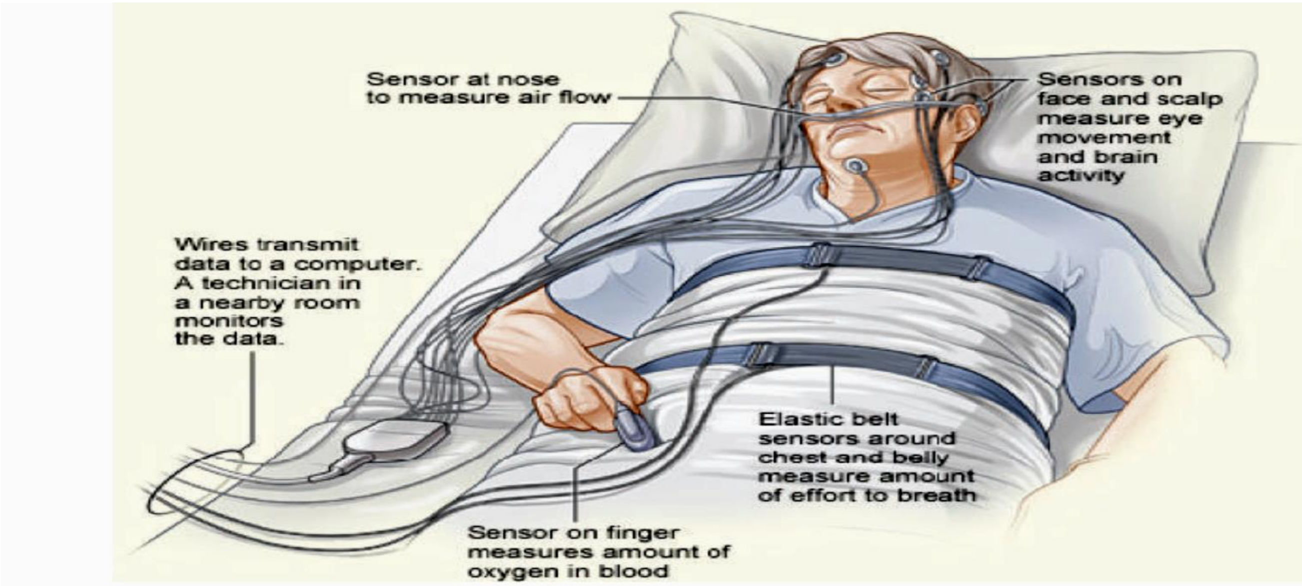
PSG definitions and devices (softwares)

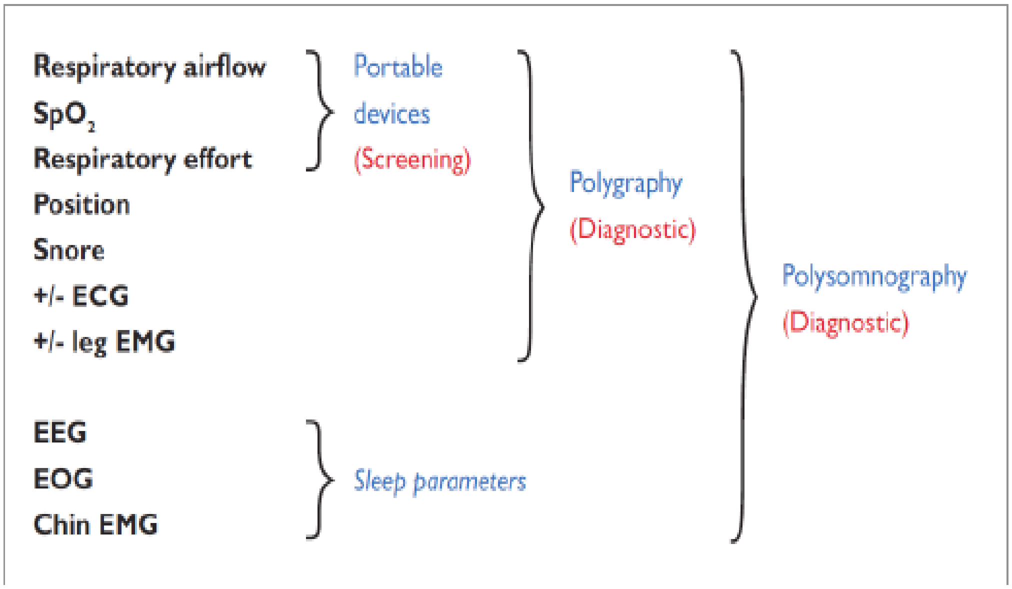
- http://www.sleepexplorer.de/

PSG recording and analysis

Polysomnography is usually performed at sleep clinics in the presence of trained technicians, typically using four to six EEG electrodes, two EOG electrodes, four EMG electrodes, two ECG electrodes and additional sensors such as **fingertip pulse oximeter(arterial oxygen saturation) (SpO2)**, thermistor (for upper airway
signals), thorax and abdomen, snoring (microphone),



PSG recording and analysis



Types of sleep studies

- Type | : The gold standard of sleep studies that is performed at sleep clinics in the presence of trained personnel at all times (include EEG, EOG, EMG, ECG, airflow, oxygen saturation and more if required).

- Type 2: All signals as in Type | but is performed out of the clinic at a patient's home. It does not require the presence of trained personnel but needs the patient to put on all the electrodes and probes appropriately.

- Type 3: A subset of only four physiological signals are recorded. including two **respiratory** signals together with the **ECG** and oxygen saturation using a portable device at home without the need for trained personnel.

- Type 4: A maximum of two signals are recorded (**airflow and/or oxygen saturation**) using a portable device at home without the need for the presence of trained personnel.

Sleep stages definitions

- Analysis of signals by trained technicians in blocks of 30-second epochs
- Using frequency content information and peak-to-peak voltage to mark the 30-second epochs in to sleep stages.
- The first set of rules for scoring of sleep were published in 1968 by Rechtschaffen and Kales, and are commonly known as R&K rules.
- These rules were revised in 2007 and some changes were recommended to address and overcome some of their inherent limitations.
- The updated set is known as the AASM (American Academy of Sleep Medicine) rules.

R&K	S1	S2	S3	S4	REM	Wake	MT
AASM	N1	N2	N3		REM	Wake	

R&K rules of sleep staging

- Wake: the EEG derivations show the presence of alpha (8-13 Hz) activity together with low voltage and mixed frequency activity.
- S1: Stage 1 is characterized by the presence of low voltage and mixed frequency activity of the EEG but without the presence of eye movements on the EOG.
- S2: presence of sleep transients known as sleep spindles and k-complexes observed on the EEG signals.

Spindles (micro-events of sleep EEG) are defined as a burst of 12-14 Hz waves with a duration of at least 0.5 seconds. A K-complex is defined as an isolated sharp negative wave followed by a positive component and duration of more than 0.5 seconds. The presence of either of these two transients and a lack of slow wave activity is used to classify an epoch as Stage 2 of sleep.

- S3: EEG content consisting of between 20-50% of high amplitude delta (0.5-2 Hz) waves.

The amplitude of these slow waves are more than 75 µV.

- S4: similar to S3 except that the EEG contains delta waves for more than 50% of the epoch duration. Together S3 and S4 stages are also known as slow wave sleep (SWS).
- REM: REM sleep is identified with the presence of low voltage and mixed frequency EEG similar to what is seen during Stage 1. It is differentiated with the presence of eye movements on the EOG.
- Movement Time: An epoch is classified as Movement Time (MT) when the EEG and EOG signals are obscured for more than half of the epoch duration.

AASM rules of sleep staging

- Wake: more than 50% of an epoch visibly consists of alpha (8-13 Hz or counts of peaks/second) activity.

If there is a large amount of artefact in an epoch (suggesting significant movement of body) it will be marked as W if the alpha rhythms are visible, otherwise it is scored as the stage that follows this epoch (N1).

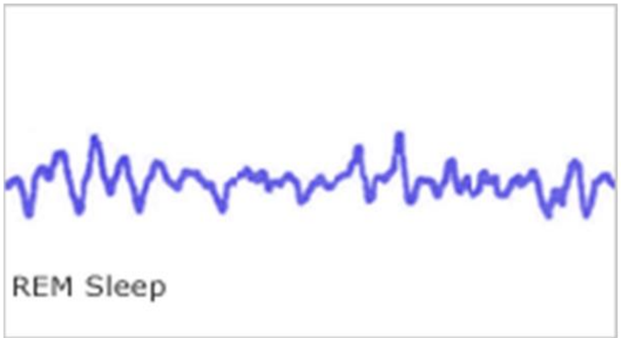
The AASM manual of classification states that **an epoch with major body movements** should be classified as Wake if alpha rhythms are present in the epoch or if a Wake epoch precedes or follows the epoch under analysis even if there are no alpha rhythms.

If neither of the two conditions are true, then the epoch should be assigned the same sleep stage as the epoch that follows it (same as last epoch).

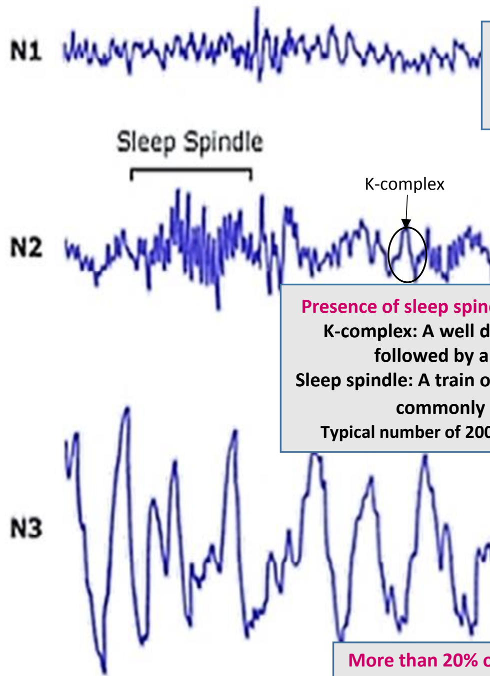
- N1: an epoch consists of less than 50% of alpha (8-13 Hz) rhythms and more than 50% of theta (4-7 Hz) rhythms, it will marked as stage 1 of NREM sleep, known as N1.
- N2: presence of either or both of two distinct features of sleep: sleep spindles and k-complexes.
- K-complex is defined as “a well delineated negative sharp wave immediately followed by a positive component standing out from the background EEG with total duration ≥ 0.5 seconds”.
- Sleep spindle is defined as “a train of distinct waves with frequency 11-16 Hz (most commonly 12-14 Hz) with a duration ≥ 0.5 seconds.
- N3: more than 20% of an epoch consists of waves in the range of 0.5-2 Hz, with **peak-to-peak amplitude of 75 µV** or more as an optionally additional criterion
- REM: eye movement activity can be observed on data sourced from EOG electrodes, EEG activity similar to that observed during N1 stage, chin EMG tone falls during this stage, which can also be used for classification of REM.

An epoch = 30 seconds.
N Hz= N counts of peaks/second

Sleep



REM sleep is the lightest type of sleep, while non-REM sleep is the deepest type.



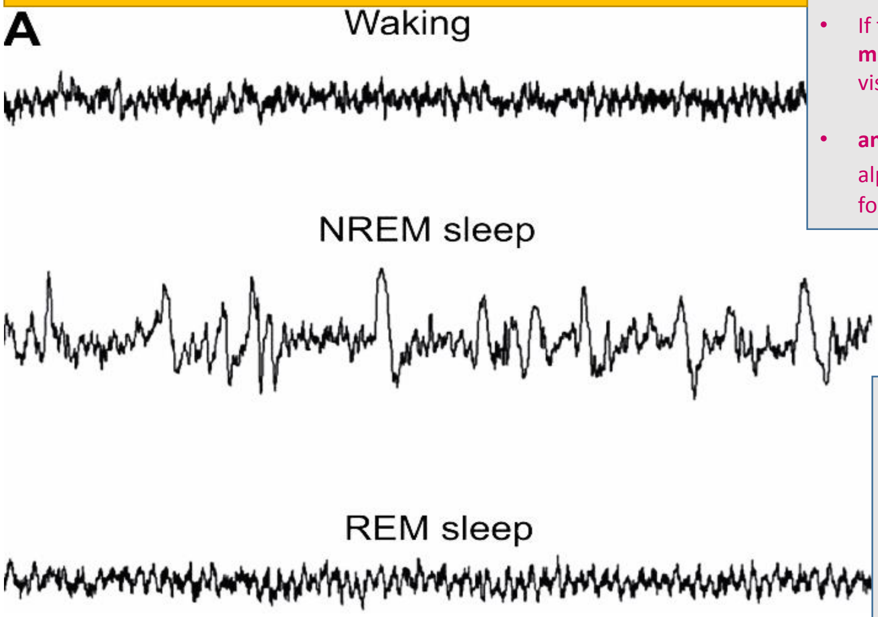
Mixed frequency without EOG
less than 50% of alpha (8-13 Hz) rhythms
and more than 50% of theta (4-7 Hz)

Presence of sleep spindles or k-complexes (lack of slow wave activity).
K-complex: A well delineated negative sharp wave immediately followed by a positive component (duration>=0.5s)
Sleep spindle: A train of distinct waves with frequency 11-16 Hz (most commonly 12-14 Hz) (duration ≥ 0.5 seconds).
Typical number of 200-1000 during an sleep night of healthy subjects.

More than 20% of an epoch consist of waves in 0.5-2Hz
and
peak-peak amplitude of >=75 uv
20-50% of high amplitude delta (0.5-2 Hz) waves

An epoch = 30 seconds.

N Hz= N counts of peaks (positive and negative)/second

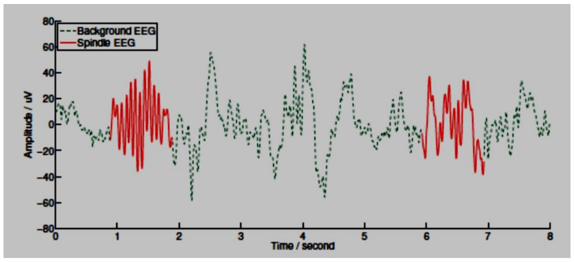


- **Presence of alpha (8-13 Hz) activity together with low voltage and mixed frequency activity.**
- **more than 50% of an epoch visibly consists of alpha (8-13 Hz) activity**
- If there is a large amount of artefact in an epoch (**suggesting significant movement of body)** it will be marked as W if the alpha rhythms are visible, otherwise it is scored as the stage that follows this epoch (N1).
- **an epoch with major body movements** should be classified as Wake if alpha rhythms are present in the epoch **or** if a Wake epoch precedes or follows the epoch under analysis even if there are no alpha rhythms.

- The presence **of low voltage and mixed frequency EEG similar to what is seen during Stage 1 (less than 50% of alpha (8-13 Hz) rhythms and more than 50% of theta (4-7 Hz))**
- It is differentiated with the presence of eye movements on the **EOG.**
- chin EMG tone falls during this stage, which can also be used for classification of REM.

More on Spindle

- Sleep spindle is a micro-event of sleep EEG and is a characteristic of NREM stages of sleep.
- According to AASM, a sleep spindle is defined as "a train of distinct waves with frequency 11-16 Hz (most commonly 12-14 Hz) with a duration ≥ 0.5 seconds"
- Typical number of 200 to 1000 during an overnight sleep (for healthy subjects)
- They are known to play a fundamental role in memory consolidation during sleep
- related to the secretion of melatonin, that helps in maintaining circadian rhythms in the body
- having an active role in the progression of sleep to slow wave stages (SWS)
- relevant indicator for early stage development of central nervous system (CNS) (cognitive)
- **decreased spindle activity during sleep in youths with major depressive disorder (MDD)** and those with high risk for the disorder
- sleep spindles are **an indicator of intellectual ability in individuals**
- direct correlation between the number of sleep spindles and IQ scores



As a review

https://www.slideshare.net/HoustonEEG/scoring-sleep-2013-webinar-n2sleep

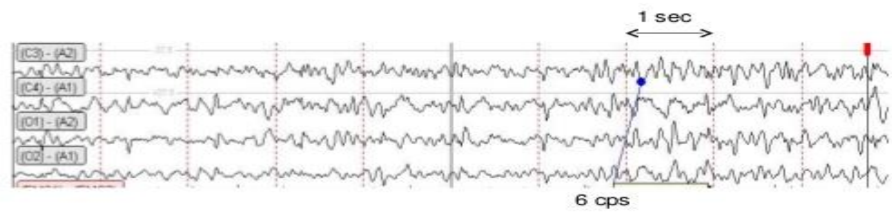
LESSON 1: SLEEP STAGE SCORING

Stage N1

The EEG consists of theta waves, 4-7 cps (4-7 Hz)

AKA: Low Voltage Mixed Frequency (LVMF)

e.g. Theta waves on a 10-second epoch



As a review

LESSON 1: SLEEP STAGE SCORING

Stage N1

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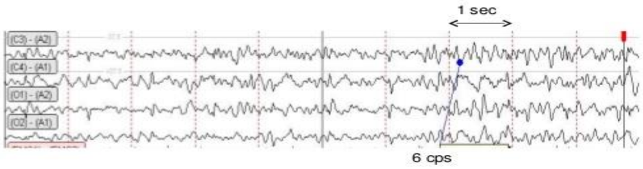


LESSON 1: SLEEP STAGE SCORING

Stage N1

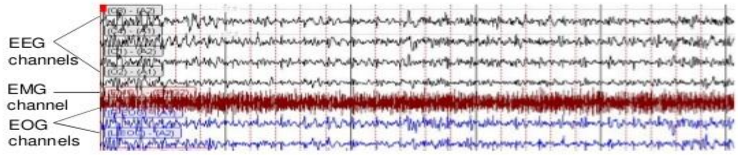
Makes up 5% of the Total Sleep Time (TST)

Vertex Sharp Waves may be present

The EOG shows Slow Eye Movements (SEMs)

The EMG is variable, but is often lower than Stage Wake

e.g. Theta waves on a 30-second epoch

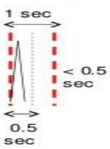


LESSON 1: SLEEP STAGE SCORING

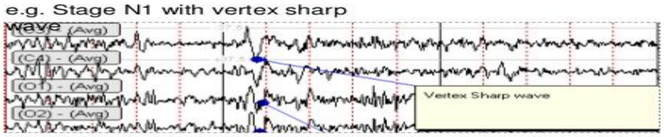
Vertex Sharp Wave

EEG characteristic:

Vertex sharp wave is a sharp negative deflection (upward)followed by a positive deflection (downward) lasting **< 0.5 second** (seen in the frontal/central regions; during the first half of the stage).



e.g. Stage N1 with vertex sharp wave

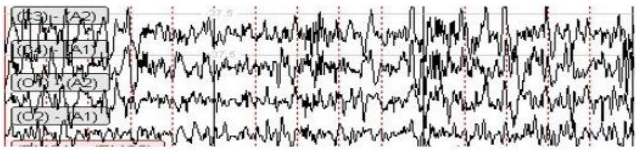


As a review

LESSON 1: SLEEP STAGE SCORING

Stage N2

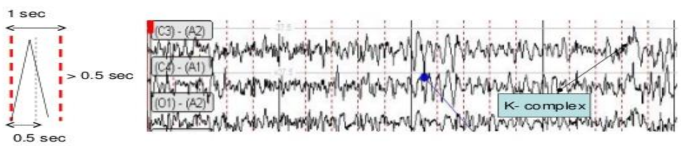
The EEG consists of Theta waves interspersed with K-complexes and/or Sleep Spindles
Can be seen in Central, Frontal, or Occipital leads
e.g. Stage N2 with K-complexes and spindles



LESSON 1: SLEEP STAGE SCORING

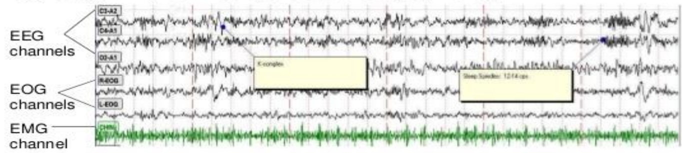
K-Complex

- Well delineated negative sharp wave (upward) followed by a positive component (downward) lasting at least 0.5 sec duration.



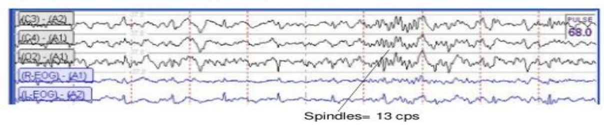
LESSON 1: SLEEP STAGE SCORING

Stage N2
Makes up 50% of the Total Sleep Time
The EEG consists of Theta waves interspersed with K-complexes and/or Spindles
The EOG activity is similar to EEG
The EMG has variable amplitude, but usually lower than Wake
e.g. Stage N2 (with K complexes and sleep spindles)



LESSON 1: SLEEP STAGE SCORING

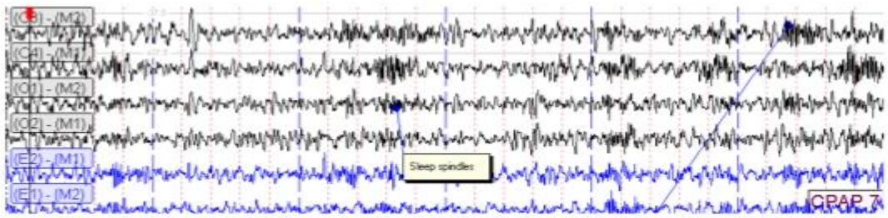
Sleep Spindles
The EEG consists of a frequency of 11-16 cps (11-16 Hz)
It can be seen in either Central or Frontal leads
The EOG is similar to EEG
e.g. Spindles on a 10-second epoch



As a review

LESSON 1: SLEEP STAGE SCORING

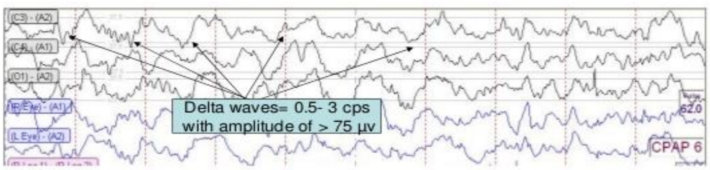
The pattern is big, black & blotchy signal occurring at 0.5-1.5 second duration
e.g. Spindles on a 30-second epoch



As a review

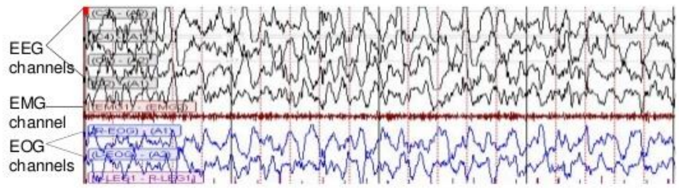
LESSON 1: SLEEP STAGE SCORING

Stage N3
The EEG consists of a frequency of a 0.5-3 cps (0.5-3 Hz) with amplitudes > 75 μV from peak-to-peak, occupying > 20% of the epoch (cumulative)
The patterns are like Ocean waves or Skyscrapers
e.g. Delta waves (Stage N3) on a 10-second epoch



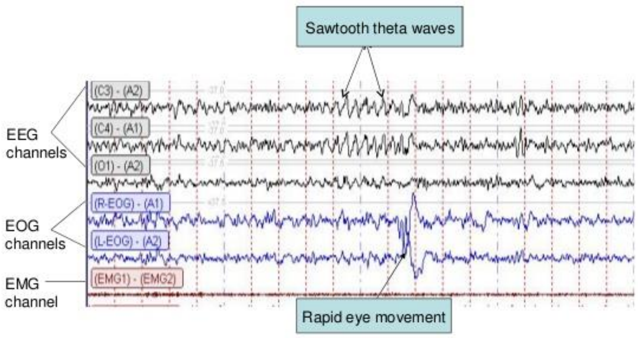
LESSON 1: SLEEP STAGE SCORING

Stage N3
Makes up 20-25% of the Total Sleep Time
It can be seen predominantly in frontal & central regions
The EOG is similar to EEG
The EMG has variable amplitude, often lower than in Stage N2 and sometimes as low as in Stage R sleep



As a review

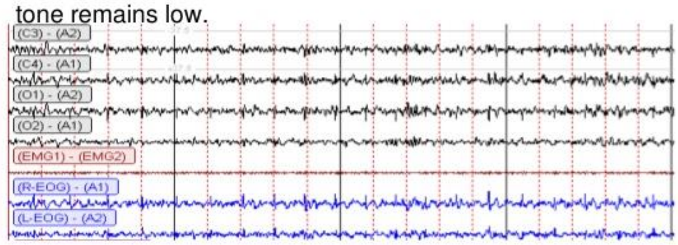
LESSON 1: SLEEP STAGE SCORING



LESSON 1: SLEEP STAGE SCORING

Continuation of Stage R

Continue to score Stage R even in the absence of rapid eye movements, for epochs following 1 or more epochs of Stage R, if the EEG continues to show LVMF activity without K-complexes or sleep spindles and the chin EMG tone remains low.

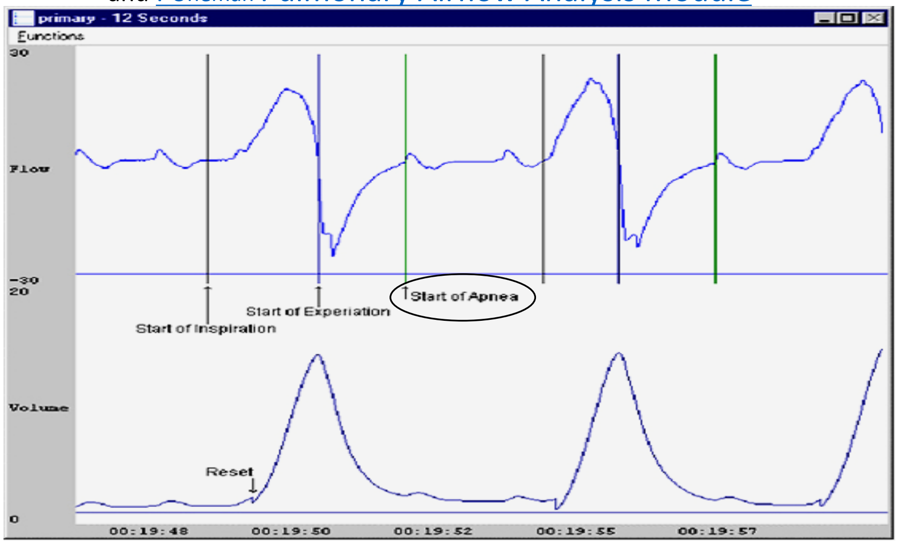


Arousal

- Arousal web page
- https://www.slideshare.net/HoustonEEG/scoring-sleep-2013-webinar-n2sleep
- **What are Arousal Disorders?**
- Arousal disorders are parasomnia disorders presumed to be due to an abnormal arousal mechanism. Forced arousal from sleep can induce episodes. The "classical" arousal disorders are sleepwalking(somnambulism), sleep terrors and confusional arousals. Experts believe the various types of arousal disorders are related and share some characteristics. These arousals occur when a person is in a mixed state of being both asleep and awake, generally coming from the deepest stage of nondreaming sleep. This means a person is awake enough to act out complex behaviors but still asleep and not aware or able to remember these actions.
- **What are the causes arousal disorders?**
- These disorders tend to run in families and are more common in children. Being over tired, having a fever or taking certain medications may make it worse. Because disorders of arousal are less common in adults, having an evaluation is important. In some cases, these disorders are triggered by other conditions, such as sleep apnea, heartburn, or periodic limb movement during sleep. A sleep specialist should evaluate the person's behaviors and medical history.
- **How are arousal disorders treated?**
- If it is a severe case that leads to injury or involves violence, excessive eating, or disturbs the bedpartner or family, treatment by a sleep specialist may be necessary. Treatment might involve medical intervention with perscription drugs or behavior modification through hypnosis or relaxation/mental imagery.

Pulmonary air flow (from thorax and abdomen piezoelectric belts)

- https://www.datasci.com/products/software/ponemah/analysis-modules/pulmonary-air-flow-and-airway-resistance
- (Pulmonary Air Flow and Airway Resistance Analysis Module)
- The Pulmonary Air Flow (PAF) and Airway Resistance Analysis Module is designed to analyze any pulmonary flow signal derived either from a **plethysmography** chamber, pneumotach, or Jacketed External **Telemetry respiratory impedance bands** (JET RIP).
- Accurate measurements of respiratory volume and rate are available through the addition of a JET Respiratory Add-On and Ponemah Pulmonary Airflow Analysis Module



A typical pulmonary flow signal with its digitally integrated volume signal, as they would appear on the monitor.

Automated validation marks for Start of Inspiration, Start of Expiration and Start of Apnea are shown (additional validation marks are available).

The validation marks provide visual, real-time verification of the accuracy of the system.

- **Respiratory Inductive Plethysmography (RIP) uses state of the art technology to monitor respiration externally in a non-invasive manner.**
- **It allows stress-free data collection from free roaming animals and is superior to piezo-resistive effort belts due to the ability to more accurately assess changes in respiratory volume.**
- **Measurement of respiratory parameters utilizes RIP and requires the placement of two bands around the chest and abdomen**
- **Two bands are placed around the chest and abdomen to measure changes in diameter**
- **After calibration, these changes in diameter enable determination of respiration rate, tidal volume, minute volume and phase shift**
- **Diagnosis: When used in combination with ECG and Blood Pressure, cardiopulmonary dependencies may be determined.**

Apnea detection

- An **obstructive apnea (OA)** : complete cessation of **airflow** for ≥10 s.
- An **obstructive hypopnea (OH)** : the occurrence of **airflow** drop ≥50% of the preceding baseline level during ≥10 s,
- or an airflow reduction of ≥30% lasting ≥10 s, and associated with either a ≥3% oxygen desaturation or a apnea (A)
- The **respiratory disturbance index (RDI)** was defined as all the OA and OH scored for one patient during the night divided by the **total sleep time (TST).**

Pulse wave amplitude (PWA)

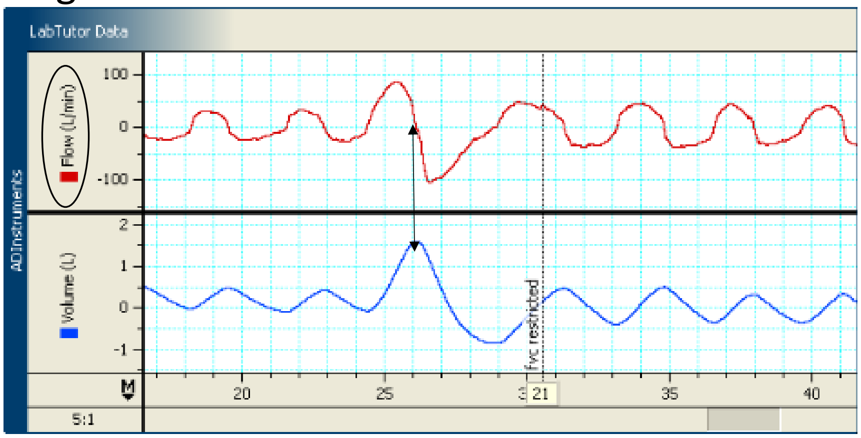
- Finger PWA was determined as the difference between the peak and the nadir values of the corresponding photoplethysmogram pulse waveform for each cardiac cycle

- PWA is given by analysis of the infrared light and his modulation.

- While heart beating is changing, the absorption of infrared light varies at the fingertip.
- An acceleration of heart beating lead to a decrease of oxygen saturation due to a higher consumption that leads to a decrease of intensity (absorption??) of infrared light.
- This measure does not depend on the stiffness of the vessels. Consequently, a decrease in PWA means a higher stress and reflect activation of the autonomous system.

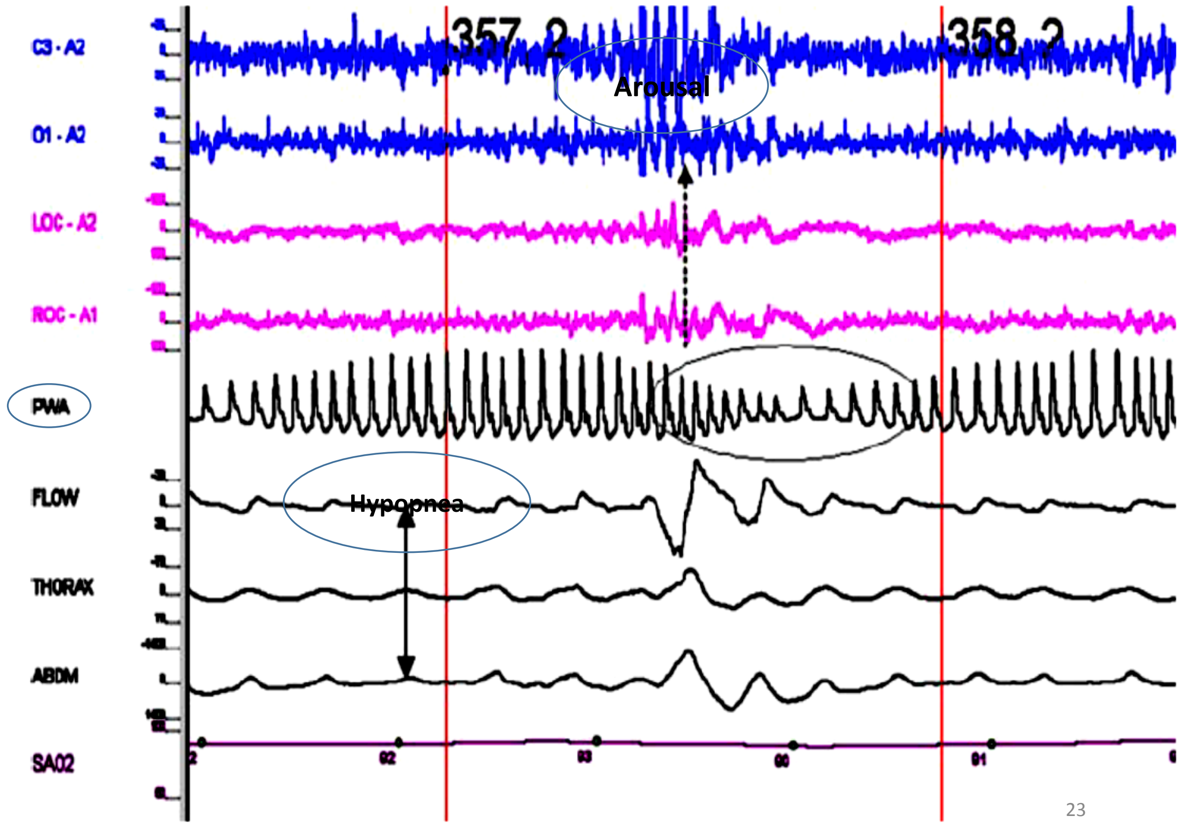
Respiratory air flow (Nasal pressure recording) (for snoring detection)

- Respiratory airflow is monitored with a nasal cannula connected to a pressure transducer (Protech2, Minneapolis, MN, USA; sampling rate, 20 Hz).
- Exactly the same as pulmonary air flow we can digitally integrate volume signal as shown in figure.



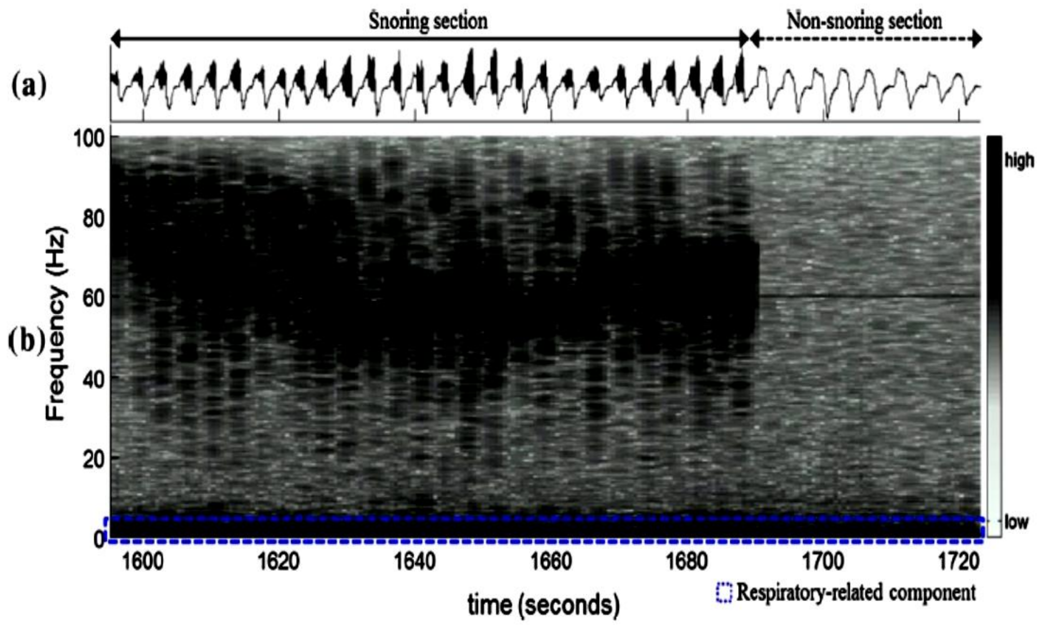
https://www.coursehero.com/file/17414038/Lab-8-Respiratory-Air-Flow-and-Volumedocx/

Fig. 1 PWA: tracing example of the PWA's decrease after a hypopnea and inducing a cortical arousal. The *oval* shows an example of a ≥30% variation of PWA. The *dashed arrow* shows a cortical arousal; the *double sense arrow* shows an obstructive hypopnea. This figure demonstrates also EEG (C3-A2, O1-A2), left and right electrooculogram (LOC, ROC), chest (THORAX) and abdominal (ABDM) piezo crystal belts, respiratory airflow (FLOW), and oxygen saturation (SAO2)



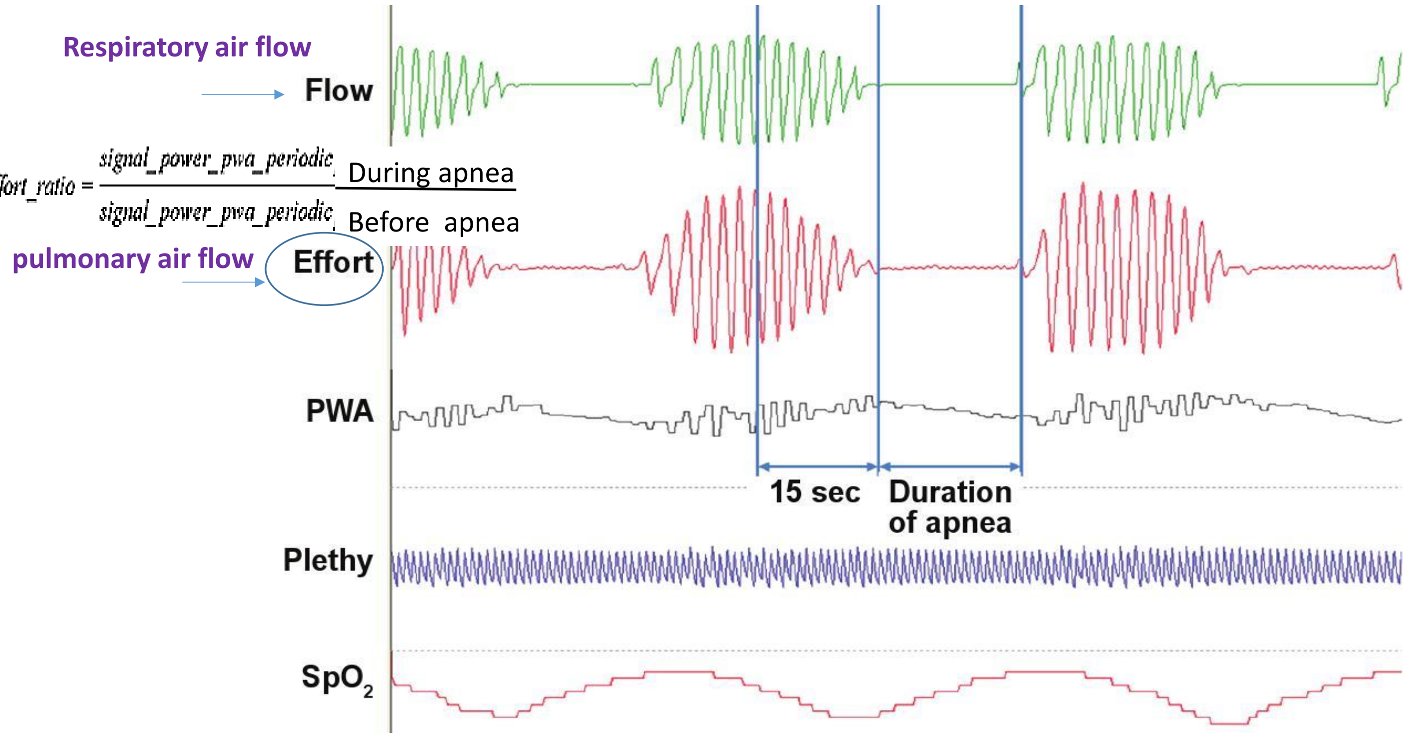
Snoring detection by nasal pressure recording

Fig. 1 Analysis of a nasal pressure recording from a patient with obstructive sleep apnea for the automatic detection of snoring: **a** raw nasal pressure recording including snoring events and **b** spectrogram analysis of the raw nasal pressure recording



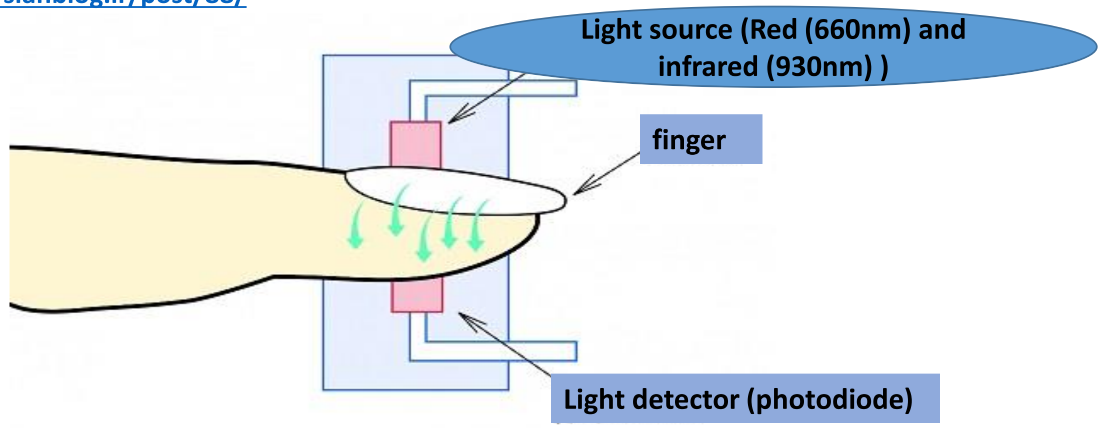
http://www.aasmnet.org/jcsm/ViewAbstract.aspx?pid=28672

$$effort\_ratio = \frac{signal\_power\_pwa\_periodic_{\text{During apnea}}}{signal\_power\_pwa\_periodic_{\text{Before apnea}}}$$



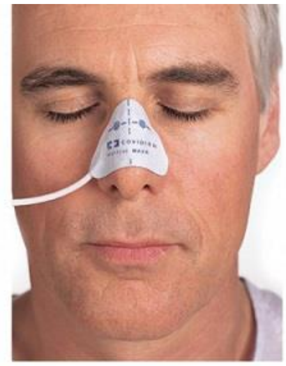
fingertip pulse oximeter(arterial oxygen saturation) (SpO2)

- The same mechanism as PWA indeed red light is added since red light is absorbed by hemoglobin
- Hemoglobin transmits oxygen to tissues
- Measuring the percent of hemoglobin saturated by oxygen (SpO2 or HbO2) for hypoxy (lower than 95%)
or hyperoxy detection
- 96 to 99% in healthy subject
- http://esfahannursing.persianblog.ir/post/88/



- Red is absorbed by hemoglobin.
- Infrared is absorbed by oxygen which is absorbed by hemoglobin.
- When spo2 is high, oxygen is attached to hemoglobin and when pressure or Spo2 is low, oxygen is released from hemoglobin.

Standard positioning



پروب پالس اکسیمتر روی بینی

Respiratory event

- Respiratory events (RE) during sleep induce **cortical arousals (A)** and marked changes in autonomic markers in sleep apnea syndrome (SAS).
- **cortical arousal**: alpha activity during at least 3 s but not more than 10 s according to the American Sleep Disorders Association (ASDA)
- **Apnea**
- **Hypopnea**
- **Snoring**
- **Detected by EEG, Pulse wave amplitude, Respiratory air flow, pulmonary air flow, oxygen saturation,**

Position

sensors

MDPI

Article

Sleep Monitoring Based on a Tri-Axial Accelerometer and a Pressure Sensor

Yunyoung Nam [1], Yeesock Kim [2] and Jinseok Lee [3,*]

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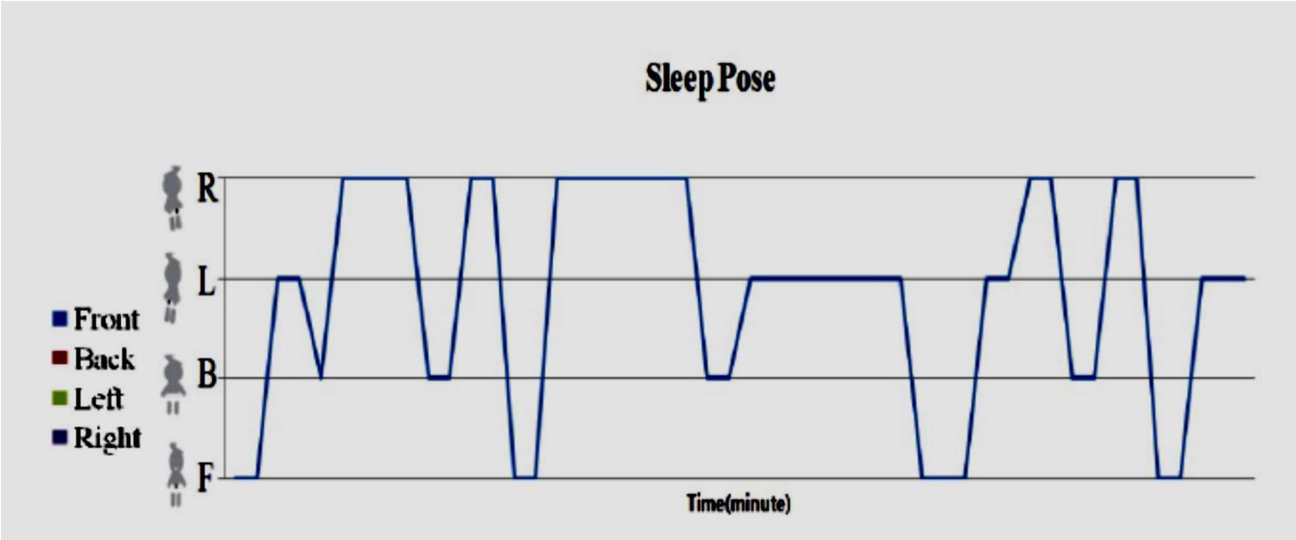
Position

- It is done by video (1frame/s or 15-20 for patients with seizure) recording or accelerometer.
- Many disorders such as apnea can be exacerbated by body orientation during sleep.
- Therefore, a valuable tool for accurate diagnosis and treatment of sleep disorders is a determination of body position on a continuous basis throughout the recording.
- **Simultaneously recorded EEG channels will determine if movements originate from wake or sleep and whether arousals correlate with limb or body movement.**

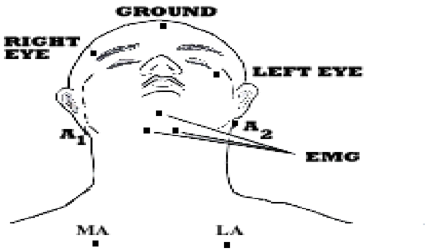
Position



Sensor		Specifications
three-axis accelerometer		Size: 5 cm, weight: 500 g, consumption current: 0.6 mA, resolution: 60 Hz, MSP430 micro controller for a micro controller (MCU): 16 bit reduced instruction set computer (RISC)

Chin EMG

- The recording of EMG activity in the chin area is used for determining the level of muscle tone, which significantly decreases during Stage R (REM) sleep and may also be reduced with sleep onset. This channel also provides supplemental information regarding patient movements and arousals and may be useful in distinguishing artifact in other channels.

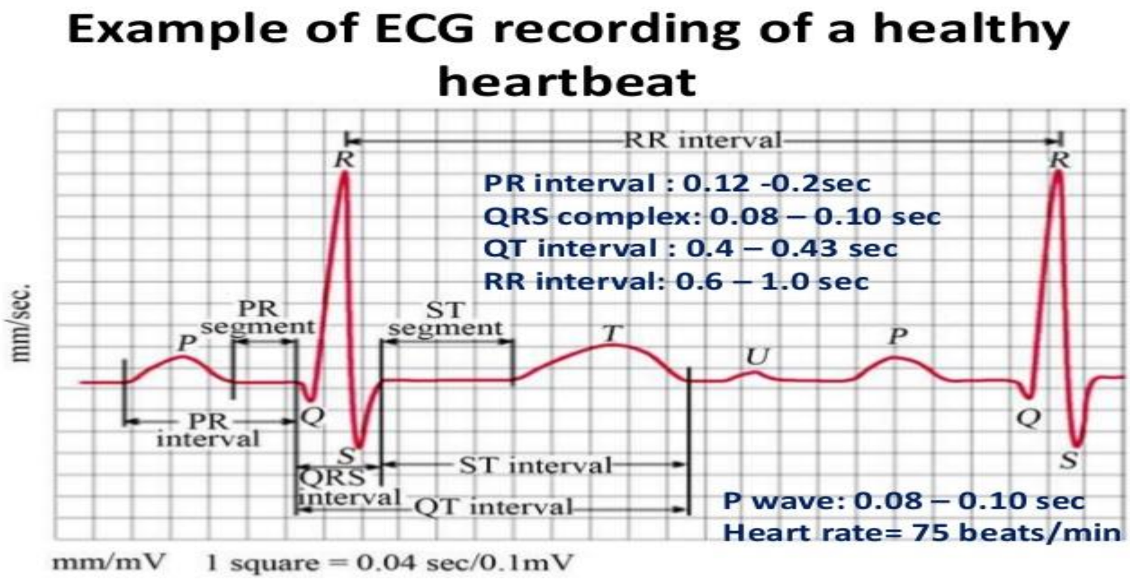


chin EMG

- **An EMG can reveal the presence of REM vs. NREM**
- **Three leads are placed on the chin (one in the front and center and the other two underneath and on the jawbone) and two are placed on the inside of each calf muscle 2-4cm apart.**
- **The facial muscles relax in REM sleep; therefore these EMG electrodes are crucial in correctly identifying REM sleep.**
- Place one chin EMG electrode on the face below the lower lip, on the ledge of the chin, this provides a stable area for attachment. For proper pickup of muscle activity, a distance of at least 3 cm must separate the electrodes.
- The other two EMG electrodes are placed on each side of the submentalis, which is a large muscle located underneath the chin. Having the participant activate this muscle may be helpful for determining the placement of the EMG electrodes. To activate the muscle, place your hand under the participant's chin, between the tip if the chin and the neck. Ask the participant to swallow. You will feel the submentalis muscle move.
- The electrodes are placed on each side of this muscle but at least 3 cm. apart from each other. Placing one electrode on the ledge of the chin (below the lower lip) and two electrodes on the belly of the submentalis muscle is also acceptable but not preferred.

ECG

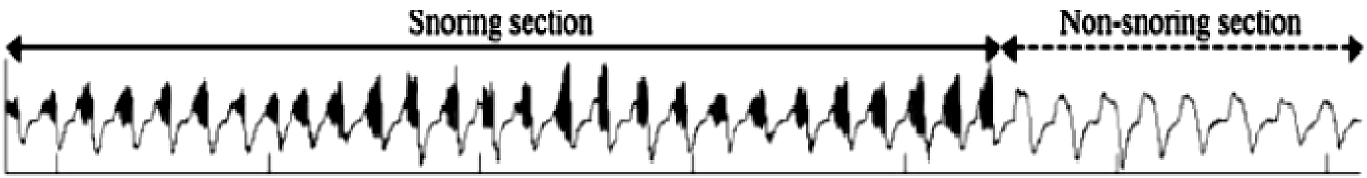
- **The ECG monitors the heart rhythm. A single ECG channel is sufficient for standard PSG monitoring**
- **One electrode is placed below the right clavicle parallel to the right shoulder and a second electrode is placed on the torso at the fourth intercostal space on the left side parallel to the left hip**



http://prajent.hubpages.com/hub/How-to-read-a-normal-ECGElectrocardiogram

Snoring definition

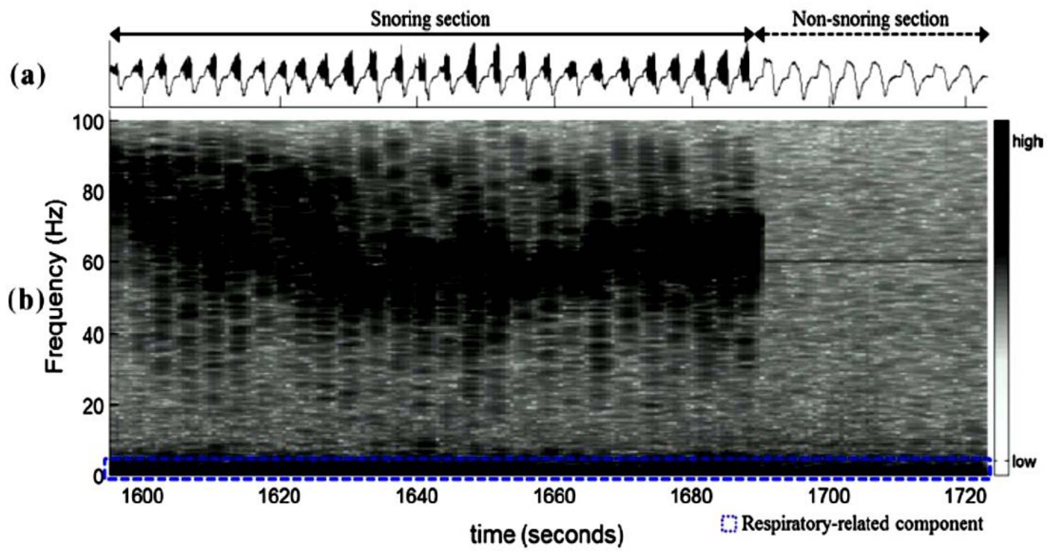
- **Snoring is the noisy sound generated during breathing by the vibration of soft tissue in the oropharynx due to partial collapse or obstruction of the upper airway**
- **Acoustic analysis using a microphone has noise and requires high sampling rate.**
- **using nasal pressure recordings recorded from a pressure transducer built into a nasal cannula during overnight sleep reflect the fluctuations in pressure caused by respiration**



- **Nasal pressure is used for the most sensitive and accurate detection of apneic events, especially hypopneas and respiratory effort-related arousals (RERA)**
- **habitual snoring is recognized as a major symptom of obstructive sleep apnea (OSA), which is characterized by repetitive obstruction of the upper airway during sleep**

Snoring definition

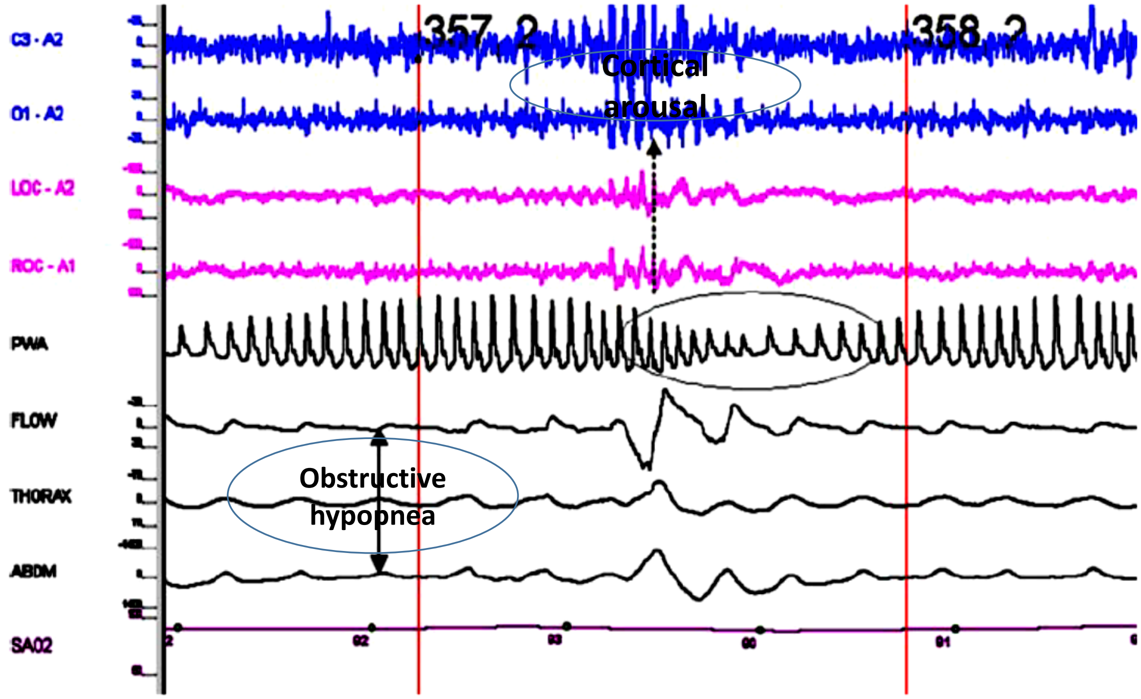
Fig. 1 Analysis of a nasal pressure recording from a patient with obstructive sleep apnea for the automatic detection of snoring: **a** raw nasal pressure recording including snoring events and **b** spectrogram analysis of the raw nasal pressure recording



Apnea definition

- An **obstructive apnea (OA)** : complete cessation of **airflow** for ≥10 s.
- An **obstructive hypopnea (OH)** : the occurrence of **airflow** drop ≥50% of the preceding baseline level during ≥10 s, or an airflow reduction of ≥30% lasting ≥10 s, and associated with either a ≥3% oxygen desaturation or a apnea (A)
- The **respiratory disturbance index (RDI)** was defined as all the OA and OH scored for one patient during the night divided by the **total sleep time (TST).**
- **cortical arousal**: alpha activity during at least 3 s but not more than 10 s according to the American Sleep Disorders Association (ASDA)

Fig. 1 PWA: tracing example of the PWA's decrease after a hypopnea and inducing a cortical arousal. The *oval* shows an example of a ≥30% variation of PWA. The *dashed arrow* shows a cortical arousal; the *double sense arrow* shows an obstructive hypopnea. This figure demonstrates also EEG (C3-A2, O1-A2), left and right electrooculogram (LOC, ROC), chest (THORAX) and abdominal (ABDM) piezo crystal belts, respiratory airflow (FLOW), and oxygen saturation (SAO2)



Periodic Leg movement (PLM) definition

- PLM is defined as follows:
- movements should last between 0.5 sec and 5 sec.
- The activity should be 8 millivolts above the resting EMG amplitude.
- **There should be 4 or 5 movements occurring successively. The time between movements (the time passing from the beginning of a movement until the beginning of another movement) should not be shorter than 5 sec and longer than 90 sec**
- Leg movements can be seen as a consequence of breathing disorders during sleep.
- Towards end of an apnea period, leg movement can be observed as a reflexive response to hypoxia and awakening.
- Leg movements can also be observed as a separate event, independent of apnea periods

Electrode montage

- Two electrodes are placed longitudinally on the anterior tibialis muscle of each leg 2-3 cm apart and secured with tape to record each leg separately.
- Although, one electrode can be placed on each leg and referenced together to record both legs on one channel, this is not optimal and may affect scoring periodic limb movements according to AASM published guidelines.
-

PSG devices

Device	electrode	Signal transmition	automatic detection/channels
Somt´e PSG by Compumedics	wired	Bluetooth (up to 10m)	Yes / six EEG, two EOG and two EMG channels (up to 24 hours of recording)
Sapphire PSG by Clevemed		wireless (up to 100 feet away)	Yes (crystal PSG software)/six EEG, two EOG and two chin EMG (12 hours of continuous recording)
DREAM by Medatec		wireless	Yes (Brainnet software)/33 channels
Morpheus by Micromed		wired/wireless	No (just online viewing)/ 12 EEG channel
Embletta Gold by EMBLA			Yes (with custom defined rules)/ a single EEG and an EOG channel (recorded for up to 24 hours)
Xltek PSG - Home Sleep by Natus		USB cable	No (Sleepworks software just for reviewing data)/24 EEG channels
Harmonie-S PSG System by Stellate (Natus)			Yes (manual scoring and real-time software for spindle and REM detection)/ 44 channels
NOX-T2 Portable Sleep Monitor by CareFusion		USB	No/ any two of the bipolar EEG and EMG channels (up to 24 hours on single charge battery)
SOMNOwatch plus EEG6 by SOMNOmedics	wired	USB	Yes (limited detection of sleep events)/four EEG, two EOG and one EMG channel for up to 46 hours.
g.Nautilus by g.tec		wireless	No/ 8, 16 or 32 channel up to 10 hours continuous recording with a range of 10 metres

PSG devices

Device	electrode	Signal transmition	automatic detection/channels
Vitaport 4 PSG-lite by Temec			No (software viewer to manually score sleep stages)/ single EEG, EOG and EMG channel (up to 16 hours of data on a single charge of its battery)
eXea PSG 3 by Bitmed (Sibel Group)			No/ 12 ExG differential channels to be recorded for up to 29 hours
BW3 PSG by Sleepvirtual			Yes (BWAnalysis PSG software)/ up to 50 channels and has ethernet connectivity to analyse data using the accompanying BWAnalysis PSG software
AURA PSG Ambulatory Systems by Grass Technologies		wireless	Yes (Twin software)/ three EEG, one EOG and two EMG (up to 12 hours with a rechargeable 3.6 V battery)
Sleep Profiler by Advanced Brain Monitoring			Yes (via a web based interface)/ 3 frontal EEG channel worn on the forehead
Zeo Sleep Manager	Wireless headband		Yes (Zeo software for Wake, Light sleep, Deep sleep and REM detection)/ forehead recording electrodes (not a medical device and has been designed for consumer use for sleep tracking)

PSG scoring softwares (offline and web-based)

PSG softwares	Type/company	electrodes/ staging
Michele Sleep Scoring	web-based/	/scored data in 15 minutes which can be edited or reviewed manually before generating the final report. **(Each 30-second epoch of data will be designated as being in stage W (awake), REM sleep, N1 Non-REM sleep, N2 Non-REM sleep, or N3 Non-REM sleep)**
Aseega	web-based/	**One or more EEG channels**/Once data is uploaded, **Aseega takes 5 minutes to perform the analysis and generate reports**
Somnolyzer 24×7	**web-based/ somnomedics**	**Full sleep staging (wake, REM, Deep Sleep)/adds expert review process on top of automated scoring to minimise errors and includes full sleep staging**
N2 Sleep	web-based/	Manually scored data with reports in 48 hours
FASS (Fully Automated Sleep Stager)	**Offline/Grass Technologies**	**EEG, EOG and chin EMG/manually changed threshold for each subject (however, works with the PSG systems made by Grass Technologies only)**
Morpheus - Automated Sleep Testing Management	**web-based/ Widemed**	**/Automatically score sleep data that is accessible from anywhere using internet.**
SleepView Web Portal	**web-based/ CleveMed**	**/manual scoring** of sleep stages by certified sleep physicians (SpO2, heart rate, body position, and CPAP level)

web-based sleep scoring service

that allows sleep technologists to upload recorded data

- Michele Sleep Scoring http://www.michelesleepscoring.com/(Each 30-second epoch of data will be designated as being in stage W (awake), REM sleep, N1 Non-REM sleep, N2 Non-REM sleep, or N3 Non-REM sleep)
- Aseega (takes 5 minutes to perform the analysis and generate reports. Aseega can score sleep stages using one or more channels of EEG.) https://www.aseegaonline.com/pub/index.html
- Somnolyzer 24×7 (full sleep staging with micro-events detection>>Somnowatch.pdf(wake, REM, Deep Sleep)

http://www.healthcare.philips.com/main/homehealth/sleep/somnolyzer/

- N2 Sleep)manually scoring and 48 hours time of response) http://www.n2sleep.com/
- FASS (Fully Automated Sleep Stager using EEG, EOG and chin EMG data and allows the thresholds to be manually changed for each subject, however works with the PSG systems made by Grass Technologies only)

http://www.grasstechnologies.com/

- Morpheus - Automated Sleep Testing Management(score sleep data that is accessible from anywhere using internet) http://www.widemed.com/
- SleepView Web Portal (a web-based solution by CleveMed for manual scoring of sleep stages by certified sleep physicians) http://www.clevemed.com/ PSG and Home Sleep Study Scoring Software

Michele Sleep Scoring

1*. Identification of sleep stages*

analysis of the frequency profile of the EEG, presence of EEG spindles, k complexes and delta waves, level of chin EMG, and eye movements. Each 30-second epoch of data will be designated as being in stage W (awake), REM sleep, N1 Non-REM sleep, N2 Non-REM sleep, or N3 Non-REM sleep.

2. *Detection of arousals*: Each 30-second epoch is searched for the presence of one or more arousals

Whenever an arousal is found, it will be classified as respiratory-related, leg movement-related or spontaneous, based on the temporal relation of the arousal to preceding events

3. *Detection of respiratory events*: Each 30-second epoch is searched for the presence of one or more respiratory events characterized by reduction (hypopnea) or complete cessation (apnea) of airflow in and out of the patient or Respiratory Effort Related Arousal (RERA)

Epoch size and signal duration

- The standard epoch size for scoring of sleep stages according to both R&K and AASM classifications is 30 seconds.
- PhysioNet database includes hypnograms with standard 30s epoch size while the two DREAMS databases listed earlier have been scored at a non-standard interval of 5 s.

Automatic detection methods

- Feature extraction (each epoch of 30s is divided to sub-epochs of 2s and for each sub-epoch spectral power in every 2Hz frequency band from 0 to 30 Hz is calculated)
- Classification
- C.-C. Chang and C.-J. Lin, “LIBSVM: A library for support vector machines,” ACM Transactions on Intelligent Systems and Technology, vol. 2, pp. 27:1–27:27, 2011, software available at http://www.csie.ntu.edu.tw/~cjlin/libsvm

A general Method of feature extraction

- The algorithm uses data from one EEG (frontal) and one EOG channel which are split into epochs of 30 seconds.
- **Each epoch is further divided into 2-second blocks and transformed to frequency domain using Fast Fourier Transform (FFT).**
- For each block of 2s EEG, spectral power in every 2 Hz frequency bin from 0-30 Hz range is calculated i.e. 0-2 Hz, 2-4 Hz, 4-6 Hz and so on.
- For the corresponding EOG block, spectral power within 0-6 Hz is also calculated similarly for every 2 Hz frequency interval.
- Subsequently, the average of every feature is calculated within a 30s epoch.
- Since each feature is calculated for a 2s block, there are 15 such values within an epoch to calculate the average.
- This results in 18 features overall (15 EEG and 3 EOG (15 and 3 are feature vector length)) computed for an epoch and are classified using a Support Vector Machine (SVM)

Diagnosis by REM

- **S. A. Imtiaz and E. Rodriguez-Villegas, "A Low Computational Cost Algorithm for REM Sleep Detection Using Single Channel EEG," Annals of Biomedical Engineering, vol. 42, no. 11, pp. 2344–2359, 2014**
- **EMG and EOG** are both important in sleep staging, particularly in **REM** stage
- Using one channel EEG for REM detection needs complicated feature extractors and higher implementation power
- Its detection, **both onset and duration**, are very important for the diagnosis of certain sleep disorders including narcolepsy and REM behaviour disorder (RBD)
- Observing the muscle activity during REM stage used for the diagnosis of RBD→ early marker for neurological disorders including Parkinson's disease[1]
- duration of REM sleep in the first cycle has been shown to correlate negatively with mood improvement on wake-up in patients with major depression

Diagnosis by REM

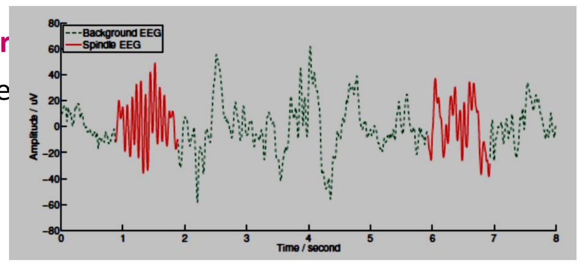
- latency from Wake to the onset of first REM cycle and the pattern of occurrence of subsequent cycles throughout the night is commonly used in the **diagnosis of narcolepsy**
- REM sleep deprivation can be used therapeutically for the improvement of depression symptoms.
- **Apart from REM, all the stages of sleep can be identified from EEG channels only**

Materials for REM Detection

- including two EOG, three EEG (Fp1-A2, Cz-A1 and O1-A2) and one sub-mental EMG channel for each subject
- data from each EEG channel was first re-sampled to a sampling frequency of 256 Hz using the **resample** function in Matlab
- **Bandpass** filtering [0.16 50]Hz
- The EEG data was split into 2-second long non-overlapping blocks (sub-epochs) and subsequently transformed to the frequency domain with a 512-point Fast Fourier Transform (**FFT**), hence obtaining a resolution of 0.5 Hz.
- The **magnitude** and **frequency coefficients** were then **used to compute various features for REM detection** in different frequency bands.

Spindle and K-complex detection

- Sleep spindle is a micro-event of sleep EEG and is a characteristic of NREM stages of sleep.
- According to AASM, a sleep spindle is defined as “a train of distinct waves with frequency 11-16 Hz (most commonly 12-14 Hz) with a duration ≥ 0.5 seconds”
- However, different methods use a wider or narrower range for detection
- **The amplitude of spindles is also a varying quantity in literature with authors having used values ranging from 8 µV to 25 µV in order to determine a suitable threshold for detection**
- They are bilateral and synchronous in their appearance, with amplitude up to 30 µV
- Typical number of 200 to 1000 during an overnight sleep
- They are known to play a fundamental role in memory consolidation during sleep
- related to the secretion of melatonin, that helps in maintaining circadian rhythms in the body
- having an active role in the progression of sleep to slow wave stages (SWS)
- relevant indicator for early stage development of CNS (cognitive)
- **decreased spindle activity during sleep in youths with major depressive disorder (MDD)** and those with high risk for the disorder
- sleep spindles are **an indicator**
- direct correlation between the



Review of methods

- Papers:
- Automatic detection of sleep spindles using Teager energy and spectral edge frequency
- An Automatic Sleep Spindle Detector based on WT, STFT and WMSD

The DREAMS Sleep Spindles Database. **two EOG, three EEG and one EMG channels**

- **sampling frequency is 200 Hz and the annotated channel is Cz-A1 except for subjects 1 and 3, for whom the annotated channel is C3-A1 and the sampling frequency 100 Hz and 50 Hz respectively**
- **first resampling all signals to a uniform sampling rate of 256 Hz**

- PRANA software package by PhiTools results an individual adjustment method for bandpass filtering and achieved a sensitivity of 92.9% with selectivity of 41.6%
- The software's performance was validated to show sensitivity and specificity of 98.96% and 88.49% respectively when tested on a subset of N2 stage segments from 10 subjects
- Improvement of the visual scoring tools for sleep stages, and respiratory, motor and arousal events
- Automated reviewing montage generation with channel recognition based on a dictionary of standard channel labels.

Table C.2: *Percentage of sleep stages in test data*

Subject / Sleep Stage %	W	N1	N2	N3	R
1	15.56	3.33	61.11	20	0
2	1.11	5.56	55.56	37.78	0
3	8.89	24.44	62.22	4.44	0
4	30	22.22	40	7.78	0
5	11.11	2.22	57.78	38.89	0
6	3.33	3.33	61.11	32.33	0

Table C.3: *Sleep spindles in each stage of the test data*

Subject / Spindles	Total	W	N1	N2	N3	R
1	134	0	0	101	33	0
2	77	0	1	68	8	0
3	44	4	0	38	2	0
4	63	31	5	25	2	0
5	103	0	0	82	21	0
6	117	0	0	90	27	0

An Automatic Sleep Spindle Detector based on WT, STFT and WMSD

Short time fourier transform

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

The magnitude squared of the STFT yields the spectrogram of the signal:

$$spectrogram\{x[n]\} = |X(\tau,\omega)|^2$$

- **The presence of peak in the spectrogram (t=0.5s and f=15Hz), corresponding to a sleep spindle (SS).**

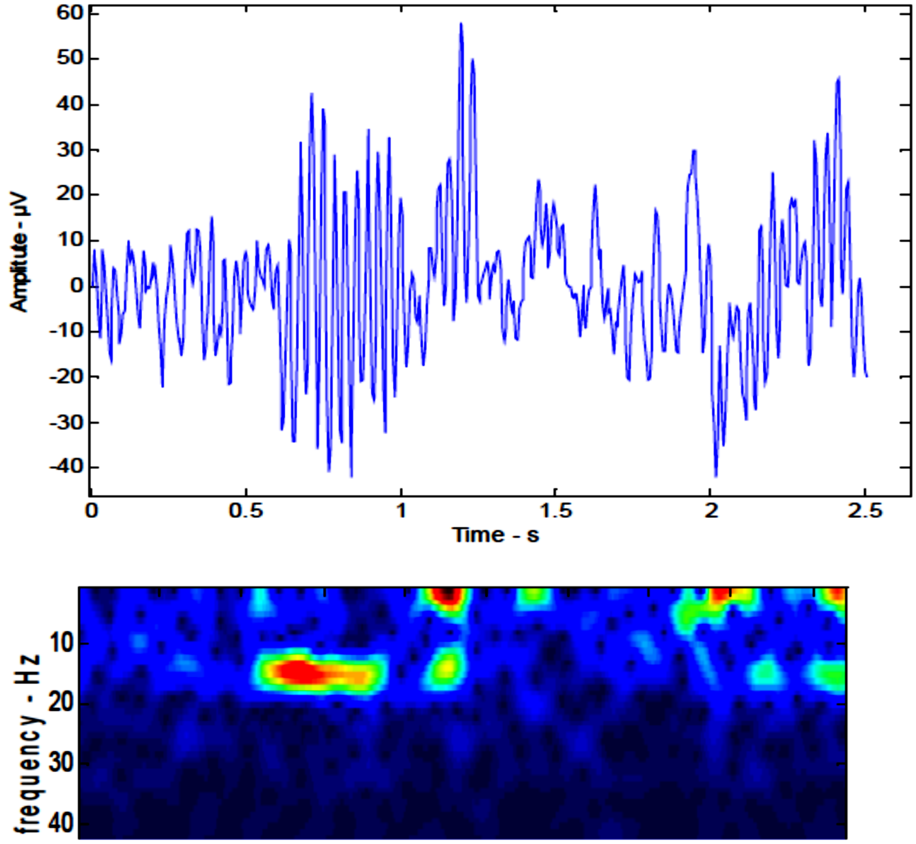


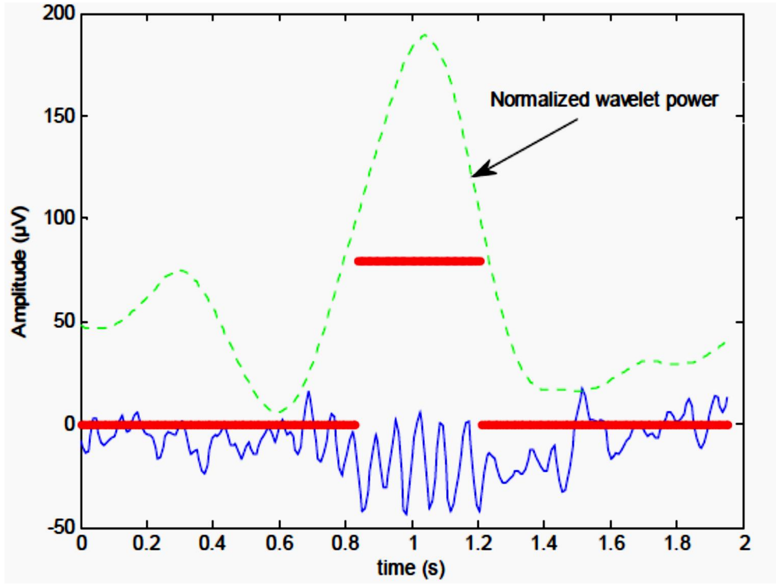
Fig. 2 Example of SS detection using STFT

Wavelet Transform (WT)

- Complex Morlet WT was used.
- A SS is detected using the **normalized wavelet power** (dashed line).

$$CWTx(a,b) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{\infty} x(t)^* \left(\frac{t-b}{a}\right) dt$$

$$w(a,b) = W^2(a,b)/\sigma^2$$



Wave Morphology for Spindle Detection (WMSD)

- The presence of a sleep spindle should not be defined unless it is of at least 0.5sec duration, i.e., one should be able to count 6 or 7 distinct waves within the half-second period.
- Because the term “sleep spindle” has been widely used in sleep research, this term will be retained. The term should be used only to describe activity between 12 and 14 cps
- **a) Detection of peaks in the signal (maxima and minima), based on a defined threshold, thus, eliminating small peaks;**
- **b) Determination of extreme to extreme time distance and conversion to frequency:** $f = \frac{1}{T}$.
- **c) Verification if the determined frequencies lie in the SS range (11-15 Hz);**
- **d) If there are more than 12 consecutive peaks (6 maxima and 6 minima) in the SS frequency band a spindle is marked.**
- **The whole process mimics the visual detection mechanism.**
- **If there are not enough consecutive points marked as belonging to a SS, in order to last at least 0.5 seconds, they are considered as non-spindle.**

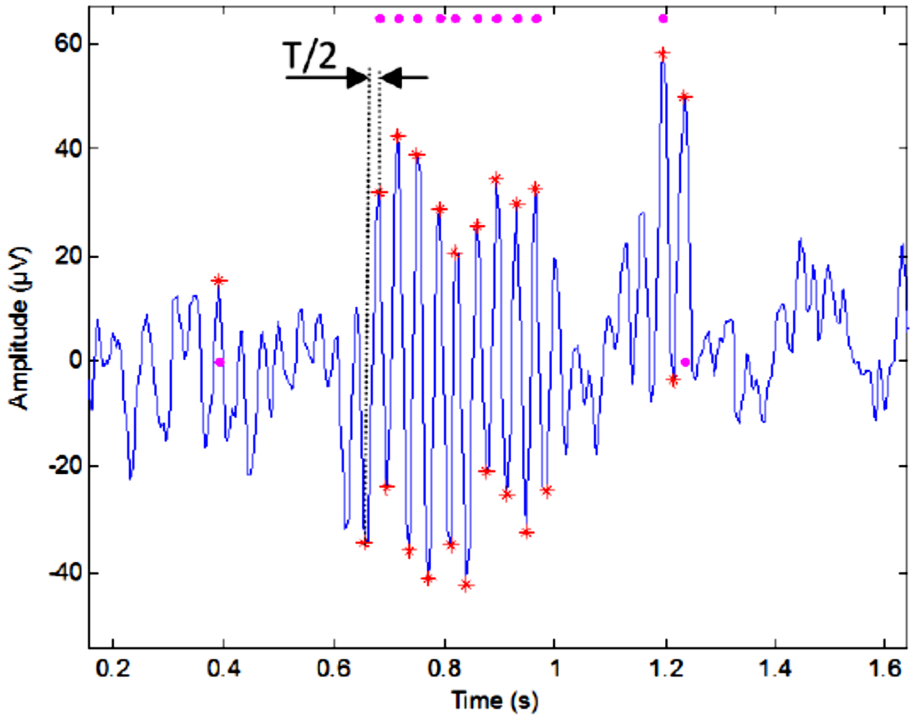


Fig. 4 Example of SS detection using WMSD

Mixed detection using WT, STFT and WMSD, the ALL algorithm

- we use a vector to characterize the signal (same length as the sampled signal).This vector defines each point as belonging to a SS or not.
- The mixed result is computed, i.e., a point is considered belonging to a SS if it is marked as SS in WT, STFT and WMSD algorithms
- **If there are not enough consecutive points marked as belonging to a SS, in order to last at least 0.5 seconds, they are considered as non-spindle.**

$$Sensitivity = SEN = \frac{TP}{TP + FN},$$

$$Specificity = SPE = \frac{TN}{FP + TN},$$

$$Accuracy = ACC = \frac{TP + TN}{TP + TN + FP + FN}.$$

several values have been used in order to obtain representative curves of the sensitivity vs specificity Relationship (ROC curve)

From C3-A2 channel, two specialists scored all concordant spindles, using the RK68 spindle definition

In the STFT case, the threshold value corresponds to the cumulative value of peaks in the spectrogram.

In the WMSD algorithm, a point is considered a maximum peak if it has the maximal value, and was preceded (to the left) by a value lower than the threshold defined.

The Normalized Wavelet Power amplitude is used as threshold in the WT case

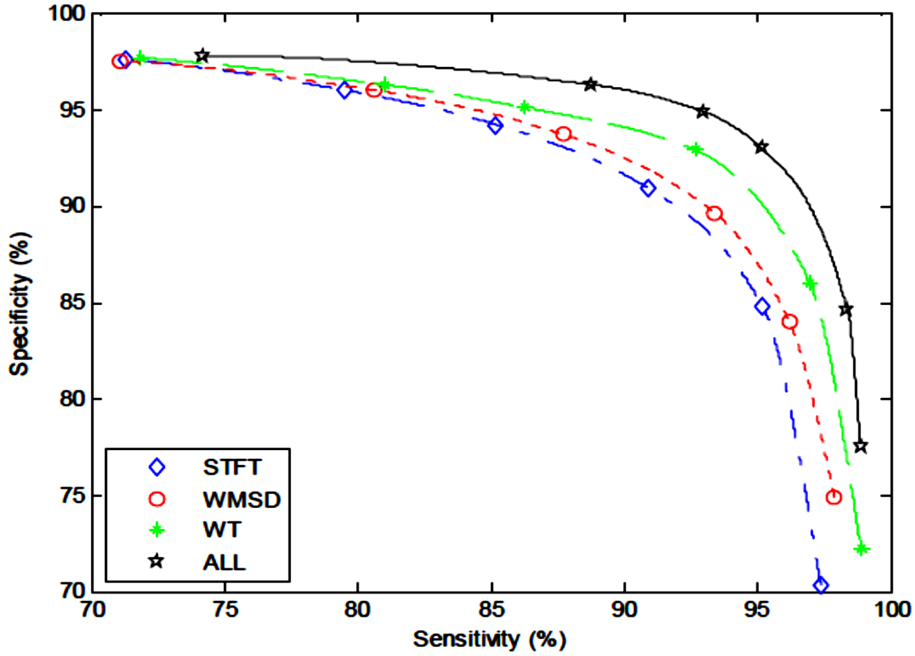


Fig. 5 Sensitivity x Specificity curves

For a better performance comparison, threshold values have been chosen so that sensitivity equals specificity. Both STFT and WMSD produced good results in sleep spindle detection. Sensibility and specificity for these algorithms is around 91%. **The WT performed slightly better around 93% sensitivity and specificity.** combination of the previous detection algorithms improved to a sensitivity and specificity of 94%.

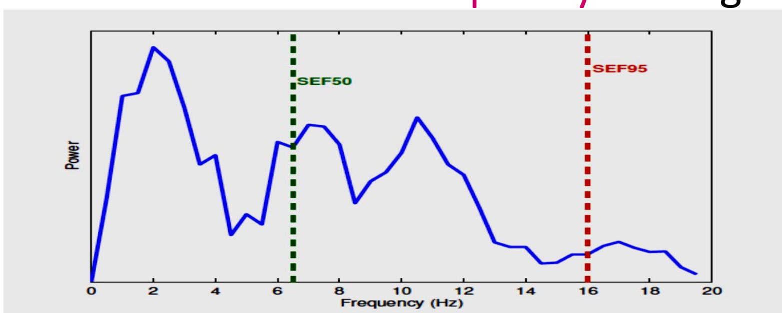
Other algorithms for automatic detection of Spindle

- **Automatic detection of sleep spindles using Teager energy and spectral edge frequency**
- The first algorithm: using **Teager energy and spectral edge frequency** to mark sleep spindles.
- The second algorithm: the use of **line length**, an efficient and low-complexity time domain feature, for automatic detection of sleep spindles

- **Other techniques such as matching pursuit ,higher order statistics and independent component analysis have been used for feature extraction**

Spectral Edge Frequency (SEF)

- **Spectral Edge Frequency (SEF)** is **the frequency** below which a certain fraction of the signal power is contained.
- **SEF50 (95):** SEF at 50 (95)% (SEF50) is the lowest frequency below which half (95%) of the signal power is present.
- SEF50 is equivalent to the median frequency of a signal.



An illustration of Spectral Edge Frequency (SEF) at 50% and 95% of the signal power in the 0-20 Hz frequency range.

- **computed from the FFT coefficients**
- n is the total number of FFT coefficients
- **X: the index to solve the equation for**
- The required frequency or the xth frequency

from the array of FFT frequency components

$$\sum_{i=1}^{x} |mag_i|^2 = 0.50 \times \sum_{i=1}^{n} |mag_i|^2$$

$$SEF50 = freq(x)$$

$$\sum_{i=1}^{x} |mag_i|^2 = 0.95 \times \sum_{i=1}^{n} |mag_i|^2$$

$$SEF95 = freq(x)$$

SEF50 is analysed in the 8-15 Hz frequency range since it covers both alpha (8-13 Hz) and spindle frequency range.
spindle-like alpha rhythms (8-13Hz) have lower median frequency in the range [8 15] Hz and therefore this feature will be used to reduce the number of false detections.

automatic detection of Spindle (one channel)

- **An automatically detected spindle is marked as True Positive (TP) if it overlaps at least partially with the reference spindle at that time.**
- **If no point of the detected spindle overlaps with the reference, it is considered as a false detection and marked as False Positive (FP).**
- **The number of spindles that went undetected by the algorithm are classified as False Negatives (FN).**
- **True Negatives (TN)** ⟹

$$TN = \frac{Total\ record\ duration}{Avg.\ detected\ spindle\ duration} - TP - FP - FN$$

$$Sensitivity = \frac{TP}{TP + FN}$$

$$Specificity = \frac{TN}{TN + FP}$$

- **Teager energy operator (TEO):**
- **a non-linear operator that can estimate the energy of a signal on-the-fly**
- **Teager energy operator, when applied to EEG signals, appropriately filtered for sleep spindle detection, demonstrates a rise in energy level when a spindle appears**
- **Well tracking sudden change in frequency and the waxing and waning amplitude of sleep spindles while suppressing soft transition**
- **SEF50: SEF50 is analysed in the 8-15 Hz frequency range since it covers both alpha (8-13 Hz) and spindle frequency range**
- **spindle-like alpha rhythms have lower median frequency in this range and therefore this feature will be used to reduce the number of false detections**

$$\psi[x(n)] = x^2(n) - x(n+1)x(n-1)$$

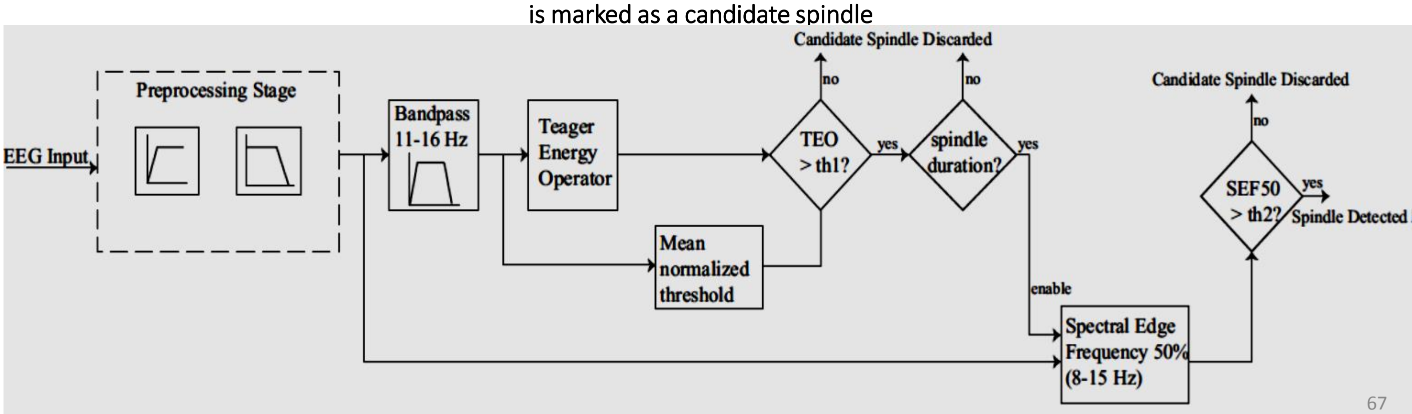
Spindle detection algorithm

Preprocessing Stage:

EEG input signal is first filtered using a first order high-pass filter with a cut-off frequency of 0.16 Hz, followed by a second order low-pass filter with 50 Hz as the cut-off frequency at the preprocessing stage. The input signal is then filtered with a fourth order Butterworth band-pass filter with lower and upper cutoff frequencies 11 Hz and 16 Hz

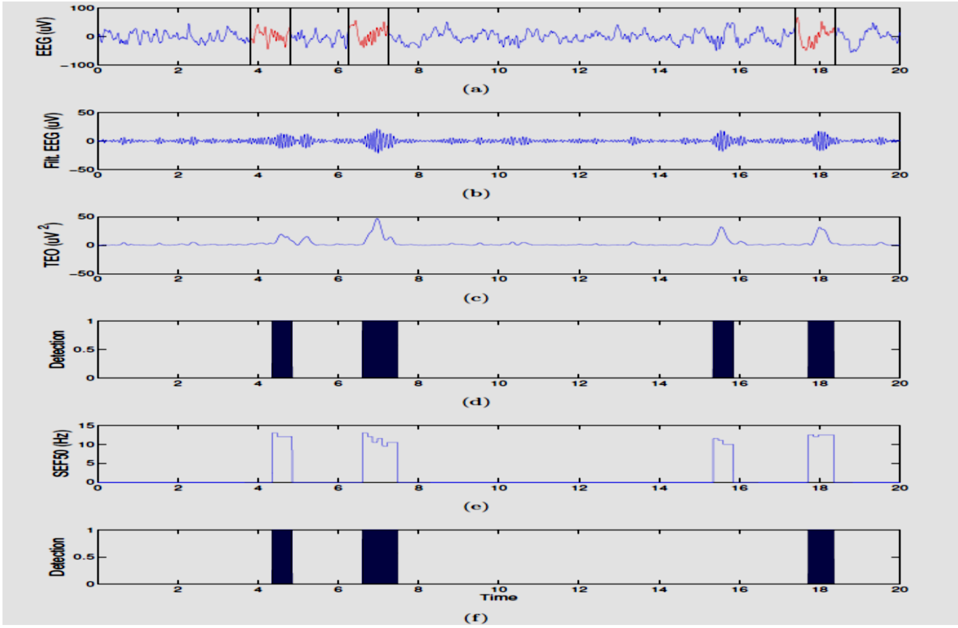
This filtered signal is then segmented into epochs of 0.25 seconds with 50% overlap between successive ones.

If the Teager energy values of all samples within the epoch >threshold, Then the epoch is marked as a candidate spindle



- **when an epoch is marked as a candidate spindle, the epochs immediately preceding and succeeding the current epoch are also marked as part of the current spindle thus creating a candidate spindle zone.**
- The threshold is determined by **taking the mean value of the Teager energy over 60 previous epochs.**
- **The number of epochs and multiplication factor for threshold are determined empirically**
- **If duration of a candidate spindle >3s or duration of a candidate spindle <0.5 seconds,** Then the candidate is discarded and not subject to any further analysis.

- **Frequency content of each epoch in the preprocessed signal, corresponding to the epoch in candidate spindle zone, is analysed using a 512-point FFT. SEF50 for each epoch in the 8-15 Hz band is computed and averaged over all epochs in candidate zone.**
- **The threshold for SEF50 is fixed at 10.7 Hz for all test cases**



(a) EEG input with three spindles marked between vertical lines;
(b) 11-16 Hz filtering output;
(c) TEO output showing high activity in the spindle areas;
(d)detected candidate spindles;
(e) SEF50 for each epoch in the candidate spindle zone;
(f) correctly detected spindles (removing one false candidate spindle)

TABLE I: *Spindle detection algorithm performance*

Subject	Total Spindles	True Pos.	Sens. (%)	Spec. (%)
1	134	111	82.8	96.7
2	77	58	75.3	98.3
3	44	39	88.6	97.7
4	63	38	60.3	97.8
5	103	87	84.5	97.1
6	117	99	84.6	98.1
All	538	432	80.3	97.6

- [10] "Automatic sleep spindles detection overview and development of a standard proposal assessment method," in *IEEE EMBC*, Boston, September 2011.
- [11] "Automated sleep-spindle detection in healthy children polysomnograms," *IEEE Trans. Biomed. Eng.*, vol. 57, no. 9, pp. 2135–46, 2010.

Comparison of this work with other algorithms

Method	Sens. (%)	Spec. (%)
[10]	70.2	98.6
[13]	75.1	96.7
This work	80.3	97.6

Spindle detection: Algorithm II (fast and low complexity)

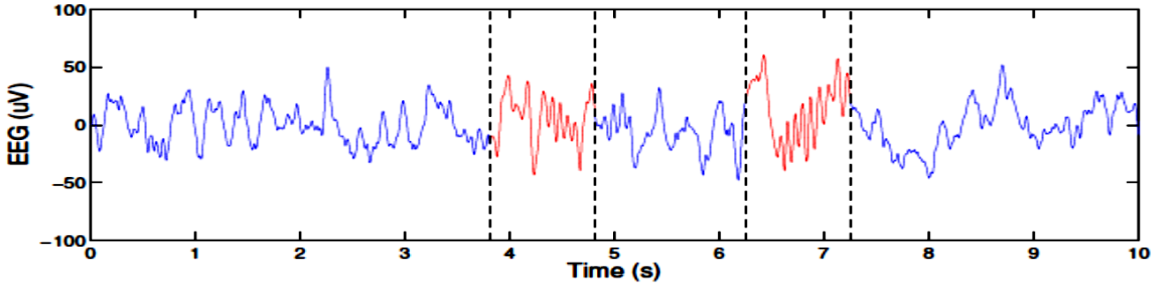
- Esteller et al. introduced line length as a low-complexity feature for seizure onset detection.
- **It is the sum of absolute differences between subsequent samples and is defined by the following equation where LL is the line length, x is the input signal and N is the number of samples in the signal (or a block of signal under analysis).**

$$LL = \sum_{n=1}^{N} |x(n-1) - x(n)|$$

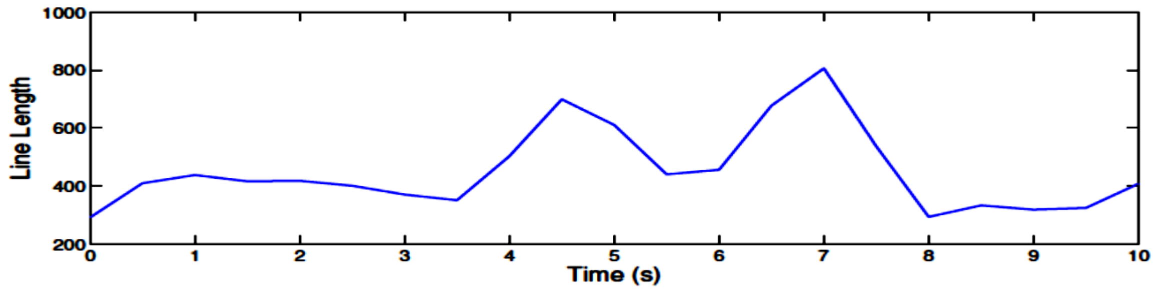
- **EEG signal for a single channel is used as input to the algorithm.**

1. **a second order Butterworth bandpass filter [11 16] Hz**
2. **Line length is calculated in blocks of 1 second (with 50% overlap)**
3. **It is normalized by a factor which is obtained by taking the median line length value of the last 80 epochs**
4. **The number of epochs to use in the computation of the median was determined empirically by trying out various values.**
5. **This normalised value is then compared against a detection threshold K.**
6. **If the value is found to be greater than K, the epoch is marked as spindle. The detection threshold also controls the sensitivity of the algorithm**

- **occurrence of a spindle in the original signal leads to a rise in the line length.**

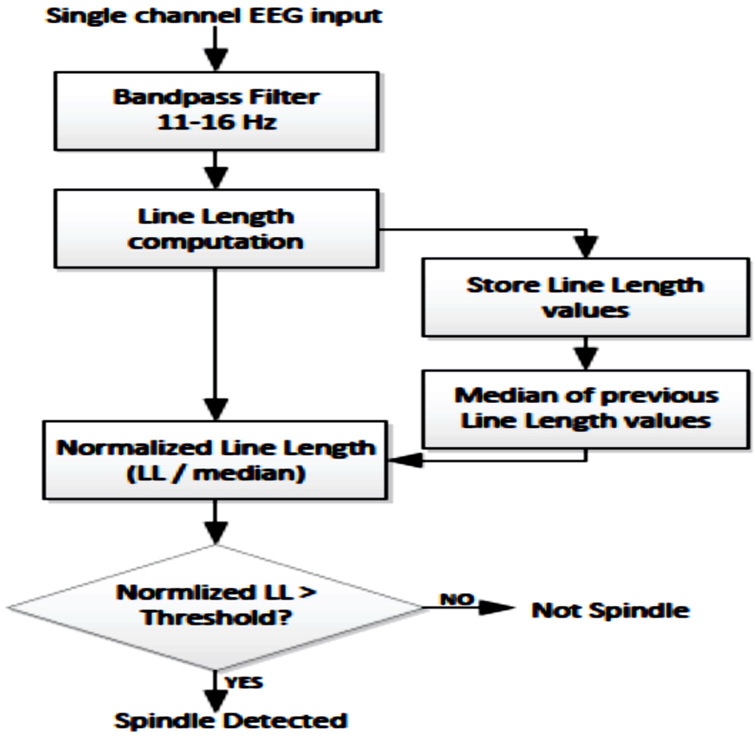


(a)



(b)

- (a) EEG signal with two sleep spindles marked between vertical lines; (b) Line length of the EEG signal (**calculated in blocks of 1 second**) showing higher values during spindle occurrence



Block diagram of sleep spindle detection Algorithm II

Table C.7: *Spindle detection performance of Algorithm II*

Subject	Total Spindles	True Pos.	Sens. (%)	Spec. (%)
1	134	121	90.3	83.4
2	77	62	80.5	94.0
3	44	44	100	85.8
4	63	28	44.4	88.1
5	103	87	84.5	88.2
6	117	108	92.3	86.5
All	538	450	83.6	87.9

Table C.8: *Sleep Spindles (SS) detected in each sleep stage - Algorithm II*

Sub	SS_{det}	SS_{Wake}	SS_{N1}	SS_{N2}	SS_{N3}	SS_{REM}
1	202	13	1	141	47	0
2	99	0	2	84	13	0
3	126	11	11	95	9	0
4	87	16	23	42	6	0
5	154	7	0	103	44	0
6	173	0	1	114	58	0
Total	841	47	38	579	177	0

conclusion

- The first algorithm using Teager energy has been developed to achieve a high detection performance.
- Its first stage involves a highly sensitive and simple non-linear operator and with a normalised threshold it obviates the need for any patient specific adjustment externally.
- The second stage which is highly specific and involves computation of FFT is called upon only when there are candidate spindles thus reducing the processing load making this algorithm suitable for online implementation.
- The second algorithm has been developed with power consumption as the main constraint as well as demonstrating the use of line length as a novel feature for spindle detection.
- Its spindle detection sensitivity was slightly higher (with more false positives) than the first algorithm
- **The overall system power consumption was 56.7 µW with only 10% of microcontroller active time** 232 **operating at clock frequency of 1 MHz.**
- **This shows that line length is not only useful for getting a good spindle detection performance but also a very efficient feature for use in resource-constrained wearable systems.**

Literature review summary for automatic sleep spindle detection

Ref	Data	Channels	Method	Result
[13]	689 epochs, 344.5 minutes	1×EEG	STFT features with ANN and SVM	Accuracy (ANN): 88.7% Accuracy (SVM): 95.4%
[14]	6 subjects, 264 spindles	Multiple	AR modelling coefficients with ANN and SVM	Accuracy (ANN): 89.1% Accuracy (SVM): 94.6%

Literature review summary for automatic sleep spindle detection

Ref	Data	Channels	Method	Result
[16]	6 subjects, 575 spindles	1×EEG	Bandpass filtering with a varying amplitude threshold and maximum frequency range	Sen: 78.4% Spe: 88.6%
[6]	725 spindles	5×EEG	Matching pursuit	Sen: 81.6% Spe: 81.6%
[24]	12 subjects, 6043 spindles	4×EEG	FFT spectrum and amplitude analysis	Sen: 70% Spe: 98.6%
[19]	12 subjects, 2140 spindles	multiple	Individually adjusted bandpass filtering	Sen: 92.9% Sel: 41.6%
[22]	16 subjects	1×EEG	Max frequency, Teager energy and harmonic decomposition	Sen: 96.2% Spe: 95.4%
[23]	95 spindles	N/A	Teager energy and wavelet packet energy ratio	Sen: 93.9%
[21]	10 subjects	1×EEG	Manual amplitude threshold for PRANA software	Sen: 99% Spe: 88.5%
[15]	56 children, 40412 spindles	2×EEG	FFT, power thresholding, EMD signal decomposition, HHT	Sen: 88.2% Spe: 89.7% Sel: 88.1%
[17]	6 subjects, 537 spindles	1×EEG	Bandpass filtering with thresholding, relative power, AR modelling	Sen: 70.2% Spe: 98.6%
[25]	13 subjects, 882 spindles	2×EEG	Bandpass filtering with thresholding and power features	Sen: 84.6% Spe: 95.3%
[26]	5 children (1), 6 adults (2)	1×EEG	Amplitude-frequency normal modelling	Sen1: 78% Spe1: 94% Sen2: 75% Spe2: 97%

K-complex detection

REM detection
Electrode montage

channels Fp1-A2 and EOG1

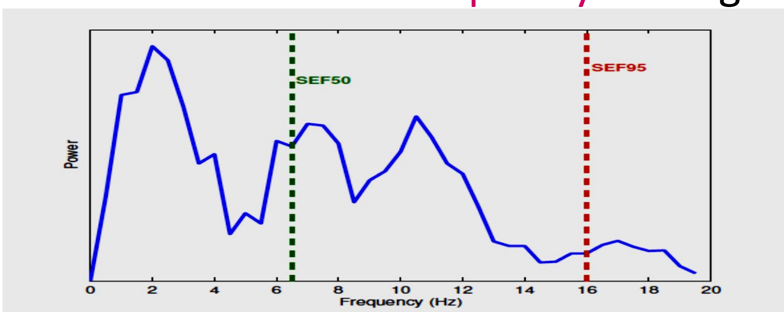
Distinguishing REM from N1 and Non-REM

- **There exists some differences in spectral power during REM stage around a certain frequency range.**
- Lower spectral power in REM in the 12-16 Hz band when compared to NREM stages (except N1)
- similar N1 and REM spectral powers between 13 Hz and 17 Hz, **higher N1 power in the 10-13 Hz** band and **lower N1 power between 1 Hz and 9 Hz** [Corsi-Cabrera et al.]

- **10-13 Hz band appears to be able to discriminate between REM and N1**
- **12-16 Hz band helps distinguishing REM from other stages**
- spectral power during non-REM stages are higher than that during REM stages between about 9-15 Hz in all subjects while the values are similar at around 8 Hz and 16 Hz frequency
- **Therefore the frequency range of 8-16 Hz is selected for analysis in this work.**

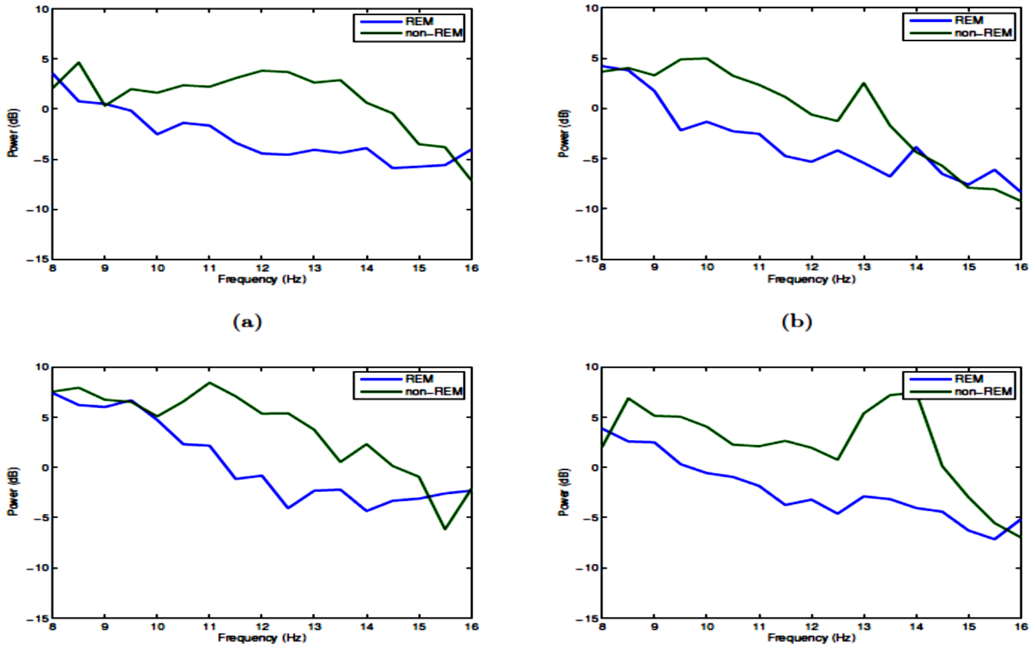
Spectral Edge Frequency (SEF)

- **Spectral Edge Frequency (SEF)** is **the frequency** below which a certain fraction of the signal power is contained.
- **SEF50 (95):** SEF at 50 (95)% (SEF50) is the lowest frequency below which half (95%) of the signal power is present.
- SEF50 is equivalent to the median frequency of a signal.



An illustration of Spectral Edge Frequency (SEF) at 50% and 95% of the signal power in the 0-20 Hz frequency range.

Frequency spectrum of REM and non-REM epochs in 8-16 Hz range for 4 training subjects



(a) (b) (c) (d)

Spectral Edge Frequency (SEF) for an epoch

- **computed from the FFT coefficients**
- n is the total number of FFT coefficients
- **X: the index to solve the equation for**
- The required frequency or the xth frequency

from the array of FFT frequency components

$$\sum_{i=1}^{x} |mag_i|^2 = 0.50 \times \sum_{i=1}^{n} |mag_i|^2$$

$$SEF50 = freq(x)$$

$$\sum_{i=1}^{x} |mag_i|^2 = 0.95 \times \sum_{i=1}^{n} |mag_i|^2$$

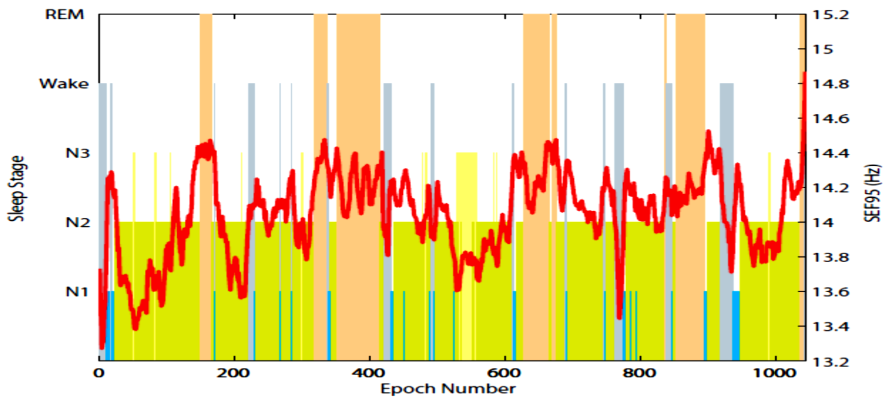
$$SEF95 = freq(x)$$

For an epoch e, its SEF50 value is calculated by taking the mean from the fifteen 2-second sub-epochs that make up the epoch.
A 9-point moving average filter is then applied to the final SEF50 value which is then plotted with the hypnogram.
For discriminating between REM and N2:
For [8 16]Hz: SEF50 has lower power(amp) for REM
For [0 16] Hz: there are overlapping powers.

SEF95

[0.5 50] Hz analysis range during REM stages →neither highest nor lowest and stay close to the 12 Hz mark.

[8 16]Hz range →SEF95 values are usually highest during the REM stages.



Hypnogram (for staging) and SEF95 (for power estimating) in the 8-16 Hz band of the EEG signal for one training subject

Distinguishing REM from other stages

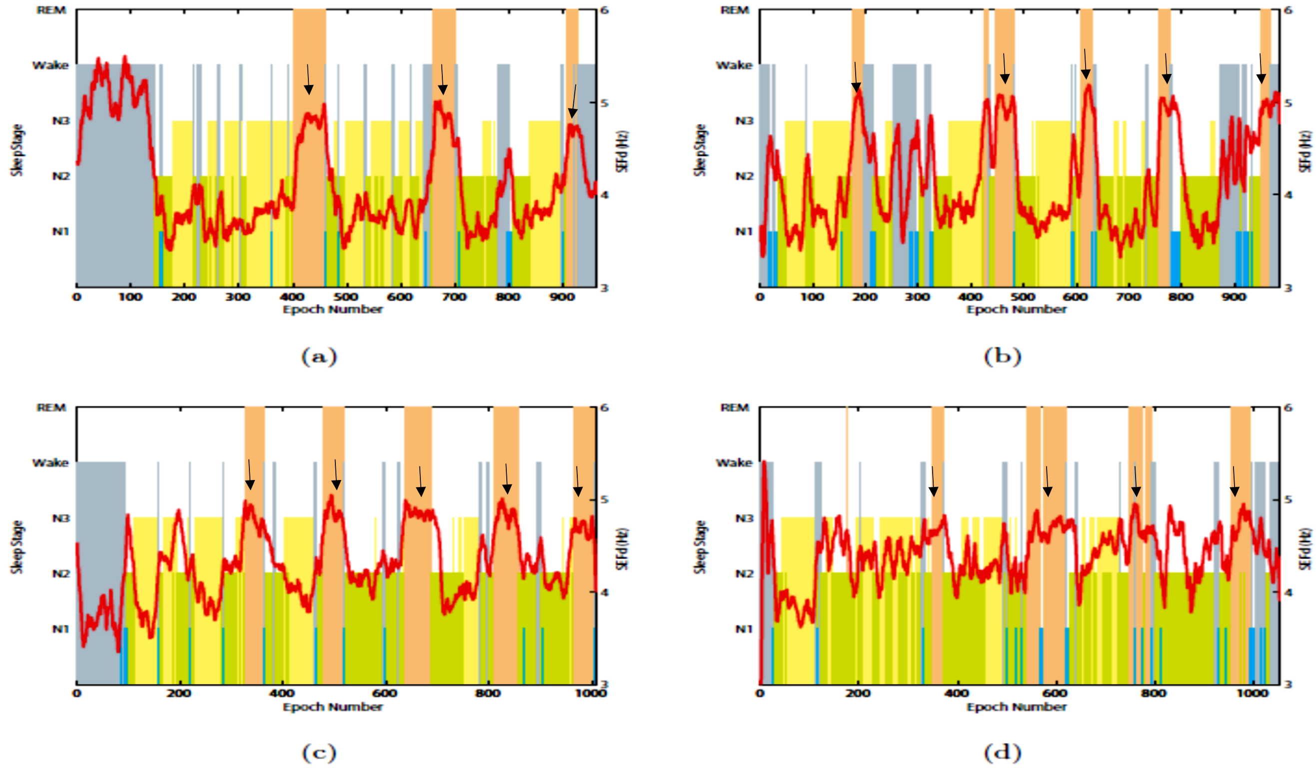
- SEF95 and SEF50 features appear to have high and low values respectively during REM
- The difference between SEF95 and SEF50 is explored as a novel feature for REM stage detection in this work, referred to as SEFd.
- It is determined by first calculating the SEFd values of fifteen 2 s sub-epochs in the 30 s EEG epoch, then averaging of all 15 values.
- se is the sub-epoch and n is its index

$$SEFd(e) = \frac{1}{15} \times \sum_{n=1}^{15} (SEF95[se_n] - SEF50[se_n])$$

Clear peaks during REM stages compared to other (N1, N2, N3, wake) when the analysis is restricted to the 8-16 Hz range

The signal power is similar in both REM and non-REM around 8 Hz,
the power in REM is lower than non-REM from 9-15 Hz,
highest around the 12 Hz mark,
the absence of 12-16 Hz activity during REM stages which is causing the power to be lower than non-REM.
no such characteristic pattern is observed when the entire frequency band is analyzed

SEFd for 4 patients



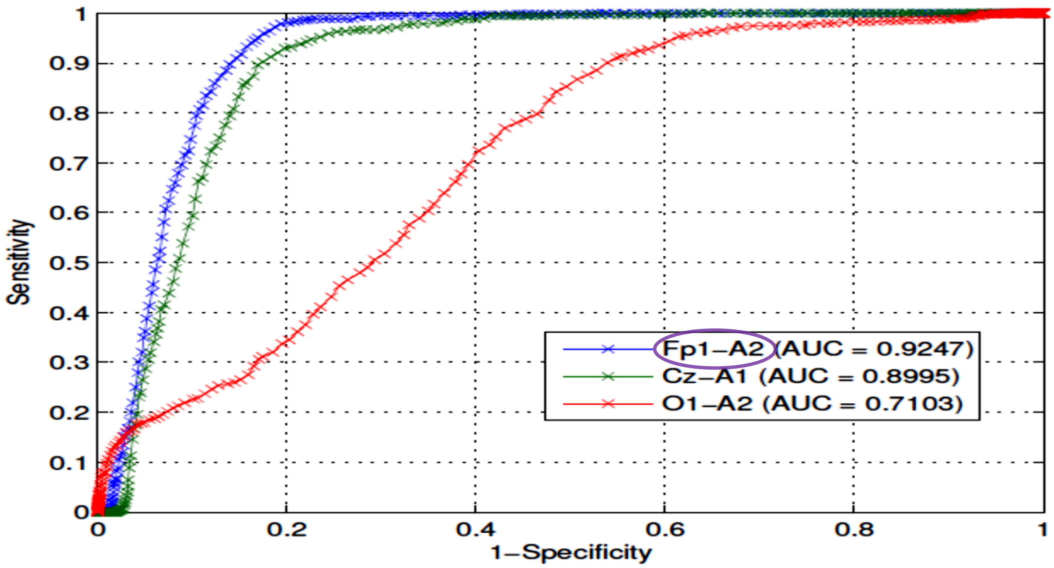
Receiver Operating Characteristics Curve

- used to show the performance of a classifier at various thresholds
- **plot of the sensitivity of the algorithm against the false positive rate computed as 1–specificity.**
- Each point on the curve corresponds to the performance of the classifier at a fixed threshold value
- the ideal classifier performance:sensitivity=1,specificity=0
- **]X,Y] = perfcurve(labels,scores,posclass) (for ROC curve)**
- The area under the ROC curve (AUC) gives an indication of the performance of the algorithm and is used to compare its performance with other classifiers
- **A classifier with higher AUC is better than the one with lower AUC.**

Table 4.3: *AUC values for the three features in different frequency ranges.*

Feature / Frequency Range	0.5-50 Hz	8-16 Hz
SEF50	0.7023	0.7530
SEF95	0.7082	0.7390
SEFd	0.6930	0.9247

ROC Curves and AUC for three EEG channels using SEFd feature from the training dataset.



REM sleep exhibits uncoupled EEG activity between frontal and posterior regions of brain.

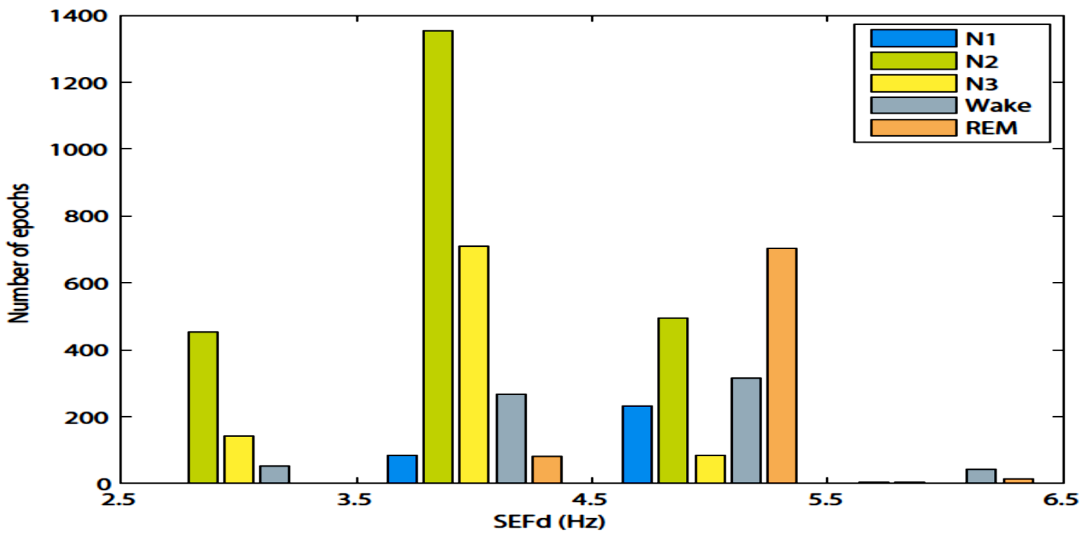
features present in the frontal region during REM sleep may be completely absent in the posterior region

Is SEFd feature enough for REM detection?

- While most of the REM epochs have SEFd values of more than 4.5 Hz, there are still some epochs from other stages overlapping in this frequency range.
- Thus two more features:

the absolute and relative powers in the 8-16 Hz frequency band

Frequency distribution of SEFd values at different sleep stages across all training subjects.



absolute power (AP) of a signal

- The **absolute power (AP) of a signal** in a fixed frequency range, f1 −f2 Hz, is calculated by summing the magnitudes obtained from Fourier coefficients between these frequencies
- f1 and f2 are 8 Hz and 16 Hz respectively and n(f1) and n(f2) are the indices at these frequencies
- AP is calculated for each 2 second sub-epoch and averaged over the standard 30 second epoch

$$AP = 20 \times \log\left(\sum_{i=n(f_1)}^{n(f_2)} |mag_i|\right)$$

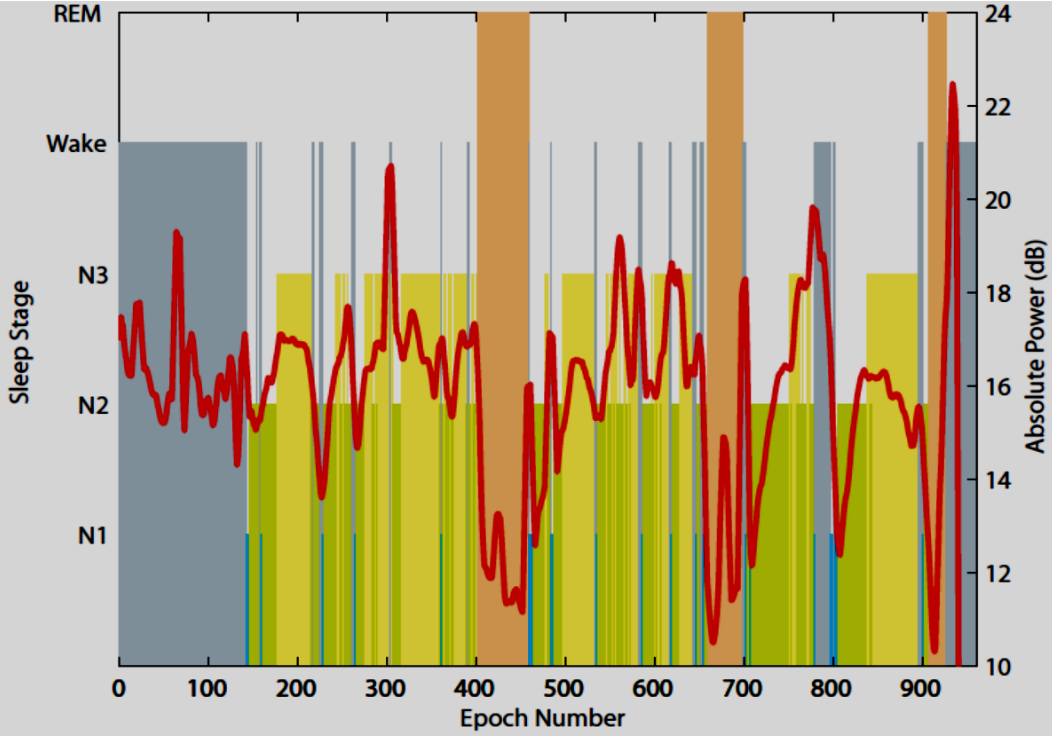
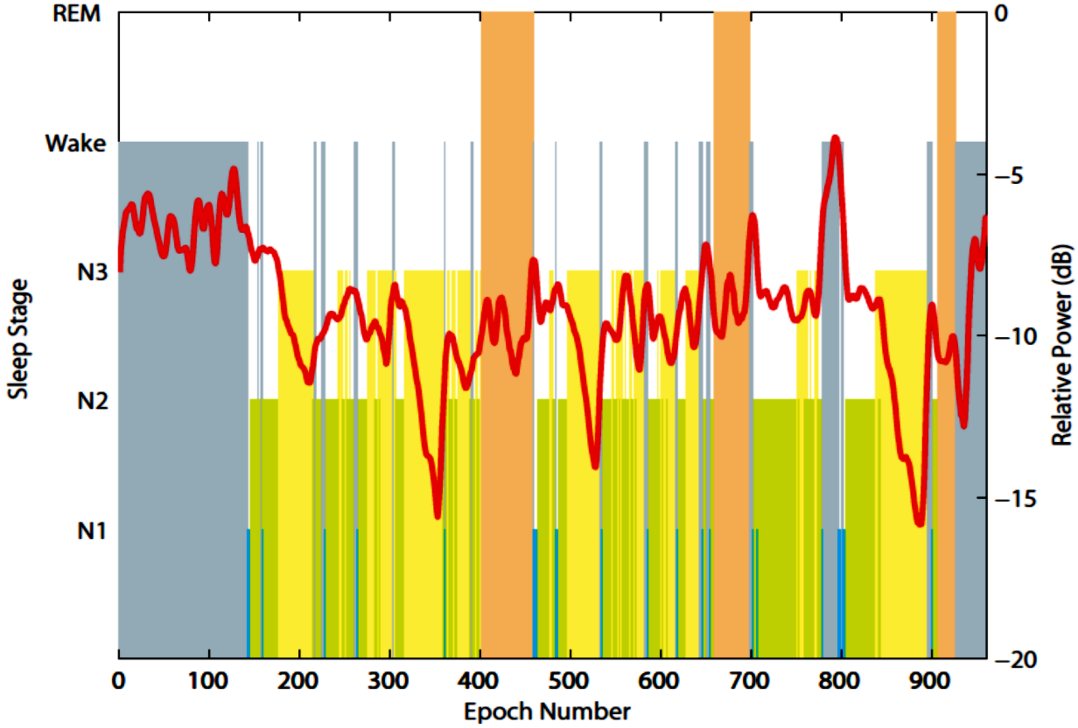


Figure 4.10: *Hypnogram and AP in the 8-16 Hz band of the EEG signal for* Subject01. *AP values can be seen to be lowest during each REM phase.*

Relative Power

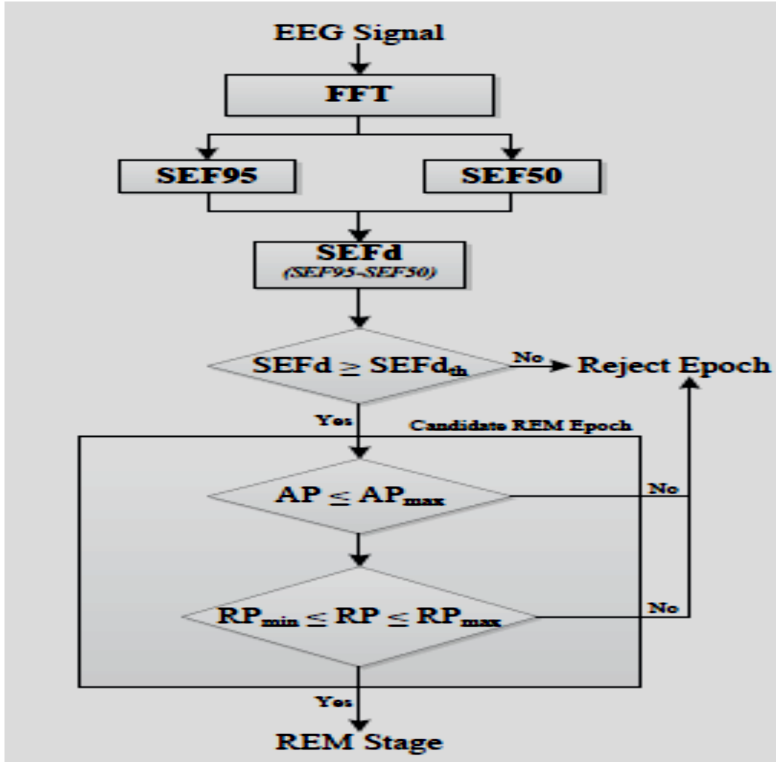
- The relative power (RP) of a signal in a fixed frequency range, f1 – f2 Hz (8-16 Hz) is calculated by taking the ratio of the absolute powers of the signal in the range of interest and the entire signal bandwidth
- RP is also calculated first for 2 second sub-epochs and then averaged over 30 second epochs

$$RP = 20 \times \log\left(\frac{\sum_{i=n(f_1)}^{n(f_2)} |mag_i|}{\sum_{i=1}^{n} |mag_i|}\right)$$



gure 4.11: *Hypnogram and RP in the 8-16 Hz band of the EEG signal for* Subject01. *RP values can be seen to be stable around -8 dB mark.*

Block diagram of the REM detection algorithm.



Establishing the threshold values

- The detection thresholds (SEFth, APmax, RPmax and RPmin) were tuned to achieve the best average performance for REM detection in terms of both sensitivity and specificity.

- giving equal weight to both sensitivity and specificity and determining the minimum distance of the curve from the (0, 1) coordinate

- Using this optimum threshold, the candidate REM epochs (with SEFd greater than this threshold) are analysed
- For these epochs, a second ROC curve is plotted by sweeping the RP and AP thresholds

Best performing thresholds for SEFd, AP and RP

Parameter	Value
SEF_{th}	4.54 Hz
AP_{max}	15.5 dB
RP_{max}	-6.08 dB
RP_{min}	-13.03 dB

Table 4.6: *Standard deviation of the three features in different sleep stages.*

	Wake	N1	N2	N3	REM	All
SEFd	1.222	1.058	1.253	1.162	0.972	1.171
AP	3.057	2.747	2.971	2.635	1.996	2.741
RP	2.498	2.414	2.695	2.915	2.172	2.593

Table 4.1: *Literature review summary for automatic REM stage detection as part of sleep staging algorithms.*

Ref	Channels	Method	Result
[12]	2×EEG 2×EOG 1×EMG	Waveform recognition and rule-based classification	Sen: 76%
[13]	1×EOG	DFT features with decision tree classification	Sen: 62% Sel: 79%
[14]	1×EEG	Bispectrum estimation	Sen: 73%
[15]	1×EEG 2×EOG 1×EMG	Decision tree with power and energy features and contextual smoothing	Sen: 91% Sel: 85%
[16]	1×EEG	Multiscale entropy and autoregressive modelling	Sen: 95% Sel: 80%
[17]	6×EEG 2×EOG	MODWT features with SVM	Sen: 71% Sel: 91%
[18]	6×EEG 2×EOG	Decision tree and multiple SVMs	Sen: 93%
[19]	2×EEG 2×EOG 1×EMG	Decision trees and SVM	Sen: 97%
[20]	2×EEG	Time-frequency image representation with SVM	Sen: 85%
[21]	1×EEG 1×EOG 1×EMG	ANN and rule-based hybrid system	Sen: 85%
[22]	2×EEG 2×EOG 1×EMG	Pattern recognition with ANN	Sen: 79%
[23]	EEG EMG	ANN and fuzzy classifier with rule-based post-processing	Sen: 85% Sel: 95%
[24]	4×EEG 1×EOG 1×EMG	Neuro-fuzzy classifier with five input patterns	Sen: 72%
[25]	EEG	WPT coefficients with ANN	Sen: 65%

Ref	Channels	Method	Result
[11]	1×EEG 1×EOG 1×EMG	ANN with 33 spectral, entropy and statistical features	Sen: 63-83%
[26]	1×EEG	ANN with relative power and power spectral density	Accuracy: 82%
[27]	2×EEG 2×EOG 1×EMG	k-means clustering	Sen: 73% Spe: 88%
[28]	1×EEG	Hidden Markov Model	Sen: 68% Sel: 50%
[29]	2×EEG	Hidden Markov Model	Sen: 86%
[30]	EEG EOG EMG	Hidden Markov Model	Sen: 90%
[31]	1×EEG	Hidden Markov Model	Sen: 85%
[32]	EEG EOG EMG	Matching pursuit and rule-based classification	Sen: 80%
[33]	1×EEG	Spectral features, k-means clustering and kNN classifier	Sen: 81%
[34]	1×EEG 1×EOG 1×EMG	Hidden Markov Model	Sen: 60%
[35]	2×EEG	Entropy features with unsupervised classification	Sen: 38%
[36]	1×EEG	Multiple spectral and temporal features with fuzzy classification and contextual smoothing	Sen: 83% Sel: 89%

Kappa agreement and patient specific threshold

- **the use of patient-specific thresholds is also investigated by plotting a ROC curve for one subject at a time and then finding the best thresholds for it from the curve.**
- **All the performance measures using patient-specific thresholds are higher compared to the use of fixed thresholds with the greatest improvement seen in sensitivity and selectivity**

Comparison of results when using fixed versus patient-specific thresholds.

- **This improvement in performance will come at the cost of additional algorithm complexity.**
- **Nevertheless, the use of fixed thresholds still achieves a performance comparable to other algorithms thus highlighting the strength of the fixed threshold approach.**

	Fixed Thresholds	Patient-specific Thresholds
Sensitivity (%)	82.98	90.00
Specificity (%)	89.35	94.19
Selectivity (%)	61.48	72.86
Accuracy (%)	88.52	93.57

Performance comparison with other single-channel EEG methods that have been evaluated using PhysioNet Sleep-EDF Database.

	Method	Features	Classifier	Sen (%)	Sel(%)
This work	Spectral power	3	Thresholding	80.6	74.8
Ref. [16]	MSE, AR model	21	LDA and contextual smoothing	85.4	78.8
Ref. [26]	Spectral power	30	Neural network	82.3	-
Ref. [36]	Spectral and temporal features	Multiple	Fuzzy classifier and contextual smoothing	63.0	91.7

Discussion and conclusion

- The REM detection algorithm presented here has several advantages.
- First, its performance is comparable to most of the methods in literature including those that use multiple EEG, EOG and EMG channels.
- Second, it uses a simple thresholding method with fixed thresholds to mark REM epochs in contrast to some other systems that use complex neural networks with a large input feature set.
- This low-complexity classifier is advantageous for portable and wearable systems with limited processing cycles and power budget.
- Third, results from automatic sleep staging systems of other research groups [47]–[49] suggest overlap of REM stage with N1 in various feature spaces.
- Using only one EEG channel and therefore keeping the data rate and processing load small

Snoring detection

Med Biol Eng Comput (2015) 53:1103–1111
DOI 10.1007/s11517-015-1388-2

ORIGINAL ARTICLE

Nasal pressure recordings for automatic snoring detecti

Hyo-Ki Lee[1] · Hojoong Kim[2] · Kyoung-Joung Lee[3]

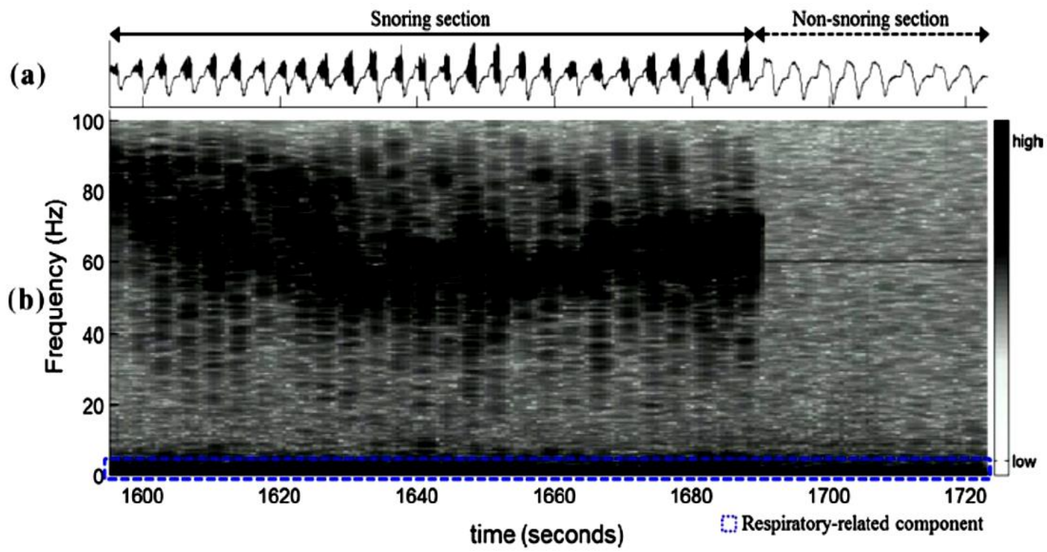
Received: 16 December 2013 / Accepted: 7 September 2015 / Published online: 21 September 2015

Snoring detection

- **Snoring is the noisy sound generated during breathing by the vibration of soft tissue in the oropharynx due to partial collapse or obstruction of the upper airway**
- using nasal pressure recordings during overnight sleep reflect the fluctuations in pressure caused by respiration
- Nasal pressure was recorded from a pressure transducer built into a nasal cannula
- used for the most sensitive and accurate detection of apneic events, especially hypopneas and respiratory effort-related arousals (RERA)
- **Acoustic analysis using a microphone has noise and requires high sampling rate.**
- continuous positive airway pressure (CPAP) system therapy
- habitual snoring is recognized as a major symptom of obstructive sleep apnea (OSA), which is characterized by repetitive obstruction of the upper airway during sleep
- **The aim of this study was to provide an automated method of snoring detection from a single nasal pressure recording without any additional sensors, such as a microphone.**

Snoring detection

Fig. 1 Analysis of a nasal pressure recording from a patient with obstructive sleep apnea for the automatic detection of snoring: **a** raw nasal pressure recording including snoring events and **b** spectrogram analysis of the raw nasal pressure recording



Apnea detection

Sleep Breath (2008) 12:33–38
DOI 10.1007/s11325-007-0126-x

ORIGINAL ARTICLE

Sleep apnea syndrome: improved detection of respiratory events and cortical arousals using oxymetry pulse wave amplitude during polysomnography

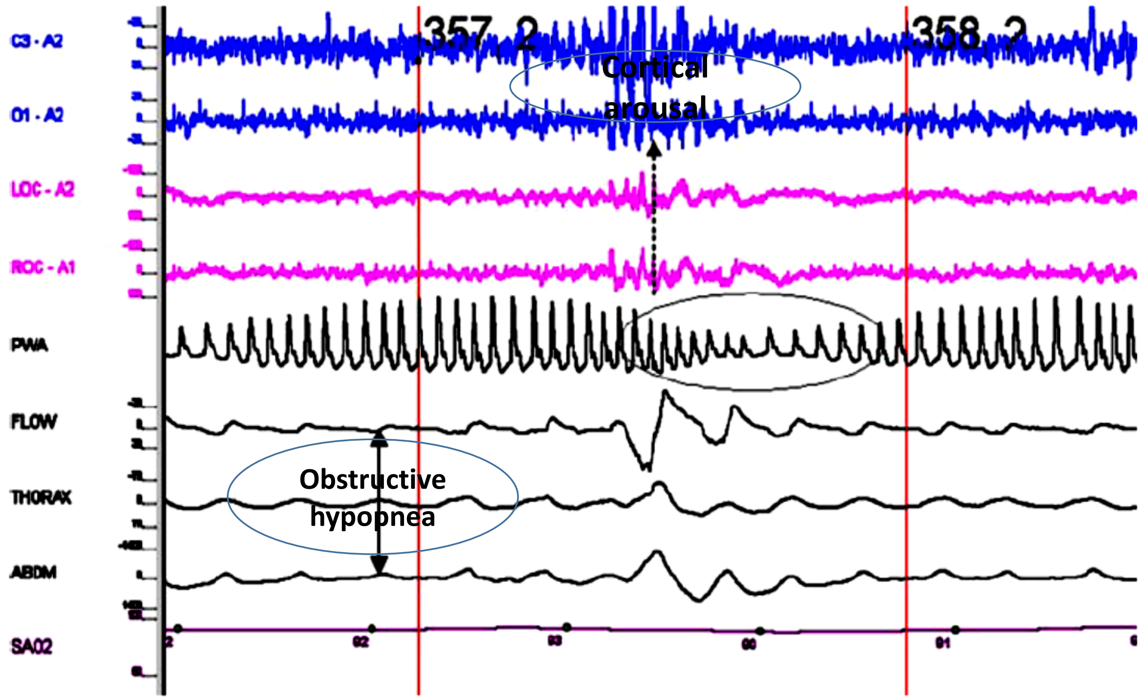
André Zacharia · José Haba-Rubio · Raphaël Simon · Gregor John · Pascal Jordan · Alda Fernandes · Jean-Michel Gaspoz · Jean-Georges Frey · Jean-Marie Tschopp

Published online: 9 August 2007

Apnea detection

- An **obstructive apnea (OA)** : complete cessation of **airflow** for ≥10 s.
- An **obstructive hypopnea (OH)** : the occurrence of **airflow** drop ≥50% of the preceding baseline level during ≥10 s, or an airflow reduction of ≥30% lasting ≥10 s, and associated with either a ≥3% oxygen desaturation or a apnea (A)
- The **respiratory disturbance index (RDI)** was defined as all the OA and OH scored for one patient during the night divided by the **total sleep time (TST).**
- **cortical arousal**: alpha activity during at least 3 s but not more than 10 s according to the American Sleep Disorders Association (ASDA)
- **PWA is given by analysis of the infrared light and his modulation.**
- **While heart beating is changing, the absorption of infrared light varies at the fingertip. An acceleration of heart beating lead to a decrease of oxygen saturation due to a higher consumption that leads to a decrease of intensity of infrared light. This measure does not depend on the stiffness of the vessels. Consequently, a decrease in PWA means a higher stress and reflect activation of the autonomous system.**

Fig. 1 PWA: tracing example of the PWA's decrease after a hypopnea and inducing a cortical arousal. The *oval* shows an example of a ≥30% variation of PWA. The *dashed arrow* shows a cortical arousal; the *double sense arrow* shows an obstructive hypopnea. This figure demonstrates also EEG (C3-A2, O1-A2), left and right electrooculogram (LOC, ROC), chest (THORAX) and abdominal (ABDM) piezo crystal belts, respiratory airflow (FLOW), and oxygen saturation (SAO2)



Repetetive Leg movement (RLM) detection using PSG

Hindawi Publishing Corporation
Computational and Mathematical Methods in Medicine
Volume 2016, Article ID 2041467, 7 pages
http://dx.doi.org/10.1155/2016/2041467

Research Article

Detection of Periodic Leg Movements by Machine Learning Methods Using Polysomnographic Parameters Other Than Leg Electromyography

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Academic Editor: Kazuhisa Nishizawa

- Leg movements can be seen as a consequence of breathing disorders during sleep.
- Towards end of an apnea period, leg movement can be observed as a reflexive response to hypoxia and awakening.
- Leg movements can also be observed as a separate event, independent of apnea periods
- PLM is defined as follows:
- movements should last between 0.5 sec and 5 sec.
- The activity should be 8 millivolts above the resting EMG amplitude.
- **There should be 4 or 5 movements occurring successively. The time between movements (the time passing from the beginning of a movement until the beginning of another movement) should not be shorter than 5 sec and longer than 90 sec**

True Positives (TP): Number of epochs correctly scored as X.

False Positives (FP): Number of epochs incorrectly scored as X.

True Negatives (TN): Number of epochs correctly rejected as not X.

False Negatives (FN): Number of epochs incorrectly rejected as not X

$$Sensitivity = \frac{true\ positives\ in\ stage\ X}{true\ positives\ in\ stage\ X + false\ negatives\ in\ stage\ X}$$

$$Accuracy = \frac{no.\ of\ true\ detections}{total\ no.\ of\ epochs}$$

$$Selectivity = \frac{true\ positives\ in\ stage\ X}{true\ positives\ in\ stage\ X + false\ positives\ in\ stage\ X}$$

False positive rate

$$Specificity = \frac{true\ negatives\ in\ stage\ X}{true\ negatives\ in\ stage\ X + false\ positives\ in\ stage\ X}$$

Papers and database

- Thesis: Low-complexity algorithms for automatic detection of sleep stages and events for use in wearable EEG systems, Imperial College London , Department of Electrical and Electronic Engineering 2016

- (2014) Sleep-EDF Database [Expanded]. [Online]. Available: http://www.physionet.org/physiobank/database/sleep-edfx/
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- After meeting 96/2/31
- Completing stages and other respiratory events (snoring, leg movement , apnea, …)
- As alpha and delta detection algorithms have been written, working on S2 detection prior REM(eye blink) is needed.
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New references

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- the signal power of θ {4-8 Hz} is higher in REM which is an indicator of the activity of the brain during REM stage
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Sleep stage classification based *

1) Signal processing and extraction of wavelet components within the predefined frequencies
2) Estimation of the features based on relative power, different CFC estimators per frequency pair
3) Feature selection and finally
4) Classification of the sleep stages

Sleep-EDF Database [Expanded]", Physionet.org

The sleep scoring of each epoch of length 30s was realized by six experts following the Rechtschaffen and Kales guidelines

EEG recordings were sampled at 100 Hz while epoch duration is 30 s.

- Both EEG channel recordings were decomposed every 5s with Maximal Overlap Discrete Wavelet Tansform (MODWT) wavelet method and Daubechies wavelet filters (dau4).
- Wavelt is used to get a more accurate temporal resolution than band pass filtering and to distinguish true from artefactual sleep activity
- combining EOG and EMG recordings with wavelet time series to remove signals directly linked to eye movements and muscle activity
- The wavelet signals were then mapped to one of the eight predefined frequency ranges
- The predefined frequencies were: low-δ {0.1-1.5 Hz}, high-δ (K-Complex) {1.6-4 Hz}, θ {4-8 Hz},α1 {8-10 Hz}, α2 {10-13 Hz},β1 (spindle) {14-20 Hz},β2 {21-30 Hz} and γ1 {31 – 45 Hz}.

We estimated five types of features: 1) the relative signal power for each frequency band in the time domain based on the Maximal overlap discrete wavelet transform (MODWT), 2) the phase-to-amplitude coupling (PAC) that is estimated between every possible pair of frequencies, 3) the correlation coefficient between the envelopes of the frequency bands as an amplitude-amplitude cross-frequency coupling (AAC) estimator, 4) a novel complexed version of the modulation index (CMI) for estimating the phase-to-amplitude coupling between every possible pair of frequencies and 5) the original modulation index (MI). All the cross-frequency coupling estimators were computed between all possible pairs of the eight predefined frequency bands (8*7/2=28 combinations).

All features were estimated within each epoch of 30 s length and also by adopting a sliding non-overlapped window of duration of 5s, which resulted in 6 temporal non-overlapped segments per 30 s. The whole analysis leads to the extraction of 120 (8 relative signal power + 28 Phase-to-amplitude coupling (PAC) + 28 Amplitude-to-Amplitude coupling (AAC) + 28 Phase-to-Amplitude coupling (CMI) + 28 Phase-to-Amplitude coupling (MI)) total features per epoch. All the features were mapped in the [0,1] interval independently for each EEG channel.

EEG recordings of every 5s sub-epoch was decomposed using the Maximal overlap discrete wavelet transform (MODWT) wavelet method and Daubechies wavelet filters (dau4). The outcome of this process were time series with frequency profile that corresponds to the predefined frequency bands.

$$SP(fr) = \sum_{fr=1}^{frequencies} \sum_{t=1}^{T} filtered(fr,t)\char`^2 \quad (1)$$

$$RSP(fr) = \frac{SP(fr)}{\sum_{fr=1}^{frequencies} SP(fr)} \quad (2)$$