Diagnosis of Sleep Apnea by Automatic Analysis of Nasal Pressure and Forced Oscillation Impedance

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Detecting and differentiating central and obstructive respiratory events is an important aspect of the diagnosis of sleep-related breathing disorders with respect to the choice of an appropriate treatment. The purpose of this study was to evaluate the performance of a new algorithm for automated detection and classification of apneas and hypopneas, compared with visual analysis of standard polysomnographic signals. The algorithm is based on time series analysis of nasal mask pressure and a forced oscillation signal related to mechanical respiratory input impedance, measured at a frequency of 20 Hz throughout the night. The method was applied to all-night measurements on 19 subjects. Two experts in sleep medicine independently scored the corresponding simultaneously recorded polysomnographic signals. Evaluating the agreement between two scorers by a weighted kappa statistic on a second-by-second basis, we found that inter-expert variability and the discrepancy between automatic analysis and visual analysis performed by an expert were not significantly different. Implementation of this algorithm in a device for home monitoring of breathing during sleep might aid in the differential diagnosis of sleep-related breathing disorders and/or as a means for follow-up and treatment control.

Keywords: sleep-disordered breathing; diagnosis; classification; inter-observer variability

In recent years, the high prevalence of sleep-related breathing disorders has been increasingly recognized by epidemiologic studies (1, 2). One important aspect of the diagnosis of sleep-disordered breathing (SDB) with respect to the choice of an appropriate treatment is the detection and classification of different respiratory events, in particular, separating obstructive from central apneas. Diagnosis of SDB is usually performed by polysomnography (PSG) in a sleep laboratory, consisting of the measurement and recording of numerous signals used to analyze sleep and breathing. Whereas PSG currently represents the standard for the diagnosis of SDB, it is expensive, and access is limited. Moreover, the unfamiliar environment encountered in a sleep laboratory often impairs the patient's sleep. Therefore, efforts have been made to develop diagnostic approaches that rely on noninvasive, unsupervised measurements in the home of the patient (3).

One widely used approach consists of nocturnal outpatient measurements, including estimation of respiratory flow using thermistors or nasal prongs and monitoring of breathing effort by thoracic and abdominal strain gauges or respiratory inductive plethysmography. Using such devices, it is possible to distinguish central and obstructive apneas. However, signal quality may be reduced by dislocation of belts or due to patients' obesity (4).

Two other methods that have been extensively investigated in this context are the recording of pressure at the airway opening, mostly via nasal cannula (5–8), and the measurement of signals related to mechanical respiratory input impedance by the forced oscillation technique (FOT) (9–18). Both methods are highly sensitive with respect to the detection of disturbed breathing during sleep (5, 12, 13, 16). Moreover, both signals are simultaneously accessible via a nasal mask.

FOT signals in particular have been proposed as promising tools for classifying respiratory events as central or obstructive (10, 12). Argod and associates (19) have also suggested that central and obstructive hypopneas could be distinguished by analyzing nasal pressure recordings. Whereas episodes with decreased amplitude and a rounded contour are supposed to indicate a central origin, obstructive hypopneas should be associated with a flattened contour. However, this approach has not yet been investigated in a quantitative manner. Following a different approach, cardiogenic oscillations in nasal pressure signals during apneas could be used as indicators of their central origin. Ayappa and colleagues (20) have found cardiogenic oscillations in the continuous positive airway pressure (CPAP) flow signal during 60% of central apneas but never during obstructive apneas.

A further step toward a time-saving procedure for ambulatory diagnosis of SDB consists of developing an algorithm for automatic analysis of signals measured by a simple and robust device that can be easily applied by the patient. By providing time of onset, duration, and class of respiratory events, such an algorithm could quickly yield essential information about severity and type of possible sleep-related breathing disorders from data obtained during nocturnal home monitoring. Examinations using home recording equipment could thereby close a gap between screening, e.g., by oximetry, and full PSG or could sometimes even serve as substitutes for PSG in the sleep laboratory.

We have developed diagnostic software for off-line detection and classification of respiratory events on the basis of time series analysis of nasal mask pressure and of a FOT signal measured at a frequency of 20 Hz throughout the night. The goal of this study was to assess the quality of the underlying algorithm. For that purpose, we evaluated the agreement between the results of that algorithm and those of visual analysis of polysomnographic recordings performed by experts in sleep medicine. This agreement between automatic and visual analysis is compared with inter-expert agreement.

METHODS

Subjects

Nineteen male subjects were studied during an all-night PSG in the sleep laboratory of the Department of Pneumology at Freiburg Uni-

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versity Hospital. Demographic data and sleep characteristics are summarized in Table 1. All subjects were patients formerly referred to the sleep laboratory with suspected SDB and diagnosed on the basis of polysomnographic examinations. Subjects younger than 18 years were excluded from the study, as were subjects with hypercapnic respiratory failure or severe arrhythmia. The study was approved by the Human Ethics Committee of Freiburg University Hospital, and written informed consent was obtained from all subjects before participation.

Polysomnography

PSG was performed using a SIDAS-GS polygraph (Heinen and Löwenstein, Bad Ems, Germany) and consisted of neurologic monitoring, including two electroencephalogram (EEG) channels (C3A2, C4A1), left and right electrooculograms, submental and tibial electromyograms (EMG), a unipolar electrocardiogram for cardiac monitoring, and respiratory monitoring, including an oronasal thermistor. Also measured were thoracic and abdominal movements by respiratory inductive plethysmography, arterial oxyhemoglobin saturation (Sa_{O_2}) by a finger pulse oximeter, nasal mask pressure, snoring sounds by a microphone, and body position.

The FOT was applied using the "ODS-Messbox" device (Weinmann, Hamburg, Germany). A low-amplitude flow oscillation at a frequency of 20 Hz is applied at the airway opening via a nasal mask. The FOT signal, which is related to mechanical respiratory input impedance, is obtained by processing the 20-Hz component of measured nasal pressure. For further technical details on the FOT setup, *see* the work by Ficker and colleagues (16). Nasal CPAP (Somnotron 4; Weinmann) at a level of 4 cm H_2O was simultaneously applied to avoid rebreathing of expired CO_2, thereby enabling the patient to breathe virtually normally while awake.

Clinical Analysis

Polysomnograms were analyzed visually by a staff physician of the sleep laboratory in the Department of Pneumology at Freiburg University Hospital. Sleep staging was performed on the basis of the criteria of Rechtschaffen and Kales (21) and according to the scoring rules concerning EEG arousals developed by the American Sleep Disorders Association (22).

Apneas and hypopneas were detected and classified according to the following criteria adapted from the American Academy of Sleep Medicine Task Force (23).

- All events have to last 10 seconds or longer.
- Hypopnea: A decrease below 50% from baseline in the amplitude of thermistor signal or mask pressure, or a clear amplitude reduction not reaching the previous criterion but associated with an oxygen desaturation value greater than 3%, or an arousal. Baseline is the mean amplitude of stable breathing and oxygenation in the two minutes preceding onset of the event or the mean amplitude of the three largest breaths in the two minutes preceding onset of the event (the latter for individuals without a stable breathing pattern).
- Obstructive apnea: Cessation of respiratory airflow, i.e., zero thermistor signal and constant mask pressure, with persisting thoracoabdominal movements.
- Central apnea: Cessation of respiratory airflow, i.e., zero thermistor signal and constant mask pressure, without thoracoabdominal movements.
- Mixed apnea: Cessation of respiratory airflow, i.e., zero thermistor signal and constant mask pressure, without thoracoabdominal movements at the beginning but with recurring thoracoabdominal movements at the end of the event.

TABLE 1. DEMOGRAPHIC AND SLEEP CHARACTERISTICS OF PARTICIPATING SUBJECTS

	Mean ± SD
Age, year	56.9 ± 10.6
BMI, kg/m^2	32.0 ± 6.4
Recording time, minutes	350.3 ± 87.7
Total sleep time (TST), minutes	270.1 ± 89.1
Stage 1, 2, %TST	62.4 ± 14.3
Stage 3, 4, %TST	16.5 ± 11.6
REM sleep, %TST	21.2 ± 8.5

Definition of abbreviations: BMI = body mass index; REM = rapid eye movement.

Applying these definitions, the beginning and end of respiratory events observed in a PSG recording were marked and stored using a software package for computer-supported visual analysis of polysomnograms. Each second of a PSG recording was thereby attributed to one of the following categories: normal breathing (N), hypopnea (H), obstructive apnea (OA), mixed apnea (MA), or central apnea (CA).

Inter-Scorer Agreement

The weighted kappa statistic is applied to evaluate agreement between two scorers. A weighted kappa $\kappa_w(scorer1, scorer2)$ is calculated for a PSG recording analyzed by two scorers, *scorer1* and *scorer2*, following the procedure outlined in Appendix A in the online data supplement. Although $\kappa_w(scorer1, scorer2)$ is not to be misinterpreted as fractional agreement, its maximum possible value of one reflects perfect agreement between the two scorers. On the other hand, a value of zero stands for no agreement better than by chance. For further details on the weighted kappa statistic, refer to the work of Altman (24).

$\kappa_w(scorer1, scorer2)$ is evaluated on a second-by-second basis: Using the previously stored results of PSG analysis performed by *scorer1* and *scorer2*, a 5 × 5-matrix, the table of occurrences n is constructed. A cell n_{ij} of this table of occurrences contains the number of seconds of the recording that has been attributed to category i by *scorer1* and to category j by *scorer2*, i and j representing one of the five categories N, H, OA, MA, or CA. For example, $n_{OA,CA}$ contains the number of seconds that belonged to obstructive apneas according to *scorer1* and to central apneas according to *scorer2*.

Automatic Analysis

Detection and classification of respiratory events by automatic analysis of mask pressure and FOT time series is based on the evaluation of local features of these signals, the properties of which are reflected during apneas and hypopneas.

Obstructive respiratory events are characterized by upper airway narrowing. As a consequence, they are always associated with a baseline of the FOT signal higher than that during the breaths preceding and following the event, the modulus of mechanical respiratory input impedance being inversely related to upper airway diameter. Variations of the FOT signal due to breathing efforts are less pronounced during obstructive apneas than during hypopneas.

During central apneas with open airways, the FOT signal is constant at a low level compared with time intervals immediately before and after the event. However, upper airway narrowing can also occur during central apneas (25, 26), leading to a higher FOT level. In this case, oscillations reflecting cardiac activity visible in the FOT signal can be used to distinguish central from obstructive apneas. These cardiogenic oscillations have frequently been observed in respiratory signals during central apneas (20, 27, 28), but never in the course of obstructive events (20).

The algorithm is described in more detail in Appendix B in the online data supplement. A first version has been published in part (29). Briefly, FOT and mask pressure time series are analyzed on a breath-by-breath basis. Features reflecting pressure amplitude, FOT amplitude and baseline, and presence of cardiogenic oscillations in the FOT signal are extracted. Comparison of these features with thresholds constituting the parameters of the algorithm leads to detection and classification of hypopneas as well as obstructive, mixed, and central apneas. By storing onset time, duration, and class of respiratory events detected by automatic analysis in a recording, each second of this recording is attributed to one of the five classes N, H, OA, MA, or CA. Thus, the results of automatic analyses of FOT and mask pressure time series can be compared with visual analysis of the corresponding PSG recording using the weighted kappa statistic outlined previously.

Comparison of Visual and Automatic Analyses

Two experts in sleep medicine independently scored respiration during sleep by analyzing each of the 19 PSG recordings. They were explicitly advised to closely follow the aforementioned definitions to achieve the best possible agreement. Both scorers were not allowed to see the tracing of the FOT signal or the results of the analysis per-

formed by the other scorer. Onset, duration, and class of all detected events were stored for further analysis.

We used the weighted kappa statistic computed on a second-by-second basis to evaluate the agreement between scorers and automatic analysis instead of the more common procedure consisting of comparing the respective numbers of events detected in a recording. Weighted kappa computed on a second-by-second basis is more sensitive to subtle differences between two analyses that are due to varying interpretations concerning onset and duration of a particular event. On the other hand, the fact that κ_w implicitly reflects the degree of concordance with respect to detection, classification, and length of apneas and hypopneas in one single number is an important aspect for the optimization of the algorithm used for automatic analysis. Furthermore, the second-by-second approach guarantees that κ_w is a relatively smooth function of the parameters of the algorithm, which is a prerequisite for reliable optimization.

To evaluate the agreement between visual and automatic analysis, each of the 19 PSG recordings served as a test set for cross-validation once. Therefore, the 19 recordings were divided 19 times in rotation into a training set consisting of 18 recordings and a test set formed by the remaining one. For each of the 19 divisions, the following two steps were taken:

- FOT and mask pressure time series of the training set recordings were subjected to automatic analysis. The parameters of the algorithm were successively optimized to yield the maximum κ_w(*auto*, *scorer1*), i.e., the best possible agreement between automatic analysis and the first scorer when analyzing the training set.
- Using these parameters, the algorithm was applied to the remaining test set, yielding the results of automatic analysis to be used for cross-validation.

These results were used to compute κ_w(*auto*, *scorer1*) for each test set recording to quantify the agreement between the first scorer and automatic analysis. Furthermore, the agreement between the second scorer and automatic analysis was evaluated by calculating κ_w(*auto*, *scorer2*) in a similar manner, using the same parameters.

Moreover, the AHIs (AHI[*scorer1*], AHI[*scorer2*], and AHI[*auto*]) were computed, reflecting the respective numbers of events detected per hour of a recording.

RESULTS

The agreement of visual analysis of 19 PSG recordings performed by experts in sleep medicine with automatic analysis of the corresponding mask pressure and FOT signals is depicted in Figure 1, together with inter-expert agreement. Automatic analysis yielded results that are comparable to those of visual analysis of polysomnograms; the different values of the weighted kappa statistic are within their respective standard deviations (κ_w[*auto*, *scorer1*] = 0.45 ± 0.15, κ_w[*scorer1*, *scorer2*] = 0.50 ± 0.21, κ_w[*auto*, *scorer2*] = 0.40 ± 0.19, mean ± SD).

The same result is obtained when AHIs are compared. Here, automatic analysis is on average in between the two scorers (AHI[*scorer1*] = 34.2 ± 17.4, AHI[*scorer2*] = 25.4 ± 19.6, AHI[*auto*] = 30.5 ± 18.5, mean ± SD). Taking into account the predominant nature of detected events, three identical tentative diagnoses (mostly central, predominantly obstructive, or only hypopneas) would have been obtained by the different analyses for all recordings, except for one data set in which *scorer2* exclusively detected hypopneas, whereas *scorer1* and *auto* found obstructive apneas.

The weighted kappa statistic is most sensitive with respect to disagreements on single events if the total number of respiratory events in a recording is low. For example, the most prominent discrepancies between κ_w(*auto*, *scorer1*) and κ_w(*scorer1*, *scorer2*) are observed in a recording with an AHI of 5.1 per hour according to *scorer1* and 5.3 per hour according to *auto*, although similar severities of SDB were estimated by both automatic and visual analyses.

Examples of respiratory events and the respective classifications attributed by automatic analysis and scorers are presented in Figure 2. It shows obstructive apneas with paradoxical excursions of thorax and abdomen. The FOT signal is almost constant during these obstructive apneas at a high level compared with the periods of normal breathing preceding and following the event; no cardiogenic oscillations can be observed in any respiratory signal. Two examples displaying central apneas are given in the online data supplement. Event-by-event agreement between scorers and automatic analysis after optimization is presented in Table 2. The different numbers of events as detected and classified by one scorer (*scorer1*, *scorer2*, or *auto*) in all 19 recordings and the respective classifications as assigned by another scorer are displayed as: (a) *auto* and *scorer1*, (b) *scorer1* and *scorer2*, (c) *auto* and *scorer2*. For example, the number printed in bold in Table 2a indicates that a total of 97 events has been attributed to the category of hypopneas by automatic analysis, but classified as obstructive apneas by the first scorer.

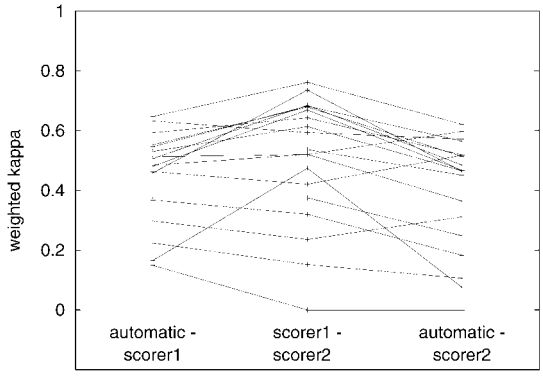

Figure 1. Agreement between automatic analysis and two scorers (automatic–scorer1, scorer1–scorer2, and automatic–scorer2) for recordings of 19 patients with SDB; weighted kappa was computed on a second-by-second basis using the weights displayed in Table E1 in the online data supplement.

The second scorer detected fewer events than both the first scorer and the algorithm. On the other hand, he judged a higher percentage of the detected events to be apneas rather than hypopneas. This is caused by different interpretations of the definitions for respiratory events, in particular of the terms "clear amplitude reduction" and "cessation of respiratory airflow".

Some events were classified as central apneas by scorers but as hypopneas by automatic analysis. This is due to the rather elevated variability of mask pressure during these events, caused by cardiogenic oscillations, but misinterpreted as breathing by the algorithm. Most of these events (140 of 199 in Table 2a, 175 of 223 in Table 2c) were observed in the recording of one subject. Nevertheless, automatic analysis revealed the central nature of these events in low levels of the FOT signal reflecting open airways.

DISCUSSION

As a main result of the present study, we found automatic detection and classification of sleep-related respiratory events on the basis of nasal mask pressure and FOT to be feasible and reliable. The algorithm provides results comparable to those of visual analysis of polysomnographic recordings performed by experts in sleep medicine. Discrepancies between two scorers (*see* Table 2) are mainly due to differing opinions concerning the duration of particular events and the extent of respiratory airflow.

Most events classified as mixed apneas by experts were assigned to obstructive apneas by automatic analysis, mainly due

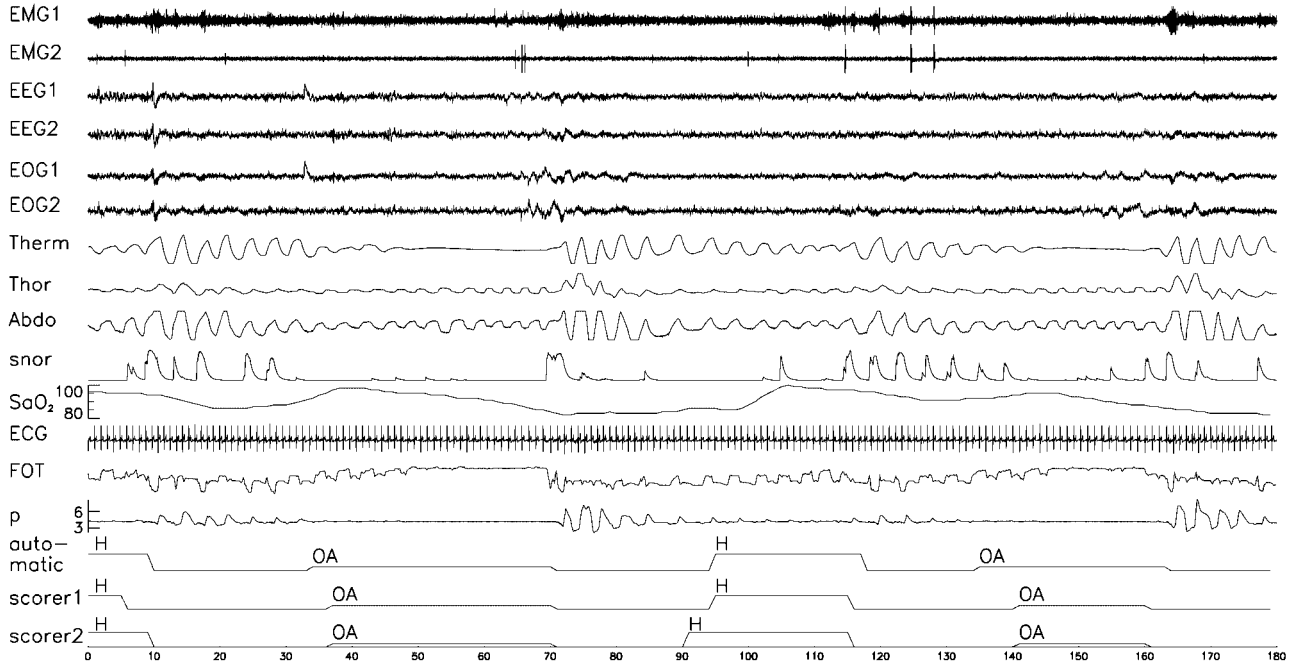

Figure 2. Examples of obstructive apneas. Three minutes extracted from a polysomnographic recording with submental (EMG1) and tibial (EMG2) EMG, two EEG channels, left and right electrooculograms (EOG1, EOG2), oronasal thermistor (Therm), thoracic (Thor) and abdominal (Abdo) inductance plethysmography, snoring sounds (snor), oxyhemoglobin saturation (Sa_{O_2}) as a percentage, electrocardiogram (ECG), estimated modulus of respiratory input impedance measured by FOT, and nasal mask pressure (p) in cm H_2O. The three bottom tracings show onset, end, and class of respiratory events as detected by automatic analysis of FOT and mask pressure as well as by visual analysis of full PSG except FOT signal performed by two scorers. H denotes hypopnea, and OA, obstructive apnea.

to the shortness of the central period at the onset of such events in our data sets. Occasionally, visually detected central apneas were classified as hypopneas by automatic analysis. This situation mainly occurred in the recording of one subject, where very pronounced cardiogenic oscillations in the mask pressure signal were observed during these events. However, as the algorithm correctly revealed the central origin of these events, the basic concern with respect to the choice of an appropriate treatment was fulfilled.

TABLE 2. OCCURRENCES FOR RESPIRATORY EVENTS AS DETECTED AND CLASSIFIED BY (*a*) AUTOMATIC ANALYSIS AND FIRST SCORER, (*b*) FIRST AND SECOND SCORER, (*c*) AUTOMATIC ANALYSIS AND SECOND SCORER

a.		*scorer 1*				
auto		N	H	OA	MA	CA
	N		959	15	0	11
	H	626	1,829	**97**	8	199
	OA	4	163	286	45	22
	MA	0	17	9	1	6
	CA	12	92	47	9	142
b.		*scorer 2*				
scorer1		N	H	OA	MA	CA
	N		186	9	0	5
	H	1,125	1,558	245	4	97
	OA	11	41	367	27	9
	MA	1	0	46	12	2
	CA	32	10	22	14	302
c.		*scorer 2*				
auto		N	H	OA	MA	CA
	N		400	21	3	6
	H	1,006	1,300	206	9	223
	OA	20	87	353	42	17
	MA	3	5	18	0	6
	CA	31	23	79	5	163

Esophageal pressure represents the gold standard for distinction of obstructive from central apneas and hypopneas; however, many patients refuse to be diagnosed by esophageal manometry (30). Because of its invasive nature, esophageal pressure monitoring is suspected to have negative side effects on sleep quality and upper airway dynamics (30, 31), the latter also influencing mechanical respiratory input impedance. Moreover, one goal of this study was to evaluate the agreement between our algorithm and experts in sleep medicine, and to compare this agreement with inter-expert variability, as encountered in a routine clinical setting. Routine examinations, however, do not include esophageal pressure monitoring in most sleep laboratories. As a consequence of all these aspects, we did not incorporate esophageal pressure into the set of signals monitored within the scope of PSG for this study.

A crucial issue is how the automatic analysis can deal with artifacts due to mask leaks, mouth breathing, swallowing, or yawning. Because we mainly addressed the fundamental possibility of automatically detecting and distinguishing obstructive and central apneas and hypopneas, our algorithm currently does not contain any features to reject such artifacts. Some of these artifacts, potentially misinterpreted as respiratory events by automatic analysis, can be indirectly detected on the basis of EEG, EMG, and Sa_{O_2} when they occur during wakefulness or are followed neither by an arousal nor by oxygen desaturation. In our data, however, this situation never occurred to an extent seriously deteriorating the agreement between automatic and visual analyses, possibly because the required duration of apneas and hypopneas is limited to a range of 10 to 240 seconds. Some other situations may also be identifiable using additional routines that could be included into the diagnostic software. For example, nasal inspiration and oral expiration re-

sults in asymmetric nasal pressure tracings and increased respiratory impedance during expiration (13). Clearly, the management of such artifacts represents a point that will have to be thoroughly evaluated before routine application of the presented approach. A further possible extension of the algorithm concerns the automatic detection of snoring, e.g., by band-pass filtering of the nasal pressure signal.

We would expect the main benefit of the presented approach to consist of closing a gap between screening and full PSG within the familiar environment, i.e., in the patient's home. After screening by other methods for outpatient monitoring of nocturnal respiration, such as pulse oximetry or nasal cannula, our method could establish the mainly central or obstructive origin of sleep-related breathing disorders. Circumventing the necessity of a baseline nasal CPAP by using FOT setups as described by Badia and colleagues (12) or Hannhart and colleagues (32), the present method could even be applied within the framework of a stand-alone screening device.

All aspects considered, the suggested approach can be useful when implemented as a device designed for outpatient differential diagnosis and/or treatment control of sleep-related breathing disorders. It relies on monitoring of only two signals that are measured via a nasal mask that can be applied by the patient, automatic analysis of the data is completed within about one minute, and reveals information about the central or obstructive origin of detected respiratory events. In particular, this approach could be of advantage when it is not possible to clearly distinguish between central and obstructive apneas by outpatient monitoring of thoracic and abdominal movements, e.g., due to obesity. In certain cases, it could even make PSG dispensable. For instance, patients with SDB of clearly established central origin such as Cheyne–Stokes respiration caused by congestive heart failure could be subjected to treatment without having to wait for a polysomnographic examination. Furthermore, the method could be applied to monitoring the effectiveness of CPAP treatment of patients with obstructive sleep apnea–hypopnea syndrome, thereby avoiding regular visits to a sleep laboratory.

References

1. Young T, Palta M, Dempsey J, Skatrud J, Weber S, Badr S. The occurrence of sleep-disordered breathing among middle-aged adults. *N Engl J Med* 1993;328:1230–1235.
2. Young T, Evans L, Finn L, Palta M. Estimation of the clinically diagnosed proportion of sleep apnea syndrome in middle-aged men and women. *Sleep* 1997;20:705–706.
3. Ross SD, Sheinhait IA, Harrison KJ, Kvasz M, Connelly JE, Shea SA, Allen IE. Systematic review and meta-analysis of the literature regarding the diagnosis of sleep apnea. *Sleep* 2000;23:519–532.
4. Kapur VK, Rapoport DM, Sanders MH, Enright P, Hill J, Iber C, Romaniuk J. Rates of sensor loss in unattended home polysomnography: the influence of age, gender, obesity, and sleep-disordered breathing. *Sleep* 2000;23:682–688.
5. Norman RG, Ahmed MM, Walsleben JA, Rapoport DM. Detection of respiratory events during NPSG: nasal cannula/pressure sensor versus thermistor. *Sleep* 1997;20:1175–1184.
6. Hosselet J-J, Norman RG, Ayappa I, Rapoport DM. Detection of flow limitation with a nasal cannula/pressure transducer system. *Am J Respir Crit Care Med* 1998;157:1461–1467.
7. Sériès F, Marc I. Nasal pressure recording in the diagnosis of sleep apnoea hypopnoea syndrome. *Thorax* 1999;54:506–510.
8. Hernández L, Ballester E, Farré R, Badia JR, Lobelo R, Navajas D, Montserrat JM. Performance of nasal prongs in sleep studies. *Chest* 2001;119:442–450.
9. Farré R, Peslin R, Rotger M, Navajas D. Inspiratory dynamic obstruction detected by forced oscillation during CPAP: a model study. *Am J Respir Crit Care Med* 1997;155:952–956.
10. Yen F-C, Behberani K, Lucas EA, Burk JR, Axe JR. A noninvasive technique for detecting obstructive and central sleep apnea. *IEEE Trans Biomed Eng* 1997;44:1262–1268.
11. Navajas D, Farré R, Rotger M, Badia R, Puig-de-Morales M, Montserrat JM. Assessment of airflow obstruction during CPAP by means of forced oscillation in patients with sleep apnea. *Am J Respir Crit Care Med* 1998;157:1526–1530.
12. Badia JR, Farré R, Montserrat JM, Ballester E, Hernández L, Rotger M, Rodriguez-Roisin R, Navajas D. Forced oscillation technique for the evaluation of severe sleep apnoea/hypopnoea syndrome: a pilot study. *Eur Respir J* 1998;11:1128–1134.
13. Badia JR, Farré R, Kimoff RJ, Ballester E, Hernández L, Rotger M, Navajas D, Montserrat JM. Clinical application of the forced oscillation technique for CPAP titration in the sleep apnea/hypopnea syndrome. *Am J Respir Crit Care Med* 1999;160:1550–1554.
14. Lorino AM, Lofaso F, Duizabo D, Zerah F, Goldenberg F, d'Ortho MP, Harf A, Lorino H. Respiratory resistive impedance as an index of airway obstruction during nasal continuous positive airway pressure titration. *Am J Respir Crit Care Med* 1998;158:1465–1470.
15. Reisch S, Daniuk J, Steltner H, Rühle KH, Timmer J, Guttmann J. Detection of sleep apnea with the forced oscillation technique compared to three standard polysomnographic signals. *Respiration* 2000;67:518–525.
16. Ficker JH, Wiest GH, Asshoff G, Fuchs FS, Schmelzer AH, Harsch IA, Hahn EG. Sensitivity of a simplified forced oscillation technique for detection of upper airway obstruction. *Respir Physiol* 2001;124:243–249.
17. Badia JR, Farré R, Rigau J, Uribe ME, Navajas D, Montserrat JM. Forced oscillation measurements do not affect upper airway muscle tone or sleep in clinical studies. *Eur Respir J* 2001;18:335–339.
18. Farré R, Rigau J, Montserrat JM, Ballester E, Navajas D. Evaluation of a simplified oscillation technique for assessing airway obstruction in sleep apnoea. *Eur Respir J* 2001;17:456–461.
19. Argod J, Pépin JL, Lévy P. Differentiating obstructive and central sleep respiratory events through pulse transit time. *Am J Respir Crit Care Med* 1998;158:1778–1783.
20. Ayappa I, Norman RG, Rapoport DM. Cardiogenic oscillations on the airflow signal during continuous positive airway pressure as a marker of central apnea. *Chest* 1999;116:660–666.
21. Rechtschaffen A, Kales A. A manual of standardized terminology, techniques and scoring system for sleep stages of human subjects. Los Angeles: Brain Information Service and Brain Research Institute; 1968.
22. American Sleep Disorders Association. EEG arousals: scoring rules and examples. *Sleep* 1992;15:173–184. (ASDA report).
23. American Academy of Sleep Medicine Task Force. Sleep-related breathing disorders in adults: recommendations for syndrome definition and measurement techniques in clinical research. *Sleep* 1999;22:667–689.
24. Altman DG. Practical statistics for medical research. Boca Raton: Chapman & Hall; 1991. p. 403–409.
25. Badr MS, Toiber F, Skatrud JB, Dempsey J. Pharyngeal narrowing/occlusion during central sleep apnea. *J Appl Physiol* 1995;78:1806–1815.
26. Guilleminault C, Hill MH, Simmons FB, Powell N, Riley R, Stoohs R. Passive constriction of the upper airway during central apneas: fiberoptic and EMG investigations. *Respir Physiol* 1997;108:11–22.
27. Kryger MH. Monitoring respiratory and cardiac function. In: Kryger MH, Roth T, and Dement WC, editors. Principles and practice of sleep medicine. Philadelphia: W. B. Saunders Company; 1989. p. 702–716.
28. Morrell MJ, Badr S, Harms CA, Dempsey JA. The assessment of upper airway patency during apnea using cardiogenic oscillations in the airflow signal. *Sleep* 1995;18:651–658.
29. Steltner H, Staats R, Vogel M, Virchow C, Matthys H, Guttmann J, Timmer J. Detection and classification of sleep-disordered breathing using acoustic input impedance and nasal pressure. In: Brause RW and Hanisch E, editors. Medical data analysis. Proceedings of the International Symposium on Data Analysis. Lecture Notes in Computer Science 1933. Heidelberg: Springer; 2000. p. 61–66.
30. Loiodice C, Selek M, Loire M, Lévy P, Pépin JL. Measurement of respiratory effort (esophageal pressure) and estimation of resistance of the upper airway in polysomnography: indications, limitations and results. *Neurophysiol Clin* 1998;28:507–520.
31. Chervin RD, Aldrich MS. Effects of esophageal pressure monitoring on sleep architecture. *Am J Respir Crit Care Med* 1997;156:881–885.
32. Hannhart B, Teculescu D, Medina JJ, Marchand M, Peslin R, Polu JM. Airway obstruction detected continuously by forced oscillation technique during sleep apnea in obese patients did not appear to be only an inspiratory-related event [abstract]. *Am J Respir Crit Care Med* 2000;161:A352.