Systematic comparison of different algorithms for apnoea detection based on electrocardiogram recordings

T. Penzel[1] **J. McNames**[2] **P. de Chazal**[3] **B. Raymond**[4] **A. Murray**[5] **G. Moody**[6]

[1]Department of Respiratory Critical Care Medicine, Hospital of Philipps University, Marburg, Germany
[2]Electrical & Computer Engineering, Portland State University, Portland, Oregon, USA
[3]Department of Electronic & Electrical Engineering, University College, Dublin, Ireland
[4]Department of Respiratory Physiology, Birmingham Heartlands Hospital, UK
[5]Regional Medical Physics Department, Freeman Hospital, Newcastle upon Tyne, UK
[6]Harvard-MIT Division of Health Sciences & Technology, Cambridge, Massachusetts, USA

Abstract—*Sleep apnoea is a common disorder that is usually diagnosed through expensive studies conducted in sleep laboratories. Sleep apnoea is accompanied by a characteristic cyclic variation in heart rate or other changes in the waveform of the electrocardiogram (ECG). If sleep apnoea could be diagnosed using only the ECG, it could be possible to diagnose sleep apnoea automatically and inexpensively from ECG recordings acquired in the patient's home. This study had two parts. The first was to assess the ability of an overnight ECG recording to distinguish between patients with and without apnoea. The second was to assess whether the ECG could detect apnoea during each minute of the recording. An expert, who used additional physiological signals, assessed each of the recordings for apnoea. Research groups were invited to access data via the world-wide web and submit algorithm results to an international challenge linked to a conference. A training set of 35 recordings was made available for algorithm development, and results from a test set of 35 different recordings were made available for independent scoring. Thirteen algorithms were compared. The best algorithms made use of frequency-domain features to estimate changes in heart rate and the effect of respiration on the ECG waveform. Four of these algorithms achieved perfect scores of 100% in the first part of the study, and two achieved an accuracy of over 90% in the second part of the study.*

Keywords—*Heart rate variability, Sleep apnoea, Physiologic signal database, PhysioNet, ECG, Estimated respiration*

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1 Introduction

SLEEP APNOEA is a common sleep disorder, with a reported prevalence of 4% in adult men and 2% in adult women (YOUNG *et al.*, 1993). Excessive daytime sleepiness is the most common complaint. An increased risk of accidents and a link between sleep apnoea and arterial hypertension have been proven in recent large-cohort studies (NIETO *et al.*, 2000). Sleep apnoea is now regarded as an important risk factor for the development of cardiovascular diseases (YOUNG *et al.*, 1997). It is successfully treated with home ventilation using nasal continuous positive airway pressure (NCPAP). If patients are treated at an early stage of the disease, their night-time and daytime blood pressure can be lowered, and the adverse health effects can be reduced (DIMSDALE *et al.*, 2000).

The traditional methods for assessment of sleep-related breathing disorders are sleep studies (polysomnography), with the recording of electro-encephalography (EEG), electro-oculography (EOG), electromyography (EMG), electrocardiography (ECG), oronasal airflow, respiratory effort and oxygen saturation (AMERICAN ACADEMY OF SLEEP MEDICINE (AASM), 1999). Sleep studies are expensive for patients, because they require overnight evaluation in sleep laboratories, with dedicated systems and attending personnel. Limited and less expensive studies are increasingly performed in a home setting.

According to the AASM (1999) criteria, patients are diagnosed with obstructive sleep apnoea if they have five or more apnoea events per hour of sleep during a full night sleep period (AASM, 1999). Each apnoea event is defined as a respiratory pause lasting at least 10 s. During each event, respiration ceases owing to upper-airway obstruction. If the upper-airway obstruction is only partial and flow is lower than 50% of normal, the resulting airflow limitation is called a hypopnoea. A patient with severe sleep apnoea can have up to 600 single apnoea events per night, with a typical duration of 40 s each, and few, if any, sustained periods of normal (unobstructed) breathing.

In 1984, cyclical variation in heart rate was described as being characteristic of obstructive sleep apnoea (GUILLEMINAULT *et al.*, 1984). Until now, this ordered variation in heart rate has been applied to the detection of sleep apnoea by only a few groups (PENZEL *et al.*, 1990; HILTON *et al.*, 1999; ROCHE *et al.*, 1999).

This paper describes a comparison of different algorithms to detect sleep apnoea from ECG recordings alone.

Correspondence should be addressed to Dr Thomas Penzel; email: penzel@mailer.uni-marburg.de

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2 Methods

2.1 *Recordings and subjects*

Seventy sleep recordings were collected for the comparison of apnoea detection algorithms. A single channel of ECG was extracted from all polysomnographic recordings, with a sampling rate of 100 Hz. Each minute of each recording was visually scored by an expert (Thomas Penzel) for sleep apnoea and hypopnoea events on the basis of respiration and oxygen saturation signals, using amplitude criteria for airflow and desaturation (Fig. 1). No differentiation between apnoea and hypopnoea events was made when events of disordered breathing were scored. After completion of the expert scoring, the recordings were arranged in three groups, as follows:

(i) Group A (apnoea): recordings with clear occurrence of sleep apnoea (100 min or more). Forty recordings fulfilled this criterion.
(ii) Group B (borderline): recordings with some degree of sleep apnoea (between 5 and 99 min). The recordings revealed either mild apnoea, up to an apnoea index of 15 events per hour, or obstructive snoring in otherwise healthy subjects. Ten recordings fulfilled this criterion.
(iii) Group C (control): recordings of healthy subjects with neither sleep apnoea (fewer than 5 min) nor habitual snoring. Twenty recordings fulfilled this criterion.

The sleep recordings originated from 32 subjects (25 men, 7 female), who were recruited for previous studies of healthy volunteers and patients with obstructive sleep apnoea. Four subjects contributed a single recording each, 22 subjects contributed two recordings each, two subjects contributed three recordings each, and four subjects contributed four recordings each.

The 70 recordings were divided into a learning set and a test set, of equal size. The 70 recordings were ranked according to the number of minutes with apnoea; from this ordered list, a randomly chosen recording from each consecutive pair of recordings was assigned to the training set, and the other recording in the pair was assigned to the test set. In this way, the distribution of apnoea durations was made roughly equal in each set of 35 recordings.

Recordings from 17 of the 32 subjects were represented both in the learning set and in the test set; eight subjects were only in the test set, and the remaining seven subjects were only in the learning set. The duration of the recordings varied between 401 and 578 min (average: 492, standard deviation: 32 min).

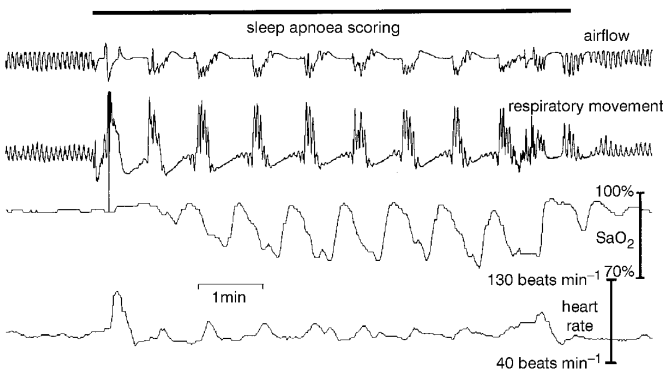

Fig. 1 *Polygraphic recording of one apnoea subject, with apnoea/hypopnoea index of 24 events per hour, illustrates repetitive apnoeas and their visual scoring based on oronasal airflow, respiratory movement over chest and oxygen saturation. Heart rate trace has been added to explain cyclical variation in heart rate that occurs in parallel with breathing disorder*

The total number of recorded minutes was 34 313. The minutes were almost equally balanced between the learning set ($n = 17\,045$) and the test set ($n = 17\,268$).

The recordings were posted on PhysioNet*. In addition to the ECG signals, respiration and oxygen saturation signals were available for eight of the recordings in the learning set, to assist researchers in studying the relationships between the respiration and ECG signals. Minute-by-minute reference annotations indicating the presence or absence of sleep apnoea were provided for the 35 training set recordings only.

2.2 *Apnoea challenge*

The comparison of the different algorithms was the result of a competition jointly conducted, between February and September 2000, by Computers in Cardiology (CINC) and PhysioNet. Computers in Cardiology is an annual IEEE-sponsored conference that provided publicity for the event and a venue for meetings and discussion of the competition entries (MOODY *et al.*, 2000; PENZEL *et al.*, 2000). PhysioNet is a web-based library of physiological data and analytic software sponsored by the US National Institutes of Health's National Center for Research Resources (NIH NCRR) (GOLDBERGER *et al.*, 2000; MOODY *et al.*, 2001). PhysioNet provided free access to the database of ECG recordings and an automatic web-based scoring program.

The competition consisted of two challenges. The first challenge was to identify the recordings in the test set with sleep apnoea (class A) and the normal recordings (class C). Assignments for class B were not scored. The score was the total number of correct classifications of class A ($n = 20$) and class C ($n = 10$), so that the maximum possible score was 30. Entrants were given the expert classifications of all the learning set recordings.

The second challenge was to label each minute in all 35 test recordings as either containing apnoea (A) or not (N). In this challenge, all 35 test recordings were scored. To aid the development of these detection algorithms, each ECG recording of the learning set was accompanied by a file with expert annotations (A) and (N) for each minute. Each entry was given a score equal to the total number of correctly labelled minutes. No distinction was made between false positives (class C labelled as class A, or an N minute labelled as an A minute) and false negatives (class A labelled as class C, or an A minute labelled as an N minute).

Participants submitted their results for both challenges through the PhysioNet web site†. An automatic scoring program returned the score to each participant via email. Participants were not given any further information about the source of their errors. Each participant was allowed to submit multiple entries, but a progressive delay was added between the time of submission and the scoring of the entry.

2.3 *Algorithms for apnoea detection*

Eight participants provided fully automatic analysis (JARVIS and MITRA, 2000; DE CHAZAL *et al.*, 2000; MIETUS *et al.*, 2000; SHINAR *et al.*, 2000; MAIER *et al.*, 2000; SCHRADER *et al.*, 2000; MARCHESI *et al.*, 2000; NG *et al.*, 2000), and five required a visual or auditory classification stage (RAYMOND *et al.*, 2000;

*The data will remain on the PhysioNet web site indefinitely (http://www.physionet.org/physiobank/database/apnea-ecg/) and are also available from the authors

†http://www.physionet.org/

Table 1 Comparison of algorithms for detection of sleep apnoea

Number	Algorithm	Method	Frequency domain	Time domain	ECG morphology
1	JARVIS *et al.* (2000)	auto	PSD, TFM	–	–
2	RAYMOND *et al.* (2000)	auto	WT	–	T-wave amplitude
		visual	–	delta RR	–
3	DE CHAZAL *et al.* (2000)	auto	PSD	RR variability	R amplitude
4	MCNAMES and FRASER (2000)	visual	PSD, TFM	–	heart rate, S amplitude, pulse energy
5	STEIN and DOMITROVICH (2000)	visual	–	cyclical variation in heart rate	–
6	MIETUS *et al.* (2000)	auto	HT amplitudes and frequencies	–	–
7	SHINAR *et al.* (2000)	auto	PSD	low-pass filter + U shape pattern detection	R duration
8	DRINNAN *et al.* (2000)	auto	PSD	–	–
		visual	PSD	–	–
9	MAIER *et al.* (2000)	auto	–	RR variability + non-linear statistics	–
10	SCHRADER *et al.* (2000)	auto	PSD + WT + HT, TFM	–	–
11	MARCHESI *et al.* (2000)	auto	–	moving averages	–
12	BALLORA *et al.* (2000)	audio	–	–	–
13	NG *et al.* (2000)	auto	WT + Bayesian hierarchical model	–	–

auto = automated system based on calculated parameters; visual = classification based on visual inspection of spectrograms or other patterns; audio = classification based on sonification; PSD = power spectral density; HT = Hilbert transform; WT = wavelet transform; TFM = time–frequency maps.

MCNAMES and FRASER, 2000; STEIN and DOMITROVICH, 2000; DRINNAN *et al.*, 2000; BALLORA *et al.*, 2000), as indicated with some keywords in Table 1.

Six participants made use of spectral analysis of heart rate variability (JARVIS *et al.*, 2000; DE CHAZAL *et al.*, 2000; MCNAMES and FRASER, 2000; SHINAR *et al.*, 2000; DRINNAN *et al.*, 2000; SCHRADER *et al.*, 2000). Two participants used the Hilbert transform to extract frequency information from the heart rate signal (MIETUS *et al.*, 2000; SCHRADER *et al.*, 2000). Three algorithms used time–frequency maps for the presentation of the heart rate variability (JARVIS *et al.*, 2000; MCNAMES and FRASER, 2000; SCHRADER *et al.*, 2000) (Fig. 2). One of the participants used a threshold for the ratio of the spectral power of the heart rate in two fixed frequency bands (0.01–0.05 cycles per beat and 0.005–0.010 cycles per beat) (DRINNAN *et al.*, 2000).

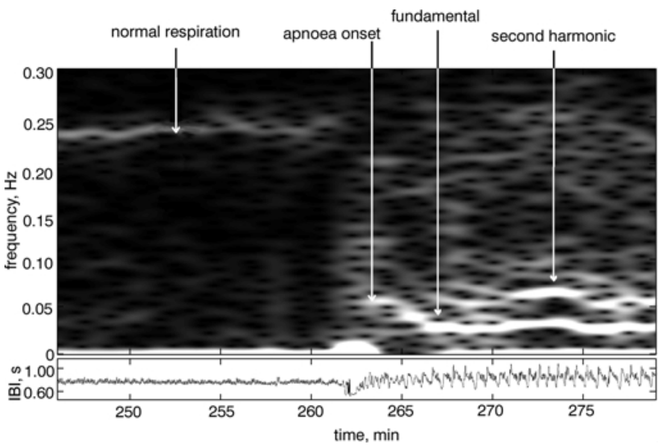

Fig. 2 *Visual detection of one method is illustrated: periods of apnoea were visually identified by looking at spectrogram (MCNAMES and FRASER, 2000) in 0.02–0.08 Hz range. A lot of energy in this region was indicative that signal contained apnoea. Frequency range of normal respiration was also inspected to see if there was a periodic pattern. This 40-year-old male had an apnoea/hypopnoea index of 33 events per hour*

Another participant combined spectral analysis, Hilbert transform frequencies and discrete wavelet analysis, to use more parameters for a subsequent feature selection (SCHRADER *et al.*, 2000).

Several algorithms used different ECG-derived parameters in addition to heart rate variability: ECG pulse energy (MCNAMES and FRASER, 2000), R-wave duration (SHINAR *et al.*, 2000) and amplitude of the S component of each QRS complex (MCNAMES and FRASER, 2000), and two used the ECG-derived respiration (EDR) technique (MOODY *et al.*, 1985) to measure the amplitude modulation of the ECG signal to estimate respiratory activity. These were based on spectral analysis of the R-wave amplitude using power spectral density (PSD) (DE CHAZAL *et al.*, 2000) and of the T-wave amplitude using the discrete harmonic wavelet transform (RAYMOND *et al.*, 2000). The latter algorithm also used time-domain techniques to identify changes in heart rate consistent with arousal from sleep, which is expected to occur at the end of each respiratory event.

Three methods were based on time-domain parameters. One of these used parameters as recommended in the standards for measurement of heart rate variability (MAIER *et al.*, 2000). This approach also added some non-linear statistical physics parameters to improve the results. The second method used a tachogram preprocessing with double moving averages and sleep apnoea detection by a transformation enhancing the difference between the regular heart rhythm and the cyclical variation of heart rate (MARCHESI *et al.*, 2000). The third time-domain method used rules applied by a human observer for the identification of the cyclical variation of heart rate (STEIN and DOMITROVICH, 2000). Apnoeas were detected from periods with at least three consecutive cycles where heart rate rose by at least 6 min^{-1} and then returned to baseline. Cycles had to be 20 s–2 min in duration.

One novel approach used audio synthesis ('sonification') of the interbeat interval series that was interpreted as an 'auditory display' by the listener. Four time-domain parameters (interbeat intervals, mean of 15 beats, mean of 5 beats, standard deviation of 300 beats) were used to generate musical events. This auditory display takes advantage of human auditory signal interpretation as opposed to visual interpretation (BALLORA *et al.*, 2000).

3 Results

Thirteen algorithms were compared for the apnoea recording identification. Four algorithms achieved the highest possible score for the apnoea screening (30/30). The results are listed in Table 2. Two of the co-author groups have data showing that visual analysis was better than the automatic analysis. The corresponding results are also given in Table 2.

Eight algorithms were compared for the minute-by-minute apnoea classification. The maximum possible score was 17 268, which is the total number of minutes in the 35 test recordings. The results are given in Table 3. Two algorithms reached more than 90% agreement. The results of both comparisons are available on the PhysioNet web-site[‡].

All algorithms that used frequency-domain techniques identified as an important parameter the spectral power in the 0.01–0.04 Hz range, either as the sum of a broad band, or as the power representing one frequency. Algorithms based on frequency-domain analysis had better results than algorithms based on time-domain analysis. Even simple parameters derived from the frequency domain resulted in good scores.

In all cases in which individual studies compared the performance of their algorithms with and without the information derived from ECG morphology (including EDR and related techniques), making use of this information did improve the performance of the algorithms. The combination of frequency-domain parameters of either heart rate variability or the ECG-derived respiration signal with R-wave morphology gave the best results.

The results of the top three algorithms from the minute-by-minute comparison (McNames and Fraser, 2000; Raymond *et al.*, 2000; de Chazal *et al.*, 2000) were also combined using a simple majority-voting decision algorithm. Each minute was labelled according to the most common label from the three sets of results. This combination yielded an accuracy of 93.1%, indicating that further improvements are possible.

To illustrate the differences and similarities of the algorithms, we depict four successful algorithms, together with the original interbeat interval time series and the expert scoring, in Fig. 3.

Table 2 Results of first challenge to identify subjects with and without apnoea

Number	Score	Algorithm	Entries
1	30	Jarvis *et al.* (2000)	3
2	30	Raymond *et al.* (2000) visual method	3
	29	automatic method	
3	30	De Chazal *et al.* (2000)	1
4	30	McNames and Fraser (2000)	3
5	29	Stein and Domitrovich (2000)	2
6	28	Mietus *et al.* (2000)	2
7	28	Shinar *et al.* (2000)	1
8	28	Drinnan *et al.* (2000) visual method	1
	27	automatic method	
9	28	Maier *et al.* (2000)	2
10	28	Schrader *et al.* (2000)	8
11	27	Marchesi *et al.* (2000)	1
12	27	Ballora *et al.* (2000)	1
13	19	Ng *et al.* (2000)	0

Number of entries reflects number of trials in competition. Ng *et al.* (2000) were not allowed to enter competition officially, because first entry arrived after deadline, although their entry was scored.

Table 3 Results of second challenge to identify each minute of apnoea and hypopnoea

Score, min and %		Algorithm	Entries
15 994	92.6%	McNames and Fraser (2000)	4
15 939	92.3%	Raymond *et al.* (2000)	8
15 432	89.4%	de Chazal *et al.* (2000)	15
15 120	87.6%	Schrader *et al.* (2000)	9
15 075	87.3%	Jarvis *et al.* (2000)	3
14 788	85.6%	Shinar *et al.* (2000)	1
14 772	85.5%	Maier *et al.* (2000)	5
14 591	84.5%	Mietus *et al.* (2000)	3

Number of entries reflects number of trials in competition. Percentages give number of correctly classified minutes for all subjects.

[‡]http://www.physionet.org/cinc-top-scores.shtml

4 Discussion and conclusions

Both comparisons showed remarkably good results in terms of sleep apnoea identification.

The result of the first comparison demonstrated that it is possible to identify quantitatively subjects with disordered breathing, based on the analysis of heart rate variability, with a satisfactory diagnostic accuracy in this selected set of data. Four algorithms implemented a method that was able to give a subject classification only and that did not give a scoring on a minute-by-minute level. These methods took part in only the first comparison.

Two methods used time-domain features by a visual evaluation of the specific pattern of cyclical variation of heart rate (Stein and Domitrovich, 2000) and by identifying the same pattern using two moving averages with different time windows (Marchesi *et al.*, 2000).

Two methods used the frequency changes of the interbeat intervals, one by the evaluation of frequency bands of a summed frequency analysis (Drinnan *et al.*, 1998), and the other by modulating a musical synthesiser with the interbeat intervals, which was called sonification (Ballora *et al.*, 2000).

Among these, the visual analysis of cyclical variation in heart rate performed best. This confirms earlier results using the visual evaluation of heart rate for the recognition of sleep apnoea (Guilleminault *et al.*, 1984; Penzel *et al.*, 1990).

The results of the second comparison demonstrated that it is possible to determine the time an individual spent with disordered breathing with an accuracy similar to the agreement between different expert evaluators of sleep recordings in this selected set of data (Whitney *et al.*, 1998). Depending on the definition of respiratory events during sleep and the extent of the accompanying drop in oxygen saturation, the intraclass correlation varies between 0.74 and 0.99 (Whitney *et al.*, 1998). The interobserver variability in recognising arousal in sleep-related breathing disorders is even worse and gives only moderate agreement, with a kappa of 0.47, where a value of 1.0 indicates complete agreement (Drinnan *et al.*, 1998).

The algorithms that performed best used frequency-domain parameters of heart rate variability or the ECG-derived respiration signal with R-wave morphology (de Chazal *et al.*, 2000; McNames and Fraser, 2000; Raymond *et al.*, 2000; Shinar *et al.*, 2000). Three of these four algorithms identified all subjects correctly, and the same three were the top-scoring algorithms in the identification of minutes spent with disordered breathing. No single method to calculate spectral power was superior. The successful algorithms either used the discrete Fourier transform or the discrete wavelet transform. The use of ECG-derived parameters provided additional performance gains. Most algorithms assumed that changes in the ECG morphology or modulation were caused by changes in position or respiration.

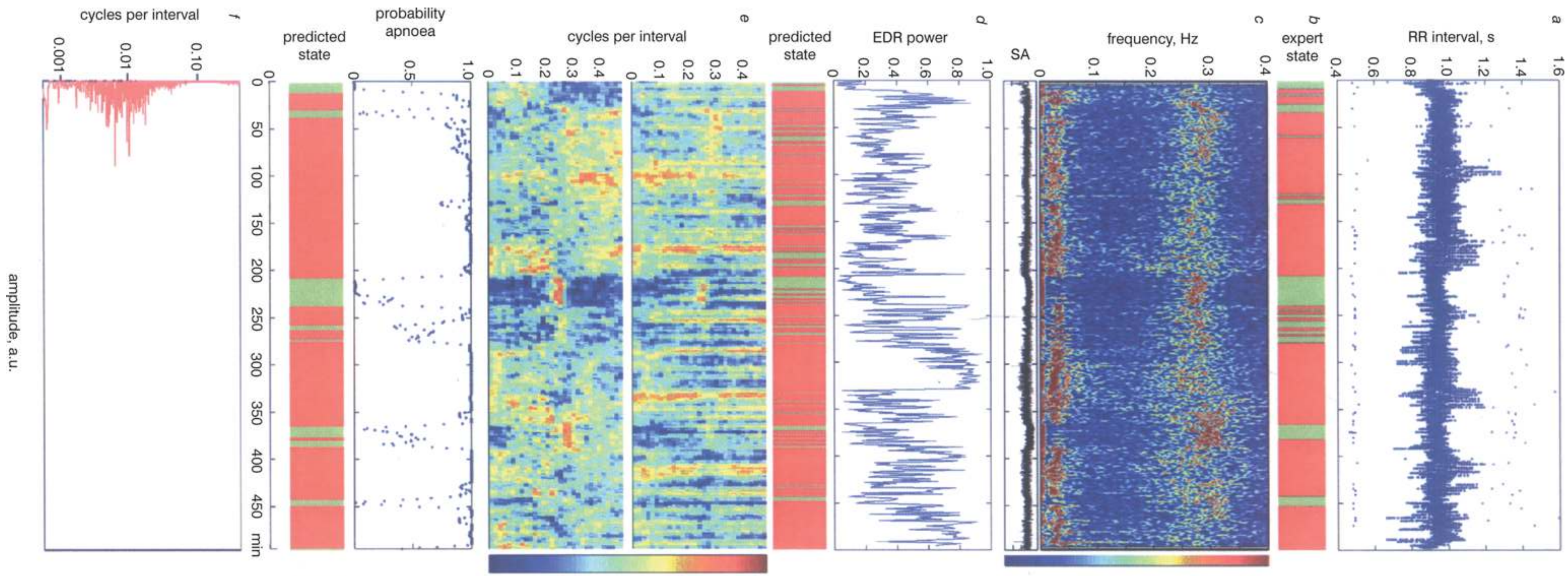

Fig. 3 *Comparison of 4 algorithms for apnoea detection in male subject aged 52 years, with apnoea/hypopnoea index of 32 events per hour, similar to that of subject in Fig. 2, but in which apnoea was much more difficult to identify. (a)–(c) Horizontal axis is for full, overnight recording duration of 496 min. (a) Original RR-interval time series. (b) Colour-coded expert scoring of each minute, with green for normal and red for disordered breathing. (c) Spectrogram (time-frequency map) of S amplitude (SA) component of all QRS complexes (blue = small, and red = large SA); S amplitude time series (120 μV axis scale) (McNames and Fraser, 2000). (d) ECG-derived respiratory (EDR) power from T-wave, normalised; predicted state, with green for normal and red for disordered breathing (Raymond et al., 2000). (e) Power spectral density (PSD) of changes in RR-intervals; PSD of ECG-derived respiratory power from R amplitude (blue = small, and red = large PSD); estimated probability of apnoea (apnoea = 1, and normal breathing = 0); predicted state, with green for normal and red for disordered breathing (de Chazal et al., 2000). (f) FFT of entire RR-interval time series showing frequency band that tended to identify apnoea (Drinnan et al., 2000)*

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Author's biography

THOMAS PENZEL was born in 1958 in Hamburg, Germany. He studied physics and mathematics in Göttingen, Berlin and Marburg. He graduated in theoretical physics (1986), received his doctorate in human biology (1991) and his habilitation in physiology (1995). In 2001, he was appointed professor at the medical faculty of the University of Marburg. Since 1982 he has worked in the sleep laboratory of the University of Marburg. From 1993–2001 he was a member of the board of the German Sleep Society. Since 2001 he has been the President of the International Society on Biotelemetry.