# Sleep Evaluation Device for Home-Care

Magdalena Smoleń[1], Klaudia Czopek[1], Piotr Augustyniak[1]

**Abstract** The influence of sleep conditions to human health and performance is currently well known but still underestimated and monitoring devices are not widespread. This paper describes measurement methodology and prototype design of a home-care sleep scoring device. The proposed solution is oriented towards low-cost equipment and easy-to-use data capture using contactless recording as far as possible. Unlike the regular laboratory systems, the quality of sleep is estimated from the video-recorded subject motion, audio-recorded acoustic effects and from the single-lead electrocardiogram being the only electrical signal recorded from the body surface. The presented prototype is built of consumer-grade devices working in a short-distance network and providing multimodal data. The information provided from different modes are partly redundant, giving opportunity for refinement of the accuracy, and partly complementary, widening the aspect of sleep analysis.

## 1 Introduction

Sleep scoring belongs currently to the most innovative multimodal diagnostic methods, and is investigated by dozens of scientists all around the World. Since during the sleep all regulatory functions are under the sole control of the autonomous nervous system, sleep scoring benefits from the absence of voluntary behavior control from the subject under investigation. A probably sole but significant drawback of this method is the requirement of advanced recording equipment and analysis software deriving diagnostic data from the polysomnogram. Sleep laboratories require expensive infrastructure and well trained laboratory staff to provide reliable patient description.

The alternative approach postulates a common use of consumer-grade sleep scoring devices in order to draw general attention to routine control of sleep quality. The

AGH University of Science and Technology, 30 Mickiewicza Ave. 30-059 Kraków Poland e-mail: m-smolen@wp.pl; klaudia.czopek@gmail.com; august@agh.edu.pl

lack of consciousness during the sleep is not a justification for neglecting the conditions in which the average human spends a third of his lifetime. Despite bad sleeping is considered among most important factors of human health and performance during the day, a commercial device for everyday control of sleep quality at home is still not available.

The aim of our research presented in this paper is to design a multimodal measurement infrastructure and analysis methods providing everyday information about the sleep quality integrated into a single coefficient. Such parameter is expected to be correlated with precedent activity (e.g. stress, alcohol intake, dormitory airing etc.) or with the subsequent day performance or feelings. The readings may be performed every morning by the subject himself or his relatives and the conclusion is expected to indicate simple means to take or events to avoid in order to improve the comfort during the night and consequently the overall feeling of living quality.

## 2 Measurement modalities and methods

The scoring of sleep and sleep-related events was developed by six task forces reviewing evidence for the scoring manual [5]. This worldwide standard, as well as other research programmes on the sleep [3] use the polysomnogram as a reliable and complete source of multimodal medical information about the patient behavior. Since the adaptation of the complete sleep scoring measurements to home care conditions is hardly feasible, the intended surveillance system has to be limited to a subset of recommended parameters. The measurements performed in polysomnography were then scored accordingly to the costs and feasibility in home care conditions:

- cost and availability of equipment,
- susceptibility for errors if operated by untrained persons (subject's relatives or the subject himself/herself),
- availability of complementary outcomes,
- automated data interpretation and integration.

These reasons led us to reduce the electrophysiological measurements, in particular the EEG and EMG, being the background of a standard polysomnography. The only direct recording we kept is the ECG, due to its lowest vulnerability to distortion and to rich informative values. The ECG signals is used to derive the respiratory wave and the pattern of heart rate variability (HRV) typical to autonomous nervous system control during the sleep. Two other measurements are:

- video-based motion estimation, which can be partly correlated with HRV,
- acoustic effects-based snore detection, which can be partly correlated with respiratory wave.

A noteworthy advantage of these methods in everyday use is no body contact requirement, the instrumentation may thus be implemented in the infrastructure of subject's house.

### 2.1 Analysis of the heart rate variability

The response of the human cardiovascular system to variations of subject's status reflects well fast changes in subject's behavior. During the sleep, the voluntary control is suppressed and the heart rate variability is solely controlled by the autonomous nervous system. During the sleep both the short-time and long-time variability indexes are low, unless the subject suffers from neurological syndromes. Long-term variability remains stable during all the sleep, whereas short-term variability may increase depending on subject's motion, respiratory obstructions or during the REM phase. Although sleep staging is not the aim of the analysis, the influence of sleep phases is noticeable in the tachogram (fig. 1). Many other aspects of the subject's

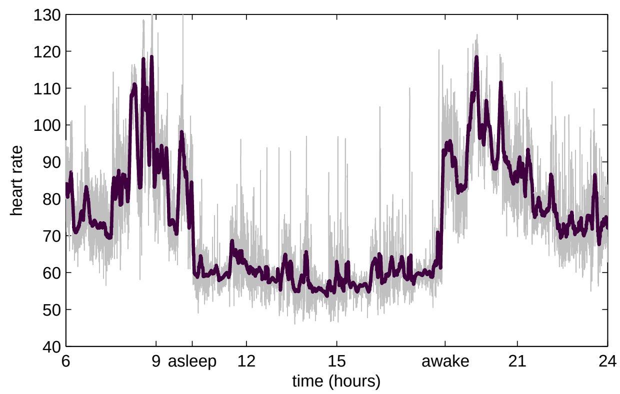


**Fig. 1** Example of overnight tachogram

health status during the sleep were recently investigated by Maier [10] and Guzik [4]. It is noteworthy that the HRV-based estimation of the subject's status involves a considerable delay, thus requires support from other methods in detection of sudden status changes.

The aim of a second analysis performed on the ECG signal is derivation of the respiratory wave (also called: *Electrocardiogram-Derived Respiratory*, EDR). Three general processing methods can be distinguished corresponding to the physical measurement principle [6]:

- differences in heart axis direction depending on variation of the heart position,
- differences in R-wave amplitude representing variable electrical properties of the thorax,
- differences in RR intervals caused by common autonomous control of both: respiration and heart rate, known as respiratory arrhythmia

The assumed recording simplicity and consequently the use of a single ECG recording channel limits the EDR processing options to the latter two methods and, as described in [6], their combination yields the most reliable result. The sample single-lead rest electrocardiogram with both amplitude and interval respiratory-related effects is presented in fig. 2.

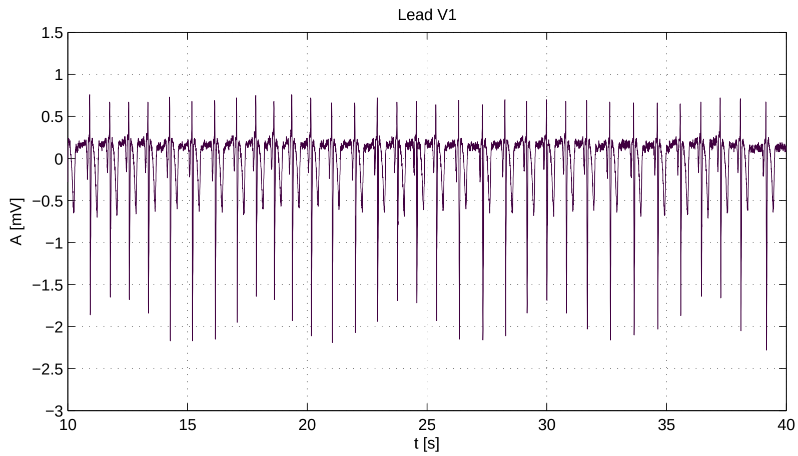


**Fig. 2** Single-lead rest electrocardiogram with amplitude and interval respiratory-related effects

## 2.2 *Analysis of the subject's motion*

Quantity assessment of the human body motion occurred during nightlong sleep provide supplementary information useful in a sleep quality evaluation [16]. The movement activity estimation enables success performance of the differentiation between awake and sleep stage. It is possible thanks to distinct some feature of the motion during these states. While subject is in an awake condition his or her movements patterns occur frequently, are relatively irregular and their temporal and spatial intensity achieves a greater value. Exact motion episode is taken into account in quantitative activity level while its time duration is longer than dozens seconds. Researchers in most studies assume 30 seconds period. Video sleep analysis could incorporate information not only about general volume of movement activity, but also data of precise recognition of the type and direction of motion as well as change of body postures.

Significant body motion during sleep could be a visible sequence and symptom of different sleep related disorders [14]. Parasomnias constitute a great deal of sleep disorders diagnosed in occurrence of some particular symptoms or behavior, probably because of partial awakening during sleep. Over twenty parasomnias are distinguished in the International Classification of Sleep Disorders (ICSD). The disorders occurred in children, limited to single episodes of anxiety during a night or talking during sleep should not be a cause of fear and does not necessitate any special diagnostic proceeding. However in case of parasomnia appearance in adults requires reliable analysis, which is significant factor of avoiding serious health problems.

Due to a close relation between several sleep disorders and motion activity during sleep, analysis of subject's motion is investigated in long-term monitoring, recognitions of early symptoms of illnesses and treatments results valuation. Obviously motion activity is not an universal marker of any sleep disturbance. For instance insomnia in its initial stage does not show any type of body movements [13]. In this case earlier mentioned ECG device is a proper sensor for accurate investigations.

## 2.3 Analysis of the acoustic effects

Snoring is a common sleep disorder which affects people of all ages, although it is most frequent for men and overweight people. From adults who snore occasionally about twenty five percent are habitual snores. These two kinds of snoring could have different influence on quality rest during sleep: usually an occasional snorer has good sleep and rest but a habitual snorer is often tired after all night sleep and does not have good quality rest.

Snoring is a common sleep disorder that affects people of all ages, although it is most frequent for men and overweight people. Among adults who snore occasionally about twenty five percent are habitual snores. These two kinds of snoring could have different influence on quality rest during sleep: usually an occasional snorer has good sleep and rest but a habitual snorer is often tired after all night sleep and does not have good quality rest.

Medical support is needed for subjects who snore to get a good night's sleep. This prospective study is aimed to show how sleep disorders influence a good night sleep. Acoustic characteristics of snoring sounds, which are approximately periodic waves with noise, can be analyzed by using a multidimensional voice program e.g. MDVP. Multiple protocols of MDVP can show differences between markers used in an automatic analysis e.g. peak frequency, soft phonation index (SPI), noise to harmonics ratio (NHR), and power ratio. Measurement results compared with norms are shown on polar diagrams that are very easy to interpret. At the same time snoring sounds were analyzed using the short-time Fourier transform (STFT) to determine the frequency and content of local sections of the samples [17].

Acoustic analysis techniques give information on the mechanism, loudness and intensity. Waveforms of snoring events over a period of 60s were analyzed. Depending on the snorer, there are from ten to fifteen respiratory cycles. The subjects have very regular respiratory cycles, unlike typical snoring patients. The frequency domain provides most important information from snoring sounds, enabling power analysis and three-dimensional graphs of energy-frequency-time, as evident in figures 3. The averaged spectrum shape of snoring event is represented with frequencies (Hz) of its formants. Different conditions in which subjects and patients snore

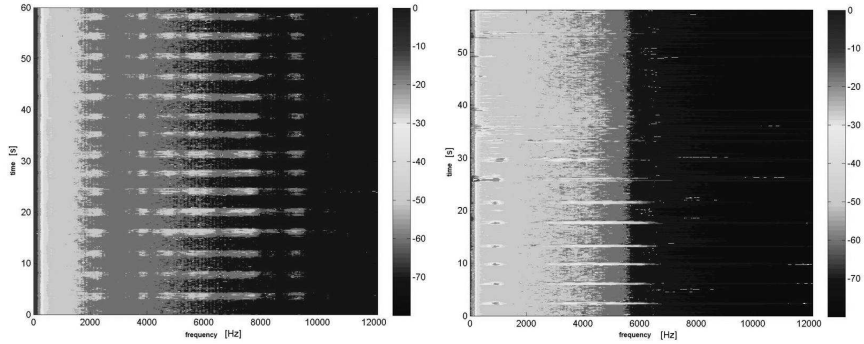


**Fig. 3** left: STFT of a normal signal, right: STFT of an abnormal signal

can affect formants range. Examining snoring sound signal during sleep, energy was mainly concentrated in low frequencies, below 6000Hz. The main components lie in the low frequency range, at about 130Hz. The pathological signal presents weak formants, while the normal signal has more periodicity in low frequencies, and introduces stronger formants. Calculated vectors of characteristics of the abnormal sound were quantitatively compared with normal sound, which allowed drawing conclusions from available data. The most important parameters were the fundamental frequency, moments M0-M2 and formants. The pathological importance of snoring has been related to its intensity (dB), maximal and mean intensity, number of breathing per minute of sleep, snoring frequency and formants structure. As can be seen in tab. 1, the mean energy is significantly higher for habitual snorers, when compared to occasional snorers.

**Table 1** Acoustic parameters of snoring sound

| | Occasional snorer | Habitual snorer | Reference subject |
|---|---|---|---|
| Minimum Energy (dB) | 44.92 | 47.20 | 45.56 |
| Maximum Energy (dB) | 61.02 | 58.67 | 47.88 |
| Mean Energy (dB) | 48.64 | 57.47 | 46.66 |
| Standard Deviation (dB) | 1.45 | 1.95 | 0.29 |
| Median Energy (dB) | 48.57 | 57.83 | 46.68 |
| number of snorers/minute | 7.00 | 10.00 | 0.00 |
| number of breathing/minute | 15.00 | 10.00 | 15.00 |
| M0 | 426.00 | 2620.00 | 427.00 |
| M1 | 44.00 | 72.00 | 44.00 |
| M2 | 2939.35 | 6267.81 | 3149.44 |
| F1 | 127.00 | 125.00 | 127.00 |
| F2 | 2499.00 | 1249.00 | 1499.00 |
| F3 | 2748.00 | 1874.00 | 2374.00 |
| F4 | 3123.00 | 2998.00 | 2748.00 |

Using the multidimensional voice program MDVP many parameters that are necessary to estimate sleep quality can be extracted, with the most useful information among them coming from the soft phonation index (SPI), noise to harmonics ratio (NHR) and fundamental frequency variation (vF0). Table 2 shows how a snorer sound is different from normal sleep sound.

**Table 2** Parameters vF0, SPI, NHR for habitual snorer (male)

| parameters | norm(m) | STD(m) | meas.1 | meas. 2 | meas. 3 | meas. 4 | meas. 5 |
|---|---|---|---|---|---|---|---|
| vF0 [%] | 0,94 | 0,43 | 68,7 | 45,3 | 43,3 | 8,02 | 43,3 |
| SPI | 6,77 | 3,78 | 7,49 | 6,37 | 2,56 | 0,63 | 5,09 |
| NHR | 0,12 | 0,01 | 3,55 | 1,54 | 2,89 | 2,79 | 3,79 |

## 3 System design

Considerations given in previous chapter led us to sketch the approach of the infrastructure of the home-care system for sleep scoring (fig. 4). This system, except for the personal recorder is built of commercially available computer and peripherals. Thanks to the use of wireless connection, the subject's motion is unconstrained and the measurement device having direct electrical contact to the subject is isolated from others mains-operated system components. The measurement of time-domain

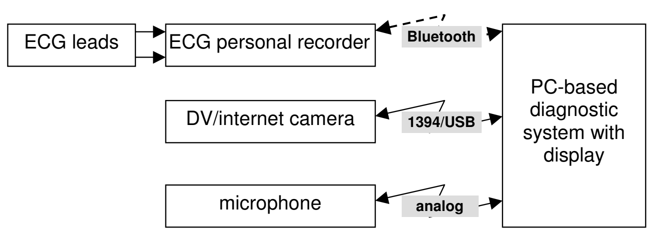


**Fig. 4** Block diagram of the home care sleep scoring system

variability of the sinus node requires acquisition of a single-lead electrocardiogram. We used two disposable chest electrodes corresponding to V1 and V2 leads in bipolar mode connected to the personal recorder. This custom-built device performs real-time filter-based beat detection [7] and shape-based classification. The output datastream lying of RR intervals, corresponding R-wave amplitudes, and beat types is then transmitted to the acquisition center via short-range wireless link (Bluetooth). The missing RR intervals were interpolated by a successive procedure minimizing their short-term variability, accordingly to the guidelines in [15]. The square root of the mean squared differences of successive NN intervals (RMSSD) and the standard deviation of the average NN interval calculated over five minutes periods (SDANN) were selected from basic time-domain heart rate variability (HRV) parameters Malik [11] as representing short-time and long-time variability respectively.

For the motion monitoring, we use black/white CCD (Charge Coupled Device) camera and additional set of nine infrared diodes placed below the camera. This kind of illuminators placement instead of location directly over the subject bed, makes possible to avoid creating non-uniformities reflected in overexposure in the center. Dependent on the room arrangement, camera could be located either in parallel either perpendicularly to the longer dim of the bed. Although the best signal to noise ratio and wider analyzed surface are obtained when a camera is put in parallel.

Basic evaluation of the general motion of the human body bases on each $250^{-\text{th}}$ video frame which corresponds to 10 sec. time interval. The absolute value of the difference only between those chosen frames is performed [8]. The image resolution is 720 pixels wide and 576 pixels high. From each of obtained difference images all pixels mean brightness is accumulated. Fig. 5 presents an example of mean brightness in dependence of sleep time. All sharp peaks emerging from the background noise refer to episodes with motion of the subject. To estimate the level of movements activity during nightlong sleep, noise level variations should be taken into consideration by referencing the value of proper peak with the level of noise at that time. Observed distinction between the value of noise in different time epochs stems from the different lightning during sleep (night/dawn). This first step of estimation

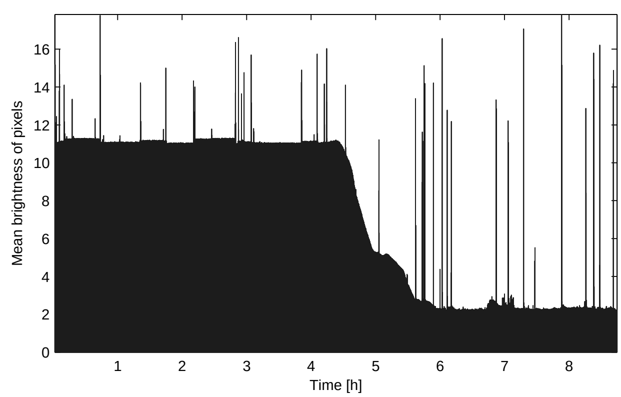


**Fig. 5** General evaluation of example motion during nightlong sleep - mean brightness in dependence of sleep time

led us to assign the threshold of noise which constrains no motion background as well. In more detailed analyses that way of activity level assessment could be overestimated. Therefore the percentage of pixels with earlier obtained overthreshold brightness is calculated for every frame of the video recording. Fig. 6 contains a comparison diagram of pixel mean brightness and the percentage of pixels scaled to the level of the noise. The movements of different segments of the body reveal also distinct differential images pattern. Fig. 7 presents an overhead assessment of the selected common motions of the human body. Three first peaks refer to the motion during whole body posture change from one-side to another. Two next peaks are responsible for lower limbs movements and others correspond to upper limbs motion.

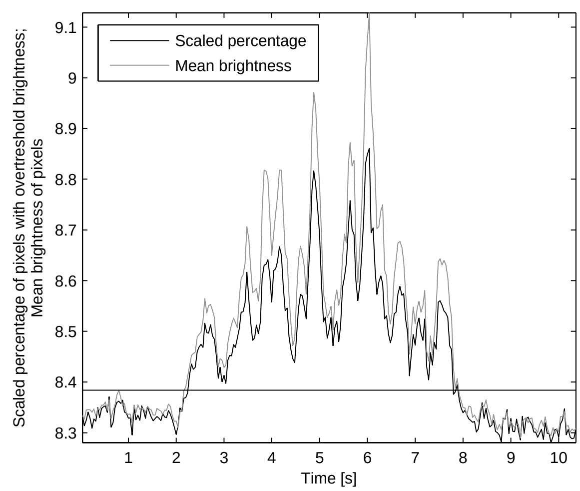


**Fig. 6** Comparison of pixel mean brightness and percent of pixels scaled to the level of the noise

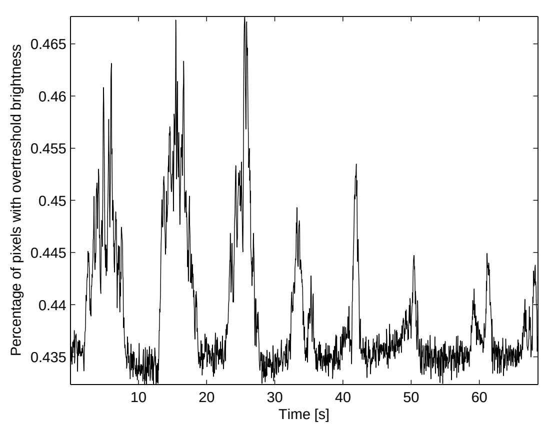


**Fig. 7** General evaluation of example motion extracted from the difference of the consecutive video frames

Measurement of the acoustic snoring signal is very easily performed using a microphone to record the signal in *Cool Edit Pro* with the sample rate set to 44100 Hz which is realistic enough to fool the human ear. Afterwards we analyze the signal using available equipment e.g. MDVP. Utilization of acoustic methods yields research results in a straightforward, graphical way. Proposed method of support for snoring individuals copes with this disorder. Based on this method people can judge what kind of disorders they are dealing with. Acoustic diagnosis of sleep disorders, especially the *Obstructive Sleep Apnea Syndrome* may help find a way of snoring rehabilitation and making decisions concerning future treatment and have influence on the quality of night sleep.

## 4 Software design

The variety of data provided by sensors in a multimodal system requires the appropriate software design including:

- sensor-specific software translating the acquired signal or image into a mode-specific message of unified format,
- system-specific data structures and exchange rules considering the informative properties of particular sources,
- final rule- or artificial intelligence-based decision and user messaging system.

As the subject measurement modes were selected as a compromise of at-home applicability and information completeness, the mode-specific information was easy to be defined as tokens (tab. 3). The system is expected to yield a single sleep quality

**Table 3** Subject information provided from basic sleep recording modes

| recording mode | subject information | data type |
|---|---|---|
| electrocardiogram | stimulation degree | short-time index (RMSSD) |
| | | long-time index (SDANN) |
| | breathing parameters | breathing frequency |
| | | breathing depth |
| video surveillance | motion estimation | body motion index |
| | | legs motion index |
| | | hands motion index |
| audio recordings | acoustic effects analysis | snoring index |
| | | environmental noise index |

index simple to understand for everyone (like the *Body Mass Index*). Unfortunately, no worldwide standard of such index exists and its development is the issue for medical scientists. Since first approach has to be made in the framework of our project, we tried to quantify all events undesirable during the sleep. The integration of these information related to the laboratory sleep scoring results or to the subjective sleep evaluation made by the subject himself or herself leads to the rule-based or AI-supported sleep evaluation.

In the case of rule-based sleep evaluation, values of respective indexes (see tab. 3) are compared to thresholds, weighted and integrated to a single output value. Since the contribution of specific parameters are not known, and may vary from one subject to another, it seems reasonable to use a AI-based decision system (e.g. based on an *Artificial Neural Network*) allowing for adaptation for subject and environment conditions. Such system has to learn its desirable functionality prior to be used for sleep evaluation.

## 5 Conclusions and future works

The multimodal system has been sketched in aspects of measurement methodology, hardware and software solutions. Future investigations are expected to reveal the strong and weak points of the prototype and their conclusions will lead to a prototype device. The presented approach has successfully eliminated the costly and uncomfortable measurements, preserving ca. 70% of the laboratory sleep scoring functionalities. If such limited device is used to relative scoring of the same subject's sleep in repeatable conditions of his or her home, we expect high usefulness in individual pursuit for optimal sleep conditions. Eliminating the electroencephalographic and electromiographic recordings are the most problematic compromise and impoverish the system performance.

During these studies five video recordings of nightlong sleep from five different subjects were investigated. Both the value and frequency of the movements parameter (mean brightness of pixels) were taken into consideration to draw a conclusion. Obtained data revealed significant inter-subject motion variability as well as motion variability in time of the same patient.

In order to assess precise motion activity of the particular parts of the body, human body recognition must be provided. It can be applied by means of artificial neural network processing [16]. Video motion recordings of long-term sleep provide a great amount of data. Therefore application prepared for acquisition of video frames must contain also a preprocessing stage operating in real time. Its main objective is data recording only while motion periods occur.

Correct interpretation remains a significant problem also in dealing with respiratory sounds such as snoring and/or breathing. Examining the snoring sound signal during various stages of sleep, we observed that light snorers snored evenly throughout all of them. The most interesting fact was that heavy snorers tend to snore more with maximum snoring intensity in the rapid eye movement sleep phase than in any other stage of sleep. Further conclusions can be made by comparing simultaneously gathered acoustic and electrocardiographic signals. During two thirty minute intervals starting at 130 and 300 minutes after recording initiated, a significant decrease in variation can be seen, especially short term *SDANN*, which is in accordance with *RMSSD*. In these intervals we also observe increased snoring sound intensity.

## 6 Acknowledgment

Scientific work supported by the Polish State Committee for Scientific Research resources in years 2009-2012 as a research project No. N N518 426736.

## References

1. American Academy of Sleep Medicine Task Force, (1999) Sleep-related breathing disorders in adults: Recommendations for syndrome definition and measurement techniues in clinical research, Sleep, vol. 22, no. 5, pp. 667-689,
2. Dorfman-Furman G., Shinar Z., Baharav A., Akselrod S., (2005) Electrocardiogram Derived Respiration During Sleep, Computers in Cardiology, vol. 32, pp. 351-354,
3. Grube G, Flexer A, Dorffner G. (2002) Unsupervised continuous sleep analysis, Methods Find Exp Clin Pharmacol, vol. 24, Suppl D, pp. 51-6,
4. Guzik P., Piskorski J. (2009) Heart Rate Assymmetry, Proc. International Congress on Electrocardiology,
5. Iber C et al. (2007) AASM Manual for Scoring Sleep, American Academy of Sleep Medicine, Westchester IL,
6. Kikta A., Augustyniak P. (2007) Comparing Methods of ECG Respiration Signals Derivation Based on Measuring the Amplitude of QRS Complexes, Journal of Medical Informatics and Technologies, vol. 11, pp. 155-163,
7. Kohler, B., Hennig, C., Orglmeister, R. (2002) The principles of software QRS detection, IEEE Engineering in Medicine and Biology Magazine, 21(1), 42-57,
8. Liao WH, Yang CM. (2008) Video-based Activity and Movement Pattern Analysis in Overnight Sleep Studies, Pattern Recognition, ICPR 2008,
9. Maier C., Dickhaus H., Laguna P., (2005) Amplitude Variability Extraction from Multi-Lead Electrocardiograms for Improvement of Sleep Apnea recognition, Computers in Cardiology, vol. 32, pp.355-358,
10. Maier C., Roedler V., Wenz H., Dickhaus H., (2009) ECG Fingerprints of Obstructed Breathing in Sleep Apnea Patients, IEEE Eng. in Medicine and Biology Magazine, vol. 28 no 6, pp: 41-48,
11. Malik M., Camm A. J. (1995) Heart Rate Variability, Wiley-Blackwell 1995.
12. Moody G.B., Mark R.G., Bump M.A., Weinstein J.S., Berman A.D., Mietus J.E., Goldberger A.L., (1986) Clinical Validation of the ECG-Derived Respiration (EDR) Technique, Computers in Cardiology 1986, vol. 13, pp.507-510,
13. Peng YT., Lin ChY., Sun MT., Landis CA., (2007), Multimodality Sensor System for Long-Term Sleep Quality Monitoring, IEEE Transactions on Biomedical Circuits and System, vol. 1, no. 3, September 2007, pp. 217-227,
14. Prusinski A., (2001), Parasomnie: Obraz Kliniczny, Diagnostyka i Postepowanie, Sen, (in Polish) vol. 1, nr 1, pp. 33-39
15. Task Force of the ESC/ASPE, (1996), Heart rate variability: Standards of measurement, physiological interpretation, and clinical use. European Heart Journal, 17, pp.354-381,
16. Yang FCh., Kuo Ch., Tsai MY., Huang SCh., (2003), Image-based Sleep Motion Recognition using Artificial Neural Networks, Proceedings of the Second International Conference on Machine Learning and Cybernetics, Wan, 2-5 November 2003, pp. 2775-2780
17. Zieliski TP., (2005), Digital Signal Processing, (in Polish) WKiL, Warszawa.