets: in the period of after awakeness, during sleep and before the transition from NREM to REM sleep [17]. During the normal REM sleep period CAP does not occur. The CAP sequence means that minimum of two CAP cycles must occur consecutively. The CAP cycle is composed of two phases A and B, when phase A represents apparent changes in frequency and/or amplitude compared with the background rhythm. The interval between two phases A is the phase B. Average duration of phase A is 10 – 12 seconds and of phase B is 20 – 30 seconds.

American Sleep Disorders Association (ASDA) understands CAP sequences and microarousals as an indication of instability or sleep disturbances with detrimental effects on sleep. On the contrary, Halász, Terzano et al. [18] presented an idea that CAP sequences and microarousals are natural parts of the healthy sleep. The physiological function of CAP could be in protection of reversibility of sleep and also kind of connection between the sleeping brain and his surrounding space, to adapt to potential changes and danger and to defend the system against perturbations. The ratio of CAP in sleep varies between 30% and 50% in healthy subjects and differs according to age. In patient with sleep disorders the ratio of CAP tends to be higher. Thus, it can be understood as a numerical representation of sleep instability.

2.3.2 The concept of sleep arousals

The term „Arousal“ indicates a temporary intrusion of wakefulness into sleep or at least the sudden transient elevation of the vigilance level based on the arousal stimuli or spontaneous vigilance level oscillation. Despite of the controversial view of the criteria and measure, spontaneous microarousals were finally decided as similar to the arousals elicited by external stimuli and usually characterized by combination of EEG desynchronization and/or synchronized EEG with specific transient EEG patterns. Periodic arousals without awaking were considered to be the regular phenomena of nocturnal sleep.

Arousals were categorized into 4 groups: delta bursts (D-bursts), K-complex bursts (K-burst), microarousals (MA) and phases of transitory activation (PAT) [14, 19]. At the lower range of arousal response are subcortical arousals: D-bursts and K-Bursts. Those are inducing autonomic activation and reflex motor responses. At the upper range are cortical arousals MA and PAT. For the polygraphic examples of the 4 visually scored arousal types see Fig. 6 [14].

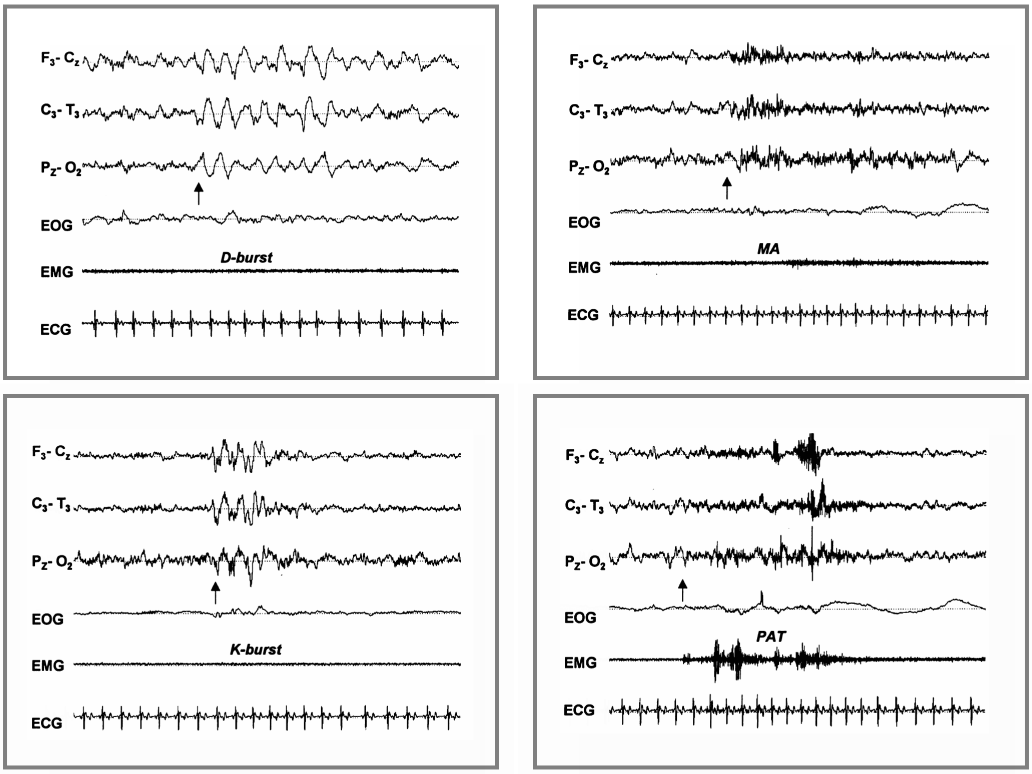


Fig. 6: Polygraphic examples of D-bursts, K-burst, MA and PAT[14]

Delta bursts (D-bursts)

D-bursts represent the sequence of delta waves, exceeding by at least one 1/3 of the amplitude of background activity, typically in stages 3 and 4, and is detectable on at least 3 EEG derivations [20]. The termination of D-burst was defined as the return to background activity.

K-complex bursts (K-burst)

K-bursts are referred to as a sequence of two or more K-complexes without alpha activity, and detectable on at least 3 EEG derivations. The K-complex was defined as a negative sharp wave of 12 – 14 Hz, which is immediately followed by a lower positive one with a minimum duration of 0,5 seconds and a minimum peak-to-peak amplitude of 75μV [21]. K-complexes are considered elementary forms of arousal during slow wave sleep (SWS) and they carry characteristics of evoked potentials. That provide subattentive information processing and, at the same time, has level-setting sleep maintenance function [15]. K-complexes are specific by low muscle tone and no eyes movements. The termination of K-burst was defined, same as in D-burst, as the return to background activity.

Microarousals (MA)

Microarousals are more complex arousal-dependent phasic events in the hierarchy of sleep arousals [15]. American Sleep Disorders Association [8] defined microarousals (MA) as events of 3 – 30 seconds characterized by a return to alpha, theta, or fast frequency, well differentiated from the background EEG activity; it means a rapid modification in EEG frequency, but different from spindles. In some studies MA lasting between 1,5 and 3 seconds are also considered [22]. Micro-arousals occur most frequently in stages 1 and 2 of NREM sleep. There is an inverse correlation between frequency of MA and the depth of sleep [23].

Schieber et al [24], in 1971, were the first who defined the criteria for MA in NREM and REM sleep. In NREM sleep the criteria for MAs involved increase in EEG frequencies in conjunction with decrease of amplitudes, disappearance of delta waves and spindles, transitory enhancement of muscle tone or phasic appearance of groups of muscle potentials, movements of the limbs or changes in body posture and transitory rise in heart rate. In REM sleep the criteria for MAs were described as temporary disappearance of eye movements and appearance of alpha activities.

The termination of MA was referred to as the onset of theta activity for at least ten seconds, which indicates the return to sleep.

Phases of transitory activation (PAT)

PAT is associated with EEG desynchronization and were defined as an acceleration of the background EEG activity with decreasing amplitude and appearance of alpha and beta activity; all associated with an increase in EMG, appearance of muscular artifacts, acceleration of heart rate, and transitory disappearance of REMs during REM sleep.

The initiation of the onset of each PAT was defined as the first occurrence of alpha activity or fast EEG activity or delta burst and K-complex [24]. The termination of PAT was, same as in MA, referred to as the onset of theta activity for at least ten seconds which indicates the return to sleep. However, in some cases it may correspond to awakening, thus the end of sleep [25].

3 Detection and scoring of arousals in EEG signal

An EEG arousal in sleep is defined as an abrupt shift in EEG frequency, lasting for 3 seconds or more, which may include theta, alpha and/or frequencies greater than 16Hz but not spindles [14]. Determining the occurrence and the frequency of occurrence of arousals from sleep is very important as it is directly related to the quality of sleep. Considering the processing of arousals in clinical studies, the definition of what constitutes arousal is critical, and criteria of detection and scoring are still controversial.

3.1 Expert visual detection and scoring

Traditionally the analysis of sleep has used two distinct visual EEG analysis methods: one for the general structure (macrostructure of sleep), the other for short time-scale events (microstructure of sleep). The detection of sleep microstructure usually follows the scoring rules defined by the American Sleep Disorder Association (ASDA). For scoring rules see Table 2 [8].

Usually the scored epochs are presented to at least three sleep experts to rate if containing arousal events or not. Many times the scoring differs from expert to expert while analyzing the same data, in part because of the ambiguity when applying the selection criteria. The considerably large interscorer variability has a great impact on the reproducibility of measurements. Drinnan et al found large disagreement in scoring ASDA defined arousals by experts from 14 sleep laboratories [26]. Also poor reproducibility was demonstrated in the scoring of ASDA defined arousals in the study of Loredo et al [27].

The frequent lack of explicit experts concordance and the time-consuming process of personal visual scoring led to many researches of automatic detection and scoring systems.

3.2 Automatic computer-aided detection

Firsts attempts at automated analysis of sleep were mainly directed towards imitating the Rechtschaffen and Kales rules. Even the rules became a gold standard for long period, they have never been appropriately validated. Today the Rechtschaffen and Kales rules is an insufficient description of sleep processes [28].

Based on ASDA rules of arousals detecting and scoring, the microstructure of the sleep EEG can be analyzed automatically. Various techniques used to perform this task usually combines methods of signal analysis, such as spectral analysis, short-time Fourier transform or wavelet transform with machine learning based classification/modeling, such as neural networks, discriminant analysis, support vector machines or k-means clustering, and/or optimization methods, such as genetic algorithms.

Overview of selected studies on microarousal automated detection is presented in Table 3 with a brief specification of each study.

Table 2: The EEG arousals scoring rules developed by ASDA [8]

The EEG arousal scoring rules	
1	Subjects must be asleep, defined as 10 continuous seconds or more of the indications of any stage of sleep, before an EEG arousal can be scored.
2	A minimum of 10 continuous seconds of intervening sleep is necessary to score a second arousal.
3	The EEG frequency shift must be of 3 seconds or greater in duration to be scored as an arousal.
4	Arousals in NREM sleep may occur without concurrent increases in submental EMG amplitude.
5	Arousals are scored in REM sleep only when accompanied by concurrent increases in submental EMG amplitude.
6	Arousals cannot be scored based on changes in submental EMG amplitude alone.
7	Artifacts, K complexes or delta waves are not scored as arousals unless accompanied by an EEG frequency shift of at least one derivation. If such activity precedes an EEG frequency shift, artifacts or delta wave activity are included in meeting duration criteria.
8	The occurrence of pen blocking artifact should be considered as an arousal only if the EEG arousal patterns are contiguous. The pen blocking event can be included in meeting duration criteria.
9	Noncurrent, but contiguous, EEG and EMG changes, which are individually less than 3 seconds but together greater than 3 seconds in duration, are not scored as arousals.
10	Intrusion of alpha activity of less than 3 seconds duration into NREM sleep at a rate greater than one burst per 10 seconds is not scored as an EEG arousal. Three seconds of alpha sleep is not scored as an arousal unless preceded by a 10 second episode of alpha free sleep.
11	Transitions from one stage of sleep to another are not sufficient of themselves to be scored as EEG arousals unless they meet the criteria indicated above.

Table 3: Microarousal automatic detection studies overview

Authors, year	**Publication**	**Specification**
Agarwal, R., 2005 [29]	Automatic Detection of Micro-Arousals.	Adaptive filtering, filtering of alpha and beta based on non-linear energy operator (NLEO), segmentation, feature extraction and set of decision rules applied.
Pacheco, O. R., Vaz, F., 1998 [30]	Integrated System for Analysis and Automatic Classification of Sleep EEG.	Estimation of fundamental frequency of EEG and EMG power, K-means based classifier, context rule module.

Authors, year	Publication	Specification
Zamora, M., Tarassenko, L., 1999 [31]	The study of micro-arousals using neural network analysis of the EEG.	Two different inputs to neural network: coefficients of AR model of EEG or relative powers encoded by bank of bandpass filters; radial basis function (RBF) network trained by 3-class set, output filtered by median filter.
Glavinovitch, A., Swamy, M. N. S., Plotkin, E. I., 2005 [32]	Wavelet-based segmentation techniques in the detection of microarousals in the sleep EEG.	DWT decomposition, segmentation into stationary segments by autocorrelation function (ACF), nonlinear operator (NLEO) and generalized likelihood ratio (GLR), FFT of segments, comparison of dominant frequency against threshold.
Gouveia, P., Oliveira, R., Rosa, A., 2003 [33]	Sleep Apnea related micro arousal detection with EEG Analysis.	FFT with 2 s Hamming windowing on 8 s long segments, search for maxima in alpha, analyses of alpha and beta activity in 28 s window centered on this maxima.
Cho, S., Lee, J., Park, H., Lee, K., 2005 [34]	Detection of arousals in patients with respiratory sleep disorders using a single channel EEG.	Artifact and mean value removal, 257 points (1,285 s) spectrogram leading to six bands evaluation, mean values in each band per 1 second, median filter applied, feature extraction on every second basis, support vector machine classification.
De Carli, F., Nobili, L., Gelcich, P., Ferrillo, F., 1999 [36]	A method for the automatic detection of arousals during sleep.	DWT decomposition, set of indices used to discriminate possible arousal segments, multichannel analysis with EMG integration.
Largo, R., Munteanu, C., Rosa, A., 2005 [37]	CAP Event Detection by Wavelet and GA Tuning.	DWT decomposition, moving averages with long and short duration and moving average ratio of signal power in each band, comparison of moving average ratio of each band against threshold with hysteresis, genetic algorithm parameters tuning.

4 Microarousal detection in PSG recordings

The main aim of this study was to develop a time-frequency analysis based automated detector of microarousals in nocturnal polysomnographic recordings. The study was a part of the research led by Dr. Sylvie Charbonnier and Dr. Suzanne Lesecq at GIPSA-lab, Grenoble, France in cooperation with PhiTools, Strasbourg, France. PhiTools also provided the data set for testing.

In order to achieve the goal following steps were performed:

- data were extracted from Oxford Mediloc 9000 format of PSG recording for further processing in Matlab environment,
- the graphic user interface for visual analyses of microarousals was designed,
- graphic user interfaces for time-frequency representation of EEG signals (spectrogram, STFT based frequency band decomposition and DWT decompositions) were designed,
- after decision on type of signal decomposition a method of data analysis based on DWT (respective wavelet packet decomposition) and further processing was suggested and implemented.

4.1 PSG recordings

Data with polysomnographic recordings were kindly provided by PhiTools. It was a subset of data used in former studies by sleep expert Dr. Emilia Sforza, Geneva, Switzerland. Dr. Sforza is a recognized medical researcher in the field of study of sleep, especially the daytime sleepiness, periodic leg movements and arousal responses with focus on microstructure of sleep (e.g. [14], [19]).

The subject sample consisted of 12 healthy men. The average age was 27,4±7,9 years, range 19 to 44 years. All participants were drug-free and without history of excessive daytime sleepiness or sleep complaints. The subjects participated in a 6-day study with 2 baseline days and nights whereas time in bed was scheduled between 10:00 PM and 6:00 AM during the 2 consecutive baseline recordings[19]. Sleep data of the first and/or second baseline night were used in the analysis.

Dr. Sforza also scored the PSG recordings for specific cortical and subcortical arousals. They were categorized into 4 groups according to Dr. Sforza's previously published criteria [14]:

- delta bursts (D-bursts),
- K-complex bursts (K-bursts),
- microarousals (MA),
- phases of transitory activation (PAT).

The final data sample designated for our research was over 100 hours of recording and contained 1551 microarousals in total.

4.1.1 Data processing

The data sample is a subject to Confidentiality agreement with PhiTools. Therefore only the data derivations, Matlab scripts and functions could be enclosed as a presentation of data processing.

Four leads of EEG (C3, C4, P3, P4 referenced to linked ears), an electrooculogram (EOG), a submental electromyogram (EMG) and an electrocardiogram (ECG) were acquired at 128 Hz sampling frequency by Oxford Medilog 9000. For further processing raw data were preprocessed using a FFT – inverse FFT filtering method at these cutoff frequencies:

- EEG 0,5 – 64 Hz
- EOG 0 – 10 Hz
- EMG 10 – 64 Hz
- ECG 5 – 40 Hz

As the signal analyses in original software PRANA® by PhiTools appeared to be time-consuming and uneconomical, data conversion to Matlab structure was essential. All individual recordings were trimmed to start exactly at 10:00 PM and last for 8 hours and were exported as text files (see Table 4). These files were finally imported into Matlab and saved as Matlab workspaces, each signal as a 3686400x1 array, one workspace per one polysomnographic recording (7 signals).

Table 4: PRANA® recording export

```
File:                C3-A2         P3-A2         C4-A1         P4-A1
Variable:            Amplitude     Amplitude     Amplitude     Amplitude
Frequency:           0.5-64Hz      0.5-64Hz      0.5-64Hz      0.5-64Hz
Unit:                uV            uV            uV            uV
Time(h):             ----------    ----------    ----------    ----------
0122:00:00.0000         6.16518      17.66772       0.73632       1.20228
0122:00:00.0078        10.26005      13.66870       0.57927       3.17173
0122:00:00.0156        12.35001      13.66604       6.42034       3.13995
0122:00:00.0234        10.43501       5.65976       8.25962      -0.89302
0122:00:00.0313         4.51503      -0.35012       8.09719      -4.92714
0122:00:00.0391         2.59001      -4.36360       7.93315      -6.96238
0122:00:00.0469         2.65993      -6.38067       3.76759      -2.99868
```

Also the expert scorings were exported. First as text files (see Table 5) which were subsequently imported into Matlab and saved as workspaces with a 2-column array. Values in first column refer to the start time of an event (in seconds from the beginning of corresponding recording), values in second column to its duration (in seconds), one workspace was saved per one recording and type of event.

Matlab scripts and functions for data extraction can be found at enclosed media at: `\scripts\1_data_export\`

Table 5: PRANA® scoring export

SEQUENCE	NUMBER	TIME(h)	DURATION(sec)	TYPE
1	1	22:13:56.466	15.678	Micro-Arousal
1	2	22:15:35.563	1.12.308	Micro-Arousal
1	3	22:16:12.513	1.7.570	Micro-Arousal
1	4	22:18:06.220	16.825	Micro-Arousal
1	5	22:19:33.082	1.10.891	Micro-Arousal

As the main focus was on microarousals, another set of workspaces was created afterwards. Stored variables were obtained by combining information from filtered signals and expert scorings. They are all of structure type with parts of signals representing only the microarousals, respective microarousals with fixed sized neighborhood of 10 seconds.

In addition a simple heart rate estimation was computed and saved as another set of workspaces with microarousals.

Matlab scripts and functions for creation workspaces with microarousal patterns only and heart rate estimation can be found at enclosed media at: `\scripts\4_support_files\`

4.2 Decision on methods of analysis

Decision on methods of analysis was based on visual qualitative analysis of extracted data as shown on Fig. 7 with respect to conclusions of former studies.

For the purpose of visual analysis and subsequent decision on methods of computer-aided analysis several graphic user interfaces (GUI) were developed. Each of GUIs was created in Matlab GUIDE and is executed from Matlab command line and designed to visualize signals or their derivations in just one specific mode.

All GUI modules and relevant Matlab scripts and functions can be found at enclosed media at: `\scripts\2_previews\`

4.2.1 GUI for browsing signals

Extending involved researchers' knowledge base about patterns and course of microarousals in provided data set was essential in early beginnings of the study. Therefore a need for fast, easy and convenient technique of displaying arousals in signals was determined. A development of GUI for browsing annotated signals using Matlab GUIDE was chosen.

Arousal browsing

The GUI for browsing in signals was developed. Four leads of EEG and EMG are displayed simultaneously. Workspaces/variables with nocturnal 8 hour signals are used as source data. Many variant parameters of signal visualization can be set (displayed signal, type of arousal, particular arousal, its offset and time resolution). The GUI can be executed by `event_draw` command (see Fig. 8).

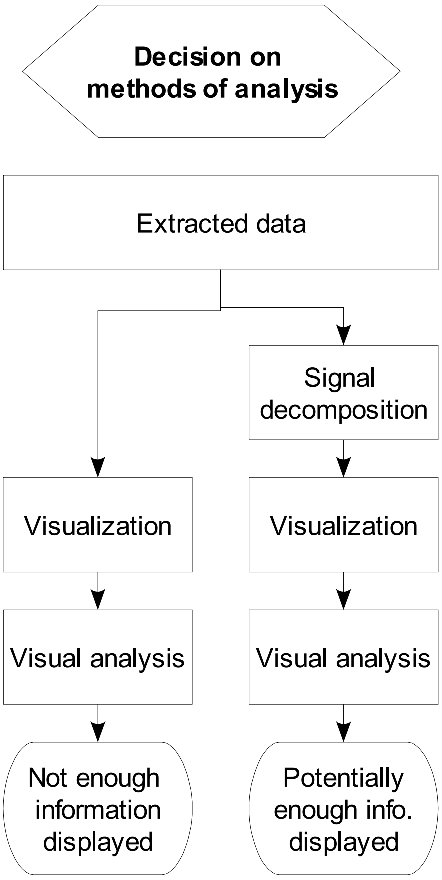


Fig. 7: Decision on methods of analysis

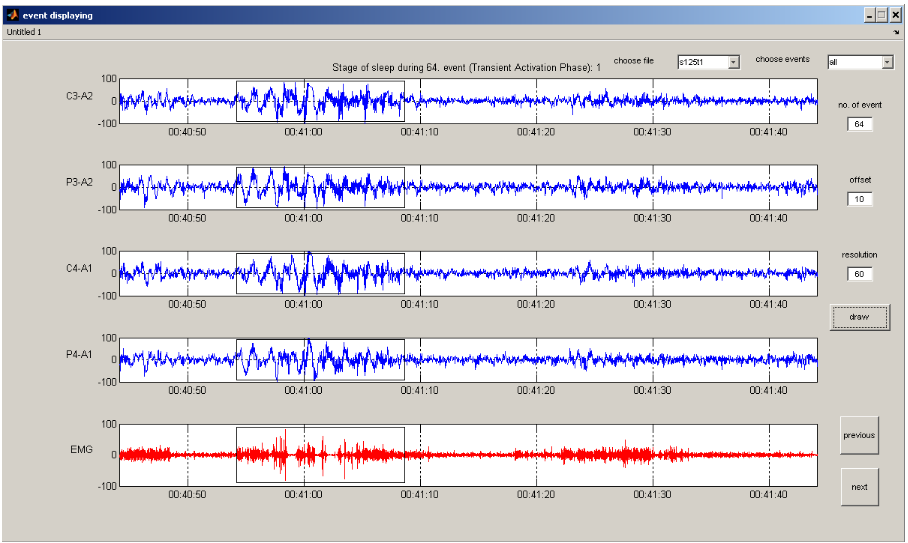


Fig. 8: Event browsing GUI

Albeit this GUI supported setting of many parameters its utilization was limited due to speed of data processing. When switching among recordings, current recording (over 90MB) had to be loaded from a hard drive. This slowed down the process of signal browsing considerably. As the speed of browsing appeared to be crucial and focus was only on microarousal and their close neighborhood, not on other arousal types or arousal free signals, another GUI was necessary to develop.

Fast microarousal browsing

For those needs specified above the GUI for fast browsing in microarousals with fixed size neighborhood was developed. Four leads of EEG, EMG and a simple estimation of heart rate are displayed simultaneously. Small set of parameters can be set (particular microarousal and time resolution). The GUI is executed by `ma_draw` command (see Fig. 9).

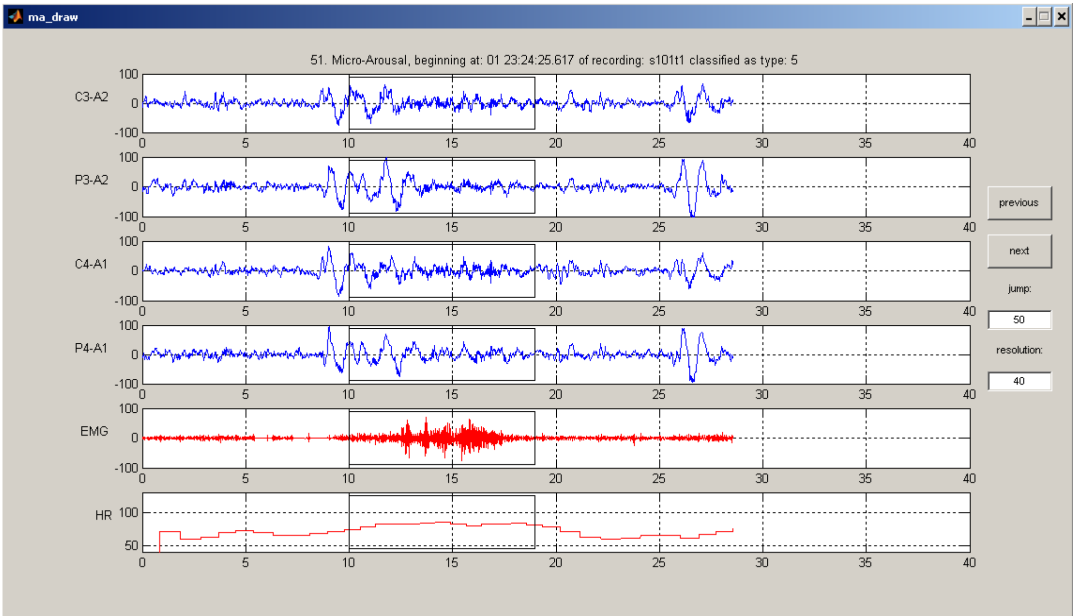


Fig. 9: Fast microarousal browsing GUI

Only one workspace with all microarousal signals in one global variable of structure type is loaded in total, thus the enhancement in speed of browsing is considerable. Whereas only microarousals were subject of the study, all relevant parameters were possible to set up and this GUI was used for extending knowledge base about patterns of microarousals with a good effect.

As a conclusion of visual analysis considering microarousal specification [8], [14] and papers on methods of microarousal detection [32], [33], [34], [35], [36], [37], focus on time-frequency analyses of microarousals and its visualization was proposed.

4.2.2 Time-frequency visualization of signals

Widely applied techniques in analysis of macrostructure and microstructure sleep EEG are methods of time-frequency signal analysis, such as short-time Fourier transform (STFT) and discrete wavelet transform (DWT). To facilitate decision on which of the methods would be the most suitable for this study, GUI modules displaying various time-frequency representations of recorded signals were developed.

Short-time Fourier transform (STFT)

The Fourier analysis has a serious drawback. In transforming to the frequency domain, time information is lost. When looking at the Fourier transform of a signal, it is impossible to tell when a particular event took place. In an effort to correct this deficiency, Dennis Gabor (1946) adapted the Fourier transform to analyze only a small section of the signal at a time — a technique called windowing the signal. The Gabor's adaptation, called the Short-Time Fourier Transform (STFT), maps a signal into a two-dimensional function of time and frequency [38].

In the continuous-time case, the function to be transformed is multiplied by a window function which is nonzero for only a short period of time. The Fourier transform of the resulting signal is taken as the window is slid along the time axis, resulting in a two-dimensional representation of the signal.

$$STFT\{x(t)\} \equiv X(\tau, \omega) = \int_{-\infty}^{\infty} x(t)\,\omega(t-\tau)\,e^{-j\omega t}\,dt \quad (1)$$

where $\omega(t)$ is the window function and $x(t)$ is the signal to be transformed. $X(\tau,\omega)$ is essentially the Fourier Transform of $x(t)\omega(t\text{-}\tau)$, a complex function representing the phase and magnitude of the signal over time and frequency. The time index τ is normally considered to be "slow" time and usually not expressed in as high resolution as time t.

In the discrete time case, the data to be transformed could be broken up into chunks or frames (which usually overlap each other). Each chunk is Fourier transformed, and the complex result is added to a matrix, which records magnitude and phase for each point in time and frequency.

$$STFT\{x[n]\} \equiv X(m, \omega) = \sum_{n=-\infty}^{\infty} x[n]\,\omega[n-m]\,e^{-j\omega n} \quad (2)$$

with signal $x[n]$ and window $w[n]$. In this case, m is discrete and ω is continuous, but in most typical applications the STFT is performed on a computer using the fast Fourier transform (FFT), so both variables are discrete and quantized. Again, the discrete-time index m is normally considered to be "slow" time and usually not expressed in as high resolution as time n.

Discrete wavelet transform (DWT)

The wavelet analysis is a windowing technique with, unlike the STFT, variable-sized regions. The wavelet analysis allows the use of long time intervals with more precise low-frequency information and shorter regions with high-frequency information [38].

The continuous wavelet transform (CWT) is defined as the sum over all time of the signal multiplied by scaled, shifted versions of the wavelet function ψ:

$$C(scale, position) = \int_{-\infty}^{\infty} f(t)\,\psi(scale, position, t)\,dt \quad (3)$$

where wavelet ψ is a waveform of effectively limited duration that has an average value of zero. The results of the CWT are many wavelet coefficients C, which are a function of scale and position.

If the signal is sampled and scales and positions are based on powers of two –

so-called dyadic scales and positions – then the analysis, the discrete wavelet transform (DWT), will be much more efficient and just as accurate.

An efficient way to implement this scheme using filters was developed in 1988 by Stephane Mallat. This algorithm is in fact a classical scheme known as a two-channel subband coder. The signal is decomposed simultaneously using a set of quadrature mirror filter: low-pass filter with impulse response *g* and a high-pass filter with impulse response *h*. The outputs giving the detail coefficients (from the high-pass filter) and approximation coefficients (from the low-pass). However, since half the frequencies of the signal have now been removed, half the samples can be discarded according to Nyquist's rule. The filter outputs are then downsampled by 2 and a mathematic formula for decomposition can be expressed as:

$$y_{low}[n] = \sum_{n=-\infty}^{\infty} x[n]g[2\mathrm{n}-k] \tag{4}$$

$$y_{high}[n] = \sum_{n=-\infty}^{\infty} x[n]h[2\mathrm{n}-k] \tag{5}$$

This decomposition is repeated to further increase the frequency resolution (see Fig. 10).

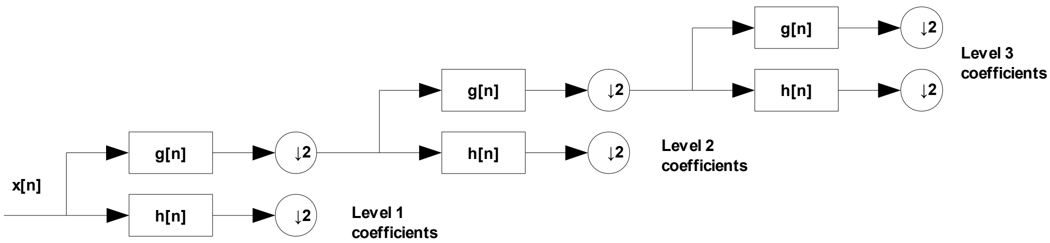


Fig. 10: DWT decomposition

STFT spectrogram preview

First, the GUI for fast preview of 2D presentation of STFTs – spectrograms – of single microarousals with fixed sized neighborhood was developed. STFT is computed using Time-Frequency toolbox (TFTB) [41] functions `window` and `tfrstft`, signals are windowed by Hamming window of different lengths. Due to exigence of maximum screen resolution only one signal and its spectrogram is displayed at a time. Parameters to set include selection of particular microarousal, signal selection (a lead of EEG or EMG) and a width of Hamming window (in seconds). The beginning and the end of the microarousal and characteristic EEG bands (beta, sigma, alpha, theta and delta) are marked on the screen. The GUI is executed by `tf_draw` command (see Fig. 11).

After thorough visual study of spectrograms following conclusions, supported by experienced supervisor, were stipulated:

- there is a clear evidence of frequency shifts and/or distribution in microarousals,
- no specific patterns can be easily recognized in spectrogram presentations,

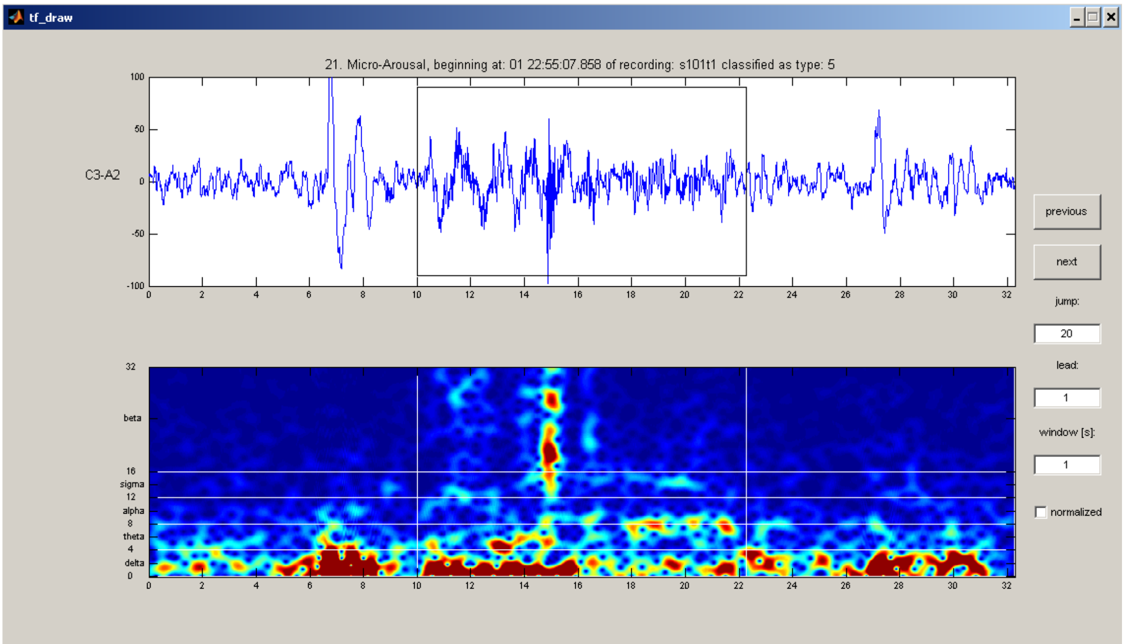


Fig. 11: STFT spectrogram preview GUI

- character of frequency shifts and/or distribution varies among microarousals,

therefore the need for a GUI with signals decomposed into characteristic EEG frequency bands was determined.

STFT signal decomposition

This GUI was developed for fast preview of frequency band decomposition of single microarousals with fixed sized neighborhood. The method of decomposition is based on STFT. Amplitudes of frequency bands at a time are computed as sums of relevant frequencies of STFT spectrum. The estimation of STFT and parameters to set are same as for the spectrogram estimation (see above). The GUI is executed by `tf_series_draw` command (see Fig. 12).

In this form of preview visual differentiation of microarousal from background was found more perspicuous and therefore a frequency band decomposition was proposed as the course of method of microarousal automated detection.

Taking in consideration that:

- STFT based on Fourier analysis consists of breaking up a signal into sine waves of various frequencies; similarly, wavelet analysis is the breaking up of a signal into shifted and scaled versions of the original (mother) wavelet; thus, by choosing proper mother wavelet, signals with sharp changes might be better analyzed with an irregular wavelet than with a smooth sinusoid [38];

- the wavelet analysis provides a powerful and flexible way to visualize neuroelectric waveforms and topographies and to decompose them into measurable component events at specific points in time and space and at specific scales of time and distance [39], [40];

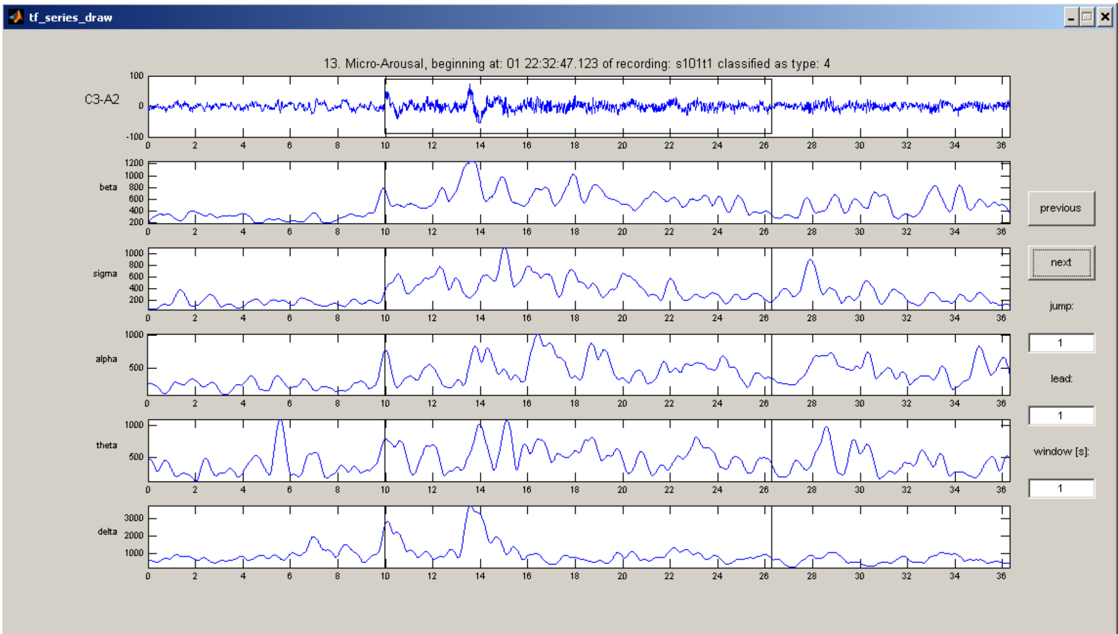


Fig. 12: STFT signal decomposition GUI

frequency band decomposition based on wavelet analysis was selected for microarousal detection. Development of GUI modules displaying signals decomposed by DWT was suggested for verification of this assumption.

Wavelet transform decomposition

The GUI for fast preview of DWT decomposition of single microarousals with fixed sized neighborhood (see Fig. 13), respective its power (see Fig. 14), was developed.

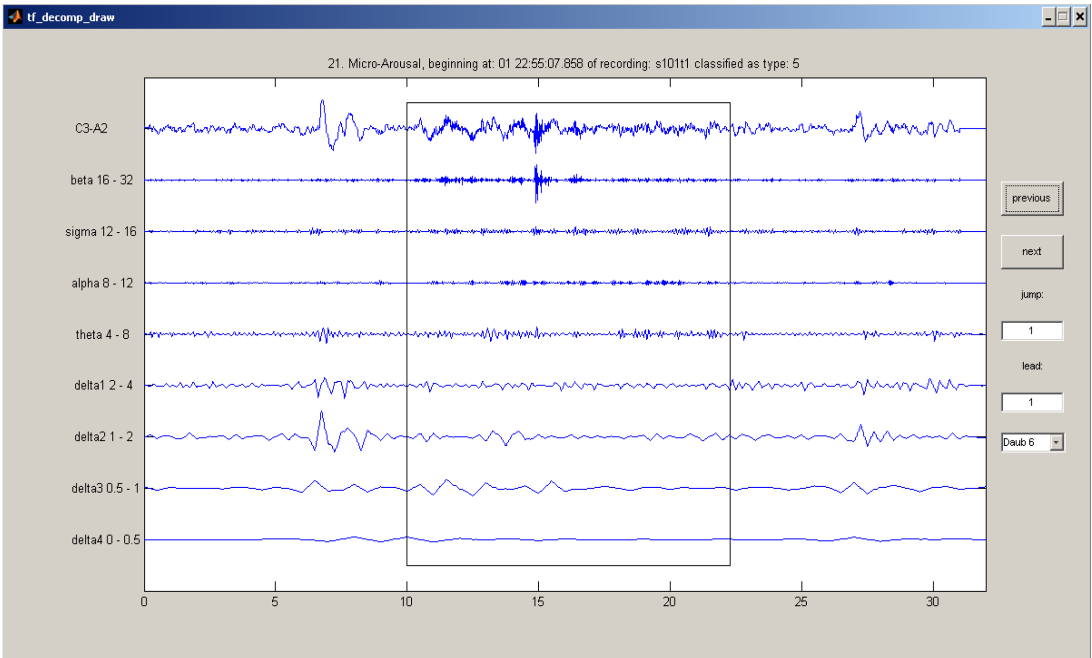


Fig 13: DWT signal decomposition GUI

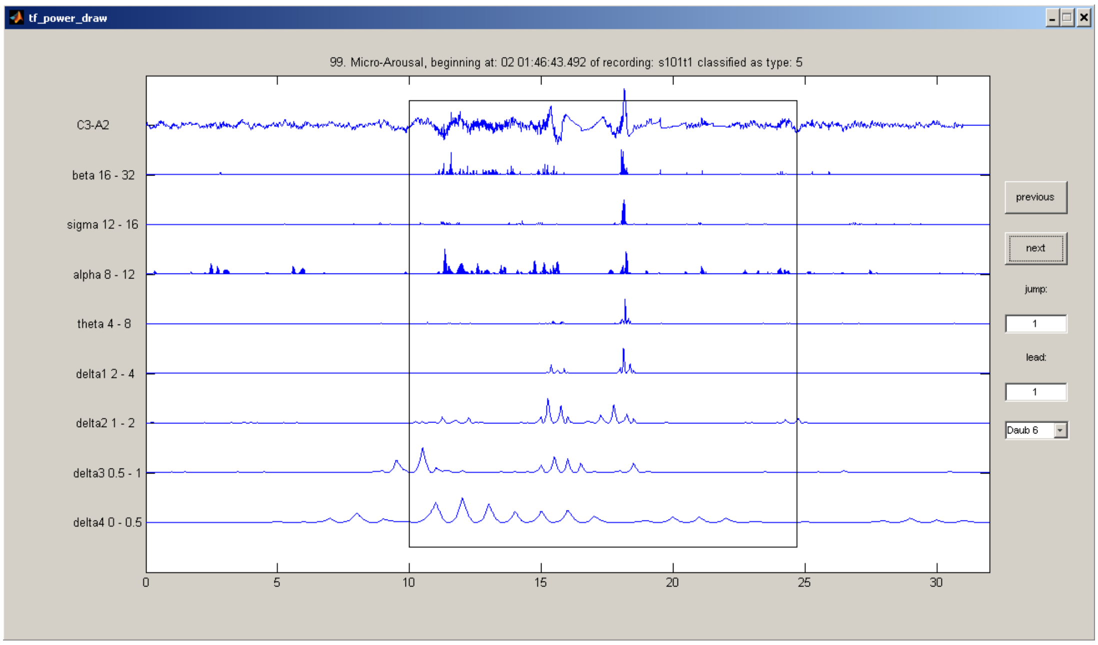


Fig. 14: Power of DWT signal decomposition GUI

WaveLab toolbox [42] functions `MakeONFilter`, `DownDyadHi` and `DownDyadLo` are used to perform the decomposition. Daubechies wavelets of variant order are chosen as mother wavelets as they are widely used in EEG DWT decomposition [36], [37], [40].

A signal is extended to dyadic length of 32 seconds and decomposed into 7 levels. Details of level 2 are then decomposed into two subbands to separate alpha activity from sleep spindles. Approximation coefficients of each level (frequency band) are normalized in time for the plot. Parameters to set include selection of particular microarousal, signal selection (a lead of EEG or EMG) and an order of Daubechies wavelet. The GUI is executed by `tf_decomp_draw`, respective `tf_power_draw` command.

As expected, DWT decomposition provided best results among all methods of time-frequency analyses. It was observed that higher order Daubechies wavelets possessed better frequency selectivity than lower ones.

4.3 Development of an algorithm for automated microarousal detection

Decision on basis of the algorithm was made – processing with DWT was selected. Following findings of related studies [36], [37], [40], acquired experience from visual analyses and the definition of microarousals by ASDA [8] and Dr. Sforza [14], a concept of detection algorithm, as shown on Fig. 15, was estimated.

Detailed description of each algorithm phase is given further in the text.

4.3.1 DWT decomposition of EEG

The algorithm analyzed data from 4 bipolar EEG channels. All signals were extended to dyadic length as this was necessary condition of DWT decomposition

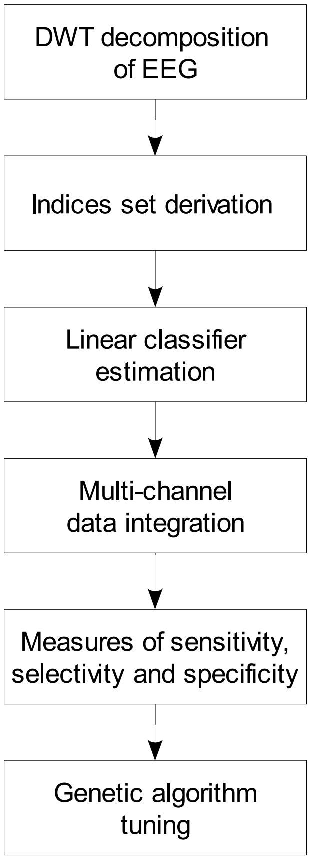


Fig. 15: Concept of detection algorithm

functions. The DWT was implemented by the Daubechies wavelet filter with 12 coefficient (referred to as Daubechies order 6) and performed in 7 levels. Details of level 2 (8-16 Hz band) was then decomposed into two subbands to differentiate alpha activity from sleep spindles and conversely details of level 6, 5 and 4 and details of level 1 and 0 were recomposed to form one delta band (0,5-4 Hz) and an extended beta band (16-64 Hz), respectively. Thus, this process originated following set of bands:

- extended beta 16 – 64 Hz,
- sigma 12 – 16 Hz,
- alpha 8 –12 Hz,
- theta 4 – 8 Hz,
- delta 0,5 – 4 Hz,
- slow delta 0 – 0,5 Hz,

of which the time resolution resulted in 0,125 s for sigma, alpha, theta and delta while increased for the beta band and decreased for slow delta band. Subsequently, the signal power of all bands was computed (see `/scripts/3_data_analysis/` for `sig_decomp2.m` and `proc_d12_long2.m`).

4.3.2 Set of indices for arousal detection

The results of wavelet transform were used to evaluate a set of indices describing EEG and EMG changes accompanying arousals as defined by ASDA [8]. In order to detect these variations, all signal powers were resampled to the same time resolution of 0,125 s, proper of the sigma, alpha, theta and delta bands (see `/scripts/3_data_analysis/` for `sig_decomp3.m, downsample.m` and `upsample.m`).

In each EEG channel, a long-term weighted moving average of power was then computed for each band to estimate a background reference value, while a short-term moving average represented the actual trend. In both cases the average value was estimated as:

$$y_i = \frac{N * y_{i-1} + x_i}{N+1} \tag{6}$$

where *{x*$_i$*}* represents the input series of band powers, *{y*$_i$*}* the output series of moving average and *N* is a coefficient qualifying the smoothing factor, a degree of weighting decrease, thus differentiating short-term and long-term averages (see `/scripts/ 3_data_analysis/` for `averages_fin.m`).

Regarding published studies on this subject [37], the coefficient *N* was set to 30 for short-term moving average and 500 for long-term moving average.

The first six indices were ratios between short-term and long-term average, indicating the actual variation for each band; the other indices involved average power in different bands and evaluated particular features that may be important in the arousal detection. They were defined as follows:

- the ratio between short-term and long-term mean frequency, where the mean frequency was computed as:

$$\bar{f} = \frac{\sum_i p_i * f_i}{\sum_i p_i} \tag{7}$$

where f_i is the central frequency of the band and p_i is its power; the index was sensitive to the frequency shift;

- the ratio between delta power and alpha plus beta power, computed for both short-term and long-term averages; this could indicate the presence of slow wave sleep (SWS);
- the ratio between short-term and long-term alpha relative power, which highlighted variations in alpha activity;
- the ratio between long-term alpha plus slow-delta power and theta plus delta power; it could indicate that the subject was already awake;
- the ratio between sigma power and alpha plus beta power, which could suggest the presence of sleep spindles;
- the ratio between beta and delta variations (each expressed as the ratio between short-term and long-term average power), which could suggest a desynchronization of the tracing.

Finally, an EMG related index was added following an assumption that microarousals can be uniquely determined from a combination of a single EEG and EMG channel. As for the EEG bands this index was derived as a ratio between short-term and long-term average of EMG power, indicating the transient increase in muscle activity (see `/scripts/ 3_data_analysis/` for `ind_step_fin.m`).

Total number of 14 indices was derived.

4.3.3 Linear classifier estimation

For each of four sets of indices the linear classifier was estimated to mark microarousal candidates every 0,125 s basic epoch. It has the form:

$$F(X[n])=\sum_{i=1}^{14} w_i * x_i[n]-\theta \tag{8}$$

where *X[n]* is the index vector *{x_i[n]}* in time *n*, *{w_i}* is the weight vector and θ is the threshold. The weights and threshold were tuned during the training phase (see below: Genetic algorithm tuning).

Actual algorithm for microarousal detection was designed as follows: When the discriminant function became positive an arousal detection mode was activated in which long-term averages were not updated. Possible arousals were marked when the discriminant function remained positive for more than 3 and up to 30 s (according to ASDA rules); an index value of 1 was then assigned to each time sample where arousal was detected, otherwise it remained 0 (see `/scripts/3_data_analysis/` for `ma_detect_fin.m`).

4.3.4 Multi-channel data integration

After that the results acquired from the four channels' detection were combined: overlapping events were linked and microarousal was scored in every time when there was an arousal marked at least in one channel (see `/scripts/3_data_analysis/` for `ma_detect_work.m`). These detections were subject of the program validation.

4.3.5 Measure of sensitivity, selectivity and specificity

For the purpose of training and the performance evaluation of the program the measures of sensitivity and selectivity were taken.

The comparison procedure was following: there is a concordance in the detection of a microarousal between expert and the program when there is a common period of at least one sampling time (i.e. 0,125 s minimum overlap). Assuming the expert scoring as a reference, Fig. 16 shows all possibilities (TP – true positive, FP – false positive, FN – false negative).

True negative (TN) as an indication flag of an event is not considered since in arousal detection of variable length and position only the presence of such an event is known. Instead the true negative time (TNt) was estimated as a total time of concordance in microarousal being not detected by neither of expert and the program. Consequently, the false positive time (FPt) was estimated accordingly.

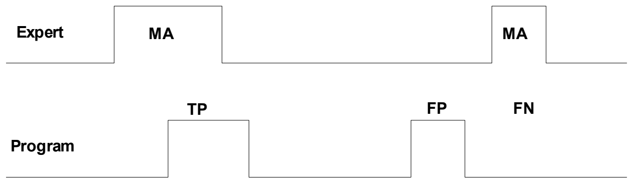


Fig. 16: Concordance in detection – situations

The measures of sensitivity, selectivity and specificity are defined as:

$$sensitivity = \frac{TP}{TP+FN} \tag{9}$$

$$selectivity = \frac{TP}{TP+FP} \tag{10}$$

$$specificity = \frac{TNt}{TNt+FPt} \tag{11}$$

where *TP, FP, TN* and *FN* stands for true positive, false positive, true negative and false negative detections, respectively.

For sensitivity and selectivity calculation in program see: `ma_detect_work.m` or `ma_detect_fitness.m` in `/scripts/3_data_analysis/`.

4.3.6 Genetic algorithm tuning

In the next stage, by using the training set of sleep recordings previously scored for arousals, the weights of the linear classifier were tuned by genetic algorithm while threshold was set to 100.

The tuning was made using Matlab Genetic Algorithm Tool (command: `gatool`) which is a graphical user interface that enables utilization of the genetic algorithm without working at the command line. Genetic algorithm tuned 14 input variables to minimize the fitness function established as product of sensitivity and selectivity with slight privilege of the first :

$$f_{fitness}(W) = -(sensitivity^{1.1} * selectivity) \tag{12}$$

where *W* is a vector of weights and sensitivity and selectivity are measured in percents; thus, the fitness function in terms of positive and negative detections was:

$$f_{fitness}(W) = -1.5849 \cdot 10^{4} \left[\left(\frac{TP}{TP+FN} \right)^{1.1} * \left(\frac{TP}{TP+FP} \right) \right] \tag{13}$$

For fitness function see: `ma_detect_fitness.m` in `/scripts/3_data_analysis/`.

Genetic algorithm was executed 10 times with following settings:

- population size = 50 of uniform distribution on interval [-20; 20];
- generations = 100;
- elite count = 2;
- selection function: tournament (of 4);

- crossover function: scattered, crossover fraction = 0,65;
- mutation function: uniform distribution of probability: 0,1.

Four recordings were selected for tuning of algorithm – the estimation of weights for the linear classifier. The remaining nine recordings were then processed by the program, microarousals were detected by the tuned algorithm using the same settings of weights.

4.4 Results

The training set included four 8 hour nocturnal polysomnographic recordings of healthy subjects; in the first recording 174 microarousals were scored by the expert, in the second recording 82 microarousals, in the third recording 84 microarousals and in the fourth 115 microarousals were scored; mean arousal length was 7,53 s.

Genetic algorithm tuning of linear classifier weights was executed 10 times on the training set. The best performance resulted in fitness value -7234,6 (specificity 81,76 %; selectivity 56,97 %). Corresponding values of weights follows in Table 6.

Table 6: GA tuned weights

w1	w2	w3	w4	w5	w6	w7
16.574	21.773	21.737	16.147	15.898	7.5804	18.707
w8	w9	w10	w11	w12	w13	w14
2.9645	-15.731	-2.1319	10.881	-11.344	-22.512	12.298

The results of automated detections of microarousals in the recordings of the training set (recordings 1 – 4) and testing set (recordings 5 – 13) are shown on Figs. 17 and 18 and reported in Table 7 with corresponding measures of sensitivity (9), selectivity (10) and specificity (11), number of correct detections (true positive) and wrong detections (false positive) and mean value of microarousal duration for every recording.

Overall measures in testing set resulted in sensitivity of 76,09 %, selectivity of 53,26 % and 97,66% specificity. Mean arousal length detected in training set was 6,67 s (compared to 7,53 s scored) while 7,37 s in testing set (compared to 8,17 s).

Table 7: Distribution of the microarousals

Rec	Reference arousals	Computer detected	True positive	False positive	Sensitivity [%]	Selectivity [%]	Specificity [%]	Arousal length [s]
1	174	221	141	80	81,03	63,80	96,68	9,45
2	182	124	68	56	82,93	54,84	98,62	5,83
3	84	113	67	46	79,76	59,29	98,76	6,36
4	115	195	96	99	83,48	49,23	97,89	5,04
5	134	173	101	72	75,37	58,38	97,55	7,91

Rec	Reference arousals	Computer detected	True positive	False positive	Sensitivity [%]	Selectivity [%]	Specificity [%]	Arousal length [s]
6	221	268	161	107	72,85	60,07	97,01	6,40
7	164	221	126	95	76,83	57,01	96,59	8,25
8	100	145	73	72	73,00	50,34	98,23	5,81
9	108	141	76	65	70,37	53,90	98,31	6,12
10	123	228	103	125	83,74	45,18	96,21	7,10
11	53	85	42	43	79,25	49,14	98,44	8,58
12	69	95	53	42	76,81	55,79	98,26	9,76
13	124	210	99	111	79,84	47,14	96,98	6,38

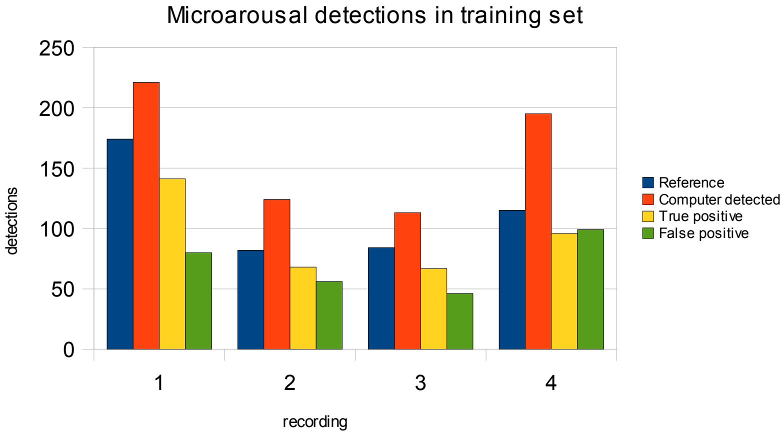


Fig. 17: Microarousal detections in training set

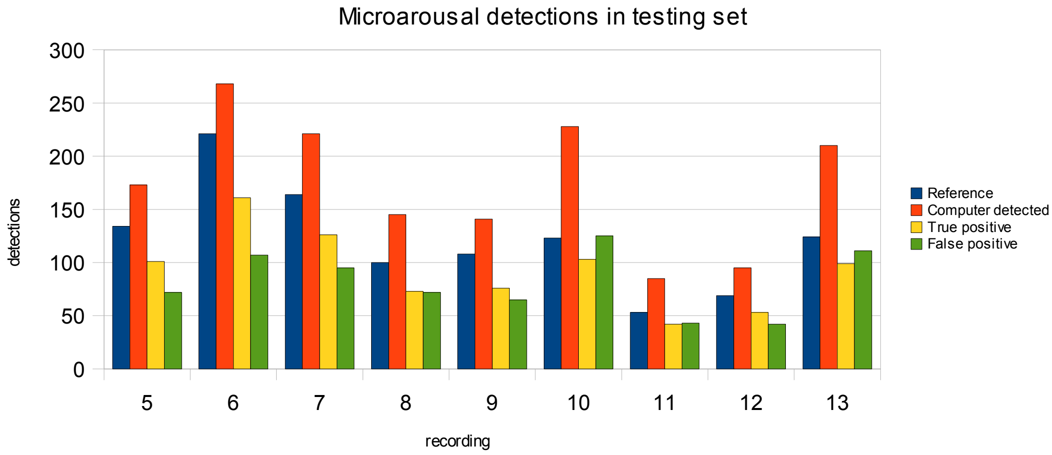


Fig. 18: Microarousal detections in testing set

Regarding a considerably high specificity of the detection algorithm, it is to further discussion whether some of false positives may also be marked as true by repeated expert scoring of the recordings.

5 Program description

5.1 Toolboxes

In the set of functions enclosed on the media several functions from two toolboxes not provided by Mathworks were used. As both toolboxes are freeware or under GNU Public License, they are both presented with documentation and examples from their authors' websites on the enclosed media. These toolboxes are:

- Time-Frequency toolbox,
- WaveLab850.

5.1.1 Time-Frequency toolbox

The Time-Frequency Toolbox (TFTB) is a collection of about 100 scripts for GNU Octave and Matlab developed for the analysis of non-stationary signals using time-frequency distributions. It is primary intended for researchers, engineers and students with some basic knowledge in signal processing [41].

The toolbox contains numerous algorithms which implements various kind of time-frequency analysis with a special emphasis on quadratic energy distributions of the Cohen and affine classes, along with their version enhanced by the reassignment method. The toolbox also includes signal generation procedures, processing/post-processing routines (with display utilities) and a number of demonstrations.

The TFTB is distributed under the terms of the GNU Public Licence.

The TFTB has been developed by François Auger, Olivier Lemoine, Paulo Gonçalvès and Patrick Flandrin under the auspices of the CNRS (Centre National de la Recherche Scientifique) within its GdR Information, Signal et Images. Parts of the Toolbox have also been written at Department of Electrical and Computer Engineering of Rice University with the support of the NSF.

Its homepage is: `http://tftb.nongnu.org/`

5.1.2 WaveLab850

WaveLab is a library of MATLAB routines for wavelet analysis, wavelet-packet analysis, cosine-packet analysis and matching pursuit. The library is available free of charge over the Internet. Versions are provided for Macintosh, UNIX and Windows machines [42].

WaveLab has been used in teaching courses in adapted wavelet analysis at Universities of Stanford and Berkeley. It is the basis for wavelet research by the authors (Jon Buckheit et al.), and may be used to reproduce the figures in their published articles, and to redo those figures with variations in the parameters.

WaveLab has over 1200 files which are documented, indexed and cross-referenced in various ways. MATLAB MEX files are used extensively to increase throughput.

In addition to routines implementing basic wavelet transforms for finite data sets (both periodic transforms and boundary-corrected transforms), wavelet-packet analysis, cosine-packet analysis and matching pursuit, the library contains scripts which the authors believe will assist in learning the practical aspects of wavelet analysis:

- Scripts that reproduce the figures in the authors' published articles, including the de-noising articles of Donoho and Johnstone.
- “Workouts”' that give a quick guide to wavelets (1-d and 2-d); wavelet analysis; wavelet synthesis; wavelet and cosine packets, including the Coifman-Wickerhauser best-basis methodology; matching pursuit; and applications such as data expansion, progressive data transmission, image compression, speech segmentation, de-noising, fast matrix multiplication in wavelet bases, etc.

WaveLab also offers:

- A library of datasets that are easily accessible to the user. Besides artificial signals that have scientific or pedagogical appeal, real data ranging from an image of Ingrid Daubechies to a recording by Enrico Caruso are included.
- A point-and-click browser that allows the user to select data, perform various transforms or de-noising operations, and then see the results without using the MATLAB command-line interface.
- Extensive documentation, including on-line documentation for each function, Contents files for each subdirectory, an *Architecture Guide* and an overview document, *About WaveLab,* that introduces the software to a first-time user.

Its homepage is: `http://www-stat.stanford.edu/~wavelab/`

5.2 Main program

Based on the detection algorithm and consecutive validation phase the main program for microarousal detection emerged. A brief overview of the program is provided on Fig. 19.

Comparing to the detection algorithm described above the program is not limited only to processed signals and consequently, some features, as sensitivity measure calculation, were removed. Though, all scripts and functions used in development phase are present on the enclosed media and referred to above.

On the following lines the main program for automated microarousal detection is listed and commented in parallel.

The program is designed as a function with input variables – time series of four EEG channels and an EMG signal (program was tuned for submental EMG). The signals are essential to be sampled at 128 Hz sampling rate, otherwise the program might not detect arousals correctly. Input variable label is optional and used in output text file name if present.

There is no output as a variable, however the program produces an output on the screen and to a text file.

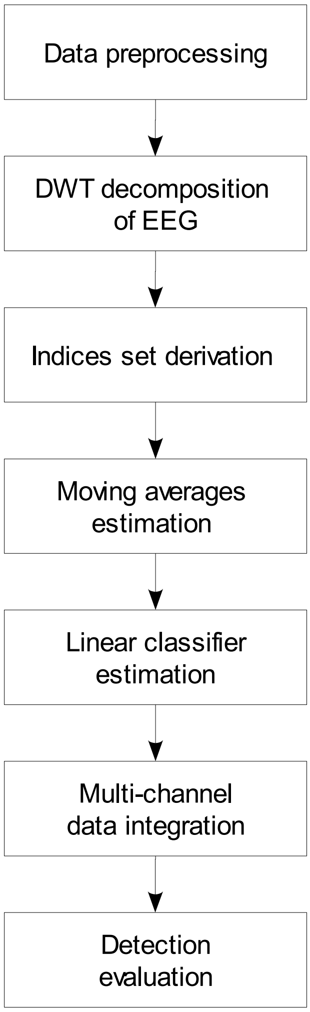


Fig. 19: Program overview

Program listing with parallel comments follows:

```
function detection(c3a2,c4a1,p3a2,p4a1,emg,label)

%DETECTION   Microarousal detection in EEG an EMG signals
%   Detects microarousals from EEG leads C3A2, C4A1, P3A2, P4A1
%   and submental EMG of same length sampled at 128 Hz.
%   For other sampling frequencies please resample the recording
%
%   Syntax: detection(c3a2,c4a1,p3a2,p4a1,emg,label)
%
%   where the first four arguments are obligatory (input signals)
%   while the argument 'label' is optional (used to label the output
%   file)
%
%   calls functions: MakeONFilter (WaveLab), decomp, downsample,
%   ma_detect_fin
```

Definition of conditions to cause an error: insufficient number of input signals or signals of different length. A standard label 'no_label' assigned if not entered as an input argument or not of string format:

```
if nargin < 5
    error('not enough input arguments, see "help detection" for help')
end

n = length(c3a2);
if (n-length(c4a1)) | (n-length(p3a2)) | (n-length(p4a1)) | ...
     (n-length(emg))
    error('input signals of different length, see "help detection" ...
    for help')
end

if nargin < 4
    label = 'no_label';
end

if ~(ischar(label))
    label = 'no_label';
end

tic
disp('')
disp(' signal decomposition started')
```

Constant declaration – sampling frequencies for original signal (fs) and for decomposed bands, moving averages and indices (fsn); description for other constants is straight in the code:

```
fs = 128;
fsn = 8;
l_ori = length(c3a2);           % original length of signal
l_dya = 2^ceil(log2(l_ori));    % smallest dyadic length bigger
                                % than length of signal
l_new = floor(l_ori*(fsn/fs));  % new length - downsampled
                                % from 128 Hz to 8 Hz
```

Orthonormal quadrature mirror filter estimation using function from WaveLab toolbox:

```
% orthonormal D12 (Daubechies 6) filter for wavelet packet decomp.
filt = MakeONFilter('Daubechies',12);
```

Extending signals to dyadic length which is necessary for processing by WaveLab wavelet filtering:

```
% padding with zeros to dyadic length
sig = zeros(l_dya, 4);
sig(1:l_ori,1) = c3a2;
sig(1:l_ori,2) = c4a1;
sig(1:l_ori,3) = p3a2;
sig(1:l_ori,4) = p4a1;
```

Original input signals cleared from the memory to manage computing resources as the signals are used no more:

```
clear c3a2 c4a1 p3a2 p4a1
```

Wavelet packet decomposition using function `decomp` – its listing with comments is given in the next chapter; resampling by functions `downsample` and `upsample` (listed in the next chapter as well):

```
% eeg decomposition, power, resample and trim
for i=1:4
    [b(:,i), s(:,i), a(:,i), t(:,i), d(:,i), ds(:,i)] = ...
        decomp(sig(:,i), filt, l_new);
end

% emg power, resample and trim
emg = emg.^2;
emg = downsample(emg,log2(fs/fsn));

disp(' decomposition done, signal powers resampled')
```

Moving averages estimation, time constants adopted from [37]:

```
% short-term and long-term moving average estimation

n_s = 30;    % short time average constant, ~4s (@8Hz)
n_l = 500;   % long time average constant, ~7min (@8Hz)

sme = zeros(l_new,6,4);    % eeg short-term moving averages
                           % [samples x band x lead]
sme(:,1,:) = b;
sme(:,2,:) = s;
sme(:,3,:) = a;
sme(:,4,:) = t;
sme(:,5,:) = d;
sme(:,6,:) = ds;

smm = emg;                  % emg short-term moving average
```

Decomposed signals cleared from the memory to manage computing resources:

```
clear b s a t d ds emg

lme = sme;
lmm = smm;
```

Calculation of moving averages according to (6):

```
for i = 2:l_new
    sme(i,:,:) = (n_s*sme(i-1,:,:)+sme(i,:,:))/(n_s+1);
    lme(i,:,:) = (n_l*lme(i-1,:,:)+lme(i,:,:))/(n_l+1);
    smm(i) = (n_s*smm(i-1)+smm(i))/(n_s+1);
    lmm(i) = (n_l*lmm(i-1)+lmm(i))/(n_l+1);
end

disp(' moving averages computed, microarousal detection started')
```

Setting of weights for linear classifier – values obtain previously during GA tuning:

```
% microarousal detection
w = [16.574776628054792,21.77348495538027,21.737710893751682, ...
    16.147279890264883,15.898717041962254, ...
    7.580421994132376,18.707008102443716,2.964576086676534, ...
```

```
    -15.731677727998544,-2.13193154140003,10.881721073284867, ...
    -11.34487648874288,-22.512275796437514,12.298098783909058;]
    % weights tuned by GA
```

Binary matrix of microarousal detection in every basic epoch (0,125 s) enumeration for every combination of EEG channel and EMG – function `ma_detect_fin` listed in next chapter:

```
detect = zeros(4,l_new); % [lead x samples]
for i = 1:4
    smi = [sme(:,:,i)';smm'];
    lmi = [lme(:,:,i)';lmm'];
    detect(i,:) = ma_detect_fin(w,smi,lmi,l_new);
end
```

Multichannel data integration – microarousal was scored in every basic epoch when there was an arousal marked at least in one channel:

```
% multichannel data integration
detect = logical(sum(detect));
```

Simple evaluation of detections (beginnings, ends, total number and durations); functions `rshift` and `lshift` are from WaveLab toolbox – they both rotates elements in the input vector, either one position right or left:

```
% evaluation
begs = find((detect + rshift(-detect))>0);    % beginnings of detections
ends = find((detect + lshift(-detect))>0);    % ends of detections
ndet = length(begs);                          % number of detections
dur = (ends - begs)/fsn;         % duration of detected arousals in [s]

disp(' microarousal detection and evaluation done')
disp('')
```

Screen output also being saved to a text file:

```
diary(['ma_detections-',label,'.txt'])
```

Microarousals reported with information about their time of occurrence and duration; detection time is in hours:minutes:seconds.miliseconds format while the beginning of the recording is referred to as 00:00:00.000:

```
for i = 1:ndet
    disp([' microarousal detected at time ', ...
        datestr(begs(i)/(24*3600*fsn),'HH:MM:SS.FFF'), ...
        ', duration: ',num2str(dur(i))]);
end
disp('')
disp([' total number of arousals: ',num2str(ndet), ...
    ', of average duration: ', num2str(mean(dur)),' s']);
disp('')

diary off
```

Report on elapsed time during run of this program:

```
elapsed_time = toc;
fprintf('elapsed time: %.2f minutes\n\n', elapsed_time/60)
```

5.3 Functions

Functions called during the run of the program for automated microarousal detection are listed bellow. Additive comments are omitted as each of the functions is broadly commented in its body.

5.3.1 decomp.m

```
function [b, s, a, t, d, ds] = decomp(x, filter, orig);

% Function to decompose signal sampled at 128Hz into bands:
%   bx - beta       16 - 64 Hz @ 128 Hz
%   sx - sigma      12 - 16 Hz @ 8 Hz
%   ax - alpha      8 - 12 Hz @ 8 Hz
%   tx - theta      4 - 8 Hz @ 8 Hz
%   dx - delta      .5 - 4 Hz @ 8 Hz
%   dsx - slow delta    0 - .5 Hz @ 1 Hz
% using wavelet orthonormal filter packet decomposition, calculate
% decomposed signals power, resample signal powers to 8 Hz and trim
% them to the original duration
% composed bands (beta and delta) are estimated by wavelet packet
% recomposition, signal power is calculated after the recomposition
%
% used functions: DownDyadHi, DownDyadLo, UpDyadHi, UpDyadLo (all
% WaveLab toolbox), upsample, downsample
% inputs: signal @128Hz of dyadic length, wavelet orthogonal filter,
% original length of signals

r1 = DownDyadHi(x,filter); %32 - 64 Hz @ 64 Hz
r = DownDyadLo(x,filter); %0 - 32 Hz @ 64 Hz

b = DownDyadHi(r,filter); %16 - 32 Hz @ 32 Hz
r = DownDyadLo(r,filter); %0 - 16 Hz @ 32 Hz

sa = DownDyadHi(r,filter); %8 - 16 Hz @ 16 Hz
r = DownDyadLo(r,filter); %0 - 8 Hz @ 16 Hz

s = DownDyadHi(sa,filter); %12 - 16 Hz @ 8 Hz
a = DownDyadLo(sa,filter); %8 - 12 Hz @ 8 Hz

t = DownDyadHi(r,filter); %4 - 8 Hz @ 8 Hz
r = DownDyadLo(r,filter); %0 - 4 Hz @ 8 Hz

d1 = DownDyadHi(r,filter); %2 - 4 Hz @ 4 Hz
r = DownDyadLo(r,filter); %0 - 2 Hz @ 4 Hz

d2 = DownDyadHi(r,filter); %1 - 2 Hz @ 2 Hz
r = DownDyadLo(r,filter); %0 - 1 Hz @ 2 Hz

d3 = DownDyadHi(r,filter); %.5 - 1 Hz @ 1 Hz
d4 = DownDyadLo(r,filter); %0 - .5 Hz @ 1 Hz

b = UpDyadHi(r1,filter) + UpDyadLo(UpDyadHi(b,filter),filter);
%~16 - 64 Hz @ 128 Hz
```

```
d = UpDyadHi(d1,filter) + UpDyadLo((UpDyadHi(d2,filter) +
UpDyadLo(UpDyadHi(d3,filter),filter)),filter); %~.5 - 4 Hz @ 8 Hz
ds = d4;

% signal power
b = b .^2;
s = s .^2;
a = a .^2;
t = t .^2;
d = d .^2;
ds = ds .^2;

% resample
b = downsample(b,log2(128/8));
ds = upsample(ds,log2(8/1));

% trim
b = b(1:orig);
s = s(1:orig);
a = a(1:orig);
t = t(1:orig);
d = d(1:orig);
ds = ds(1:orig);
```

5.3.2 downsample.m

```
function x_out = downsample(x_in,order);

% Function to resample the input signal power to 2^order times lower
% frequency while preserving the energy information (averaging)
%
% inputs: signal, order

x_out = x_in(:);
n = length(x_in);

if (mod(n, 2^order))
    n = n - mod(n, 2^order);
    x_out = x_in(1:n);
end

for i = 1:order
    x_out = (x_out(1:2:end)+x_out(2:2:end))/2;
end
```

5.3.3 upsample.m

```
function x_out = upsample(x_in,order);

% Function to resample the input signal power to 2^order times higher
% frequency while preserving the energy information ('value copy')
%
% inputs: signal, order

multi = 2^order;
l = length(x_in);
x_out =  zeros(l*multi,1);
for i = 1:multi
```

```
    x_out(i:multi:l*multi) = x_in;
end
```

5.3.4 ma_detect_fin.m

```
function index = ma_detect_fin(w, smi, lmi, orig);

% Function for micro-arousals detection in one EEG channel + EMG
%
% input: weights, short and long-averages, length of recording
% output: binary index of arousal detection
% called function: ind_step_fin
%

thres = 100;     % threshold
fs = 8;          % sampling frequency
min_ma = 3*fs; % minimal length of microarousal taken in consideration
max_ma = 30*fs;% maximal length of microarousal taken in consideration

ind = zeros(size(w));    % indices at a time
count = 0;               % number of samples of microarousal detection
                         % in a row
index = zeros(1,orig);   % index (0/1) of arousals detected in each
                         % sampling time (0,125s)

sm = smi(:,1); % short-term moving averages at a time (now at time 1)
lm = lmi(:,1); % long-term moving averages at a time (now at time 1)


for i = 1:orig-1
    ind = ind_step_fin(sm,lm);    % indices evaluation
    class = sum(w.*ind) - thres; % classifier computation
    if class > 0               % MA in time detected
        count = count + 1;     % registration of MA; lm stays 'frozen'
    elseif count               % end of MA detected
        if (count >= min_ma) && (count <= max_ma) % comply with limits
            index(i-count:i-1) = 1;     % microarousal recorded
        end
        lm = lmi(:,i+1);
        count = 0;
    else
        lm = lmi(:,i+1);
    end
    sm = smi(:,i+1);
end
```

5.3.1 ind_step_fin.m

```
function ind = ind_step_fin (sm, lm)

% Function for calculation of indices for long and short time averages
%  at a time
%
% Inputs: short and long time averages vectors at a time

% middle frequencies of bands:
f1 = 38;    %beta  16 - 64
f2 = 14;    %sigma  12 - 16
f3 = 10;    %alpha  8 - 12
```

```
f4 = 6;      %theta  4 - 8
f5 = 2.25;  %delta  .5 - 4
f6 = .25;   %delta slow 0 - .5

% sm / lm ratios
ind(1:6) = sm(1:6)./lm(1:6);
ind(7) = sm(7)./lm(7);

% short-term / long-term mean frequencies
ind(8) = ((sm(1)*f1 + sm(2)*f2 + sm(3)*f3 + sm(4)*f4 + sm(5)*f5 +
sm(6)*f6)/sum(sm(1:6))) / ...
    ((lm(1)*f1 + lm(2)*f2 + lm(3)*f3 + lm(4)*f4 + lm(5)*f5 +
lm(6)*f6)/sum(lm(1:6)));

% delta / alpha + beta (short-term)
ind(9) = sm(5) / (sm(1) + sm(3));

% delta / alpha + beta (long-term)
ind(10) = lm(5) / (lm(1) + lm(3));

% short-term / long-term alpha relative
ind(11) = (sm(3)/sum(sm(1:6))) / (lm(3)/sum(lm(1:6)));

% long-term alpha + slow delta / theta + delta
ind(12) = (lm(3) + lm(6)) / (lm(4) + lm(5));

% sigma / alpha + beta
ind(13) = sm(2) / (sm(3) + sm(1));

% beta / delta variations
ind(14) = (sm(1)/lm(1)) / (sm(5)/lm(5));
```

6 Conclusion

The aim of this study was to develop an automatic detection program for scoring the EEG arousals, based on one of time-frequency analysis methods.

The subject of the study was 13 overnight polysomnographic recordings, i.e over 100 hours in total. It was a subset of data used in former studies by sleep expert Dr. Emilia Sforza, Geneva, Switzerland, who also provided baseline arousal scoring. Dr. Sforza is a recognized medical researcher in the field of study of sleep, especially the daytime sleepiness, periodic leg movements and arousal responses with focus on microstructure of sleep.

Next, several tools for recordings' visualization were developed to facilitate the decision on methods of analysis: tools for direct signals browsing and tools for visual analysis of signal decompositions by short-time Fouier transform (using both spectrogram and frequency band decomposition) and discrete wavelet transform (with possibility to chose from variety of mother wavelet).

Following the conclusions made after extensive visualization of input recordings in different time-frequency representations and regarding the character of EEG as neuroelectric waveforms and computing efficiency, discrete wavelet decomposition with Daubechies order 6 mother wavelet was chosen.

The EEG signals were decomposed into six frequency bands and subsequently, the signal power of all bands was computed. The results of wavelet transform together with EMG recordings were resampled to 128Hz and used to evaluate a set of 14 indices describing EEG and EMG changes accompanying arousals as defined by ASDA from their short-time and long-time averages.

These indices were weighted to form linear classifier of microarousal suspicion in each EEG lead – a microarousal was marked as present when it remained suspect in period of 3 to 30 seconds.

Algorithm of detection then integrated outputs of four EEG channels and reported final outcome. Based on sensitivity and selectivity measures (specificity remained high throughout the whole algorithm development) the algorithm was optimized using Matlab Genetic Algorithm Tool. The subject of tuning were the linear classifier parameters and first four of 13 recordings were selected as training data.

A microarousal detection program emerged on basis of the tuned algorithm and resulted in average sensitivity of 76,09 %, selectivity of 53,26 % and 97,66 % specificity over all 13 recordings compared to expert visual scorings.

Regarding a considerably high specificity of the detection algorithm, it is to further discussion whether some of false positives may also be marked as true by repeated expert scoring of the recordings.

Taking into account that many times the scoring differs from expert to expert while analyzing the same data, the algorithm performance can be evaluated as comparable with another expert's scoring results.

However, some improvements in algorithm or its tuning can still be done.

Different choice of genetic algorithm tuning could lead to achievement of better value of fitness function and consequently better model for microarousal detection. Also throughout analysis of derived indices and possible selection of only a subset, or alternative approach to integration of data from multiple channels could improve the performance.

A further step can be made by associating the wavelet transform with neural networks. Yet, one of the advantages of algorithm and its implementation with tuned parameters as it is,consists in its portability and easy integration into another systems like, e.g., PRANA® by PhiTools.

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Symbol table

AASM	American Academy of Sleep Medicine
ASDA	American Sleep Disorders Association
CAP	Cyclic alternating pattern
DFT	Discrete Fourier transform
DWT	Discrete wavelet transform
EEG	Electroencephalogram
EMG	Electromyogram
EOG	Electrooculogram
FFT	Fast Fourier transform
GUI	Graphic user interface
MA	Microarousal
MT	Movement time
NREM	Non rapid eye movement
PAT	Phases of transitory activation
PSG	Polysomnography
REM	Rapid eye movement
STFT	Short-time Fourier transform
SWS	Slow wave sleep
WT	Wavelet transform
WPD	Wavelet packet decomposition