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(54) METHOD AND SYSTEM FOR MONITORING SLEEPINESS

VERFAHREN UND SYSTEM ZUR ÜBERWACHUNG DES ZUSTANDES DER SCHLÄFRIGKEIT

PROCÉDÉ ET SYSTÈME POUR SURVEILLER LA SOMNOLENCE

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Description

Field of the Invention

[0001] The present invention relates to the monitoring of sleep, including sleep state or sleepiness levels of humans in a convenient way, and more specifically to a method and system for acquiring and processing the related information.

Background

[0002] Monitoring of sleep state and sleepiness is useful in a clinical context for assessing subjects with suspected obstructive sleep apnoea, and in an industrial context for monitoring sleepiness in vehicle drivers and in actual work environments, particularly where sleepiness-related accidents can have serious consequences.

[0003] Obstructive sleep apnoea syndrome (OSAS) is a prevalent but under-diagnosed condition with serious cardiovascular consequences, and is highly treatable. Standard in-laboratory testing for OSAS involves an overnight study to assess severity of apnoea and sleep fragmentation, and may also involve an all-day study to assess daytime sleepiness. Assessment of sleep fragmentation can be achieved by analysing the overnight study to produce a chart of sleep stages, and the assessment of daytime sleepiness can be accomplished by measuring on multiple occasions over a day, the time taken for subjects to fall asleep (the so-called Multiple Sleep Latency Test).

[0004] However, due to increasing public awareness of OSAS and resource constraints in healthcare systems, in-laboratory testing for OSAS suffers from low availability in many countries. Therefore there is considerable interest among the professional societies in sleep medicine in the development of reliable low-cost techniques suitable for use in the home environment for identification of subjects with OSAS.

[0005] In the general population, the problem of sleepiness is recognised as a contributing factor to occupational and vehicular accidents. In the area of transportation safety, there is a lot of interest in methods to monitor driver fatigue. At the same time, there is interest in techniques that can complement existing in-laboratory clinical tools by assessing sleepiness over prolonged periods in the actual work environment.

[0006] A variety of techniques have been disclosed in the background art for addressing the need for sleep state and sleepiness monitoring outside of the laboratory environment.

[0007] For sleep state monitoring, portable systems incorporating the required signals for standard in-laboratory monitoring (2 channels of electroencephalography, 2 channels of electro-oculography and 1 channel of electro-myography) have been developed. However, these systems require substantial clinical support to operate in the home environment. Subjects usually have to visit the sleep clinic before and after the overnight study to have the equipment set-up and removed. They also require the attachment of electrodes to the head, which can be disruptive and inconvenient.

[0008] Another method is to use a subset of the standard signals (such as a single EEG channel) to obtain an approximation. However, EEG monitoring at home requires significant user expertise, and it does not allow concurrent apnoea detection. Methods using other signals to provide estimates have also been proposed. These methods include actimetry, ECG plus respiration, and peripheral arterial tone plus actimetry. However, actimetry alone can only distinguish between wake and sleep but not the different stages of sleep, and also does not allow concurrent apnoea detection. Peripheral arterial tone monitoring requires proprietary and costly hardware and associated software. Respiration monitoring may be prone to sensor displacement in a home environment.

[0009] For sleepiness monitoring outside laboratory conditions, methods using eyelid closures, head movements, video surveillance, EEG, and actimetry have been proposed. However, methods using eyelid closures, head movements, video surveillance are not portable, so while it is feasible for applications such as driver sleepiness monitoring, it is not suitable for applications requiring ambulatory monitoring. EEG is ambulatory, but technical difficulties for long-term monitoring exist, and again it is inconvenient to have electrodes attached to the scalp. Sleepiness can be more objectively assessed with measurements such as the Psychomotor Vigilance Test (PVT) which measures a subject's reaction times. It has been shown that in a given subject, the reaction times will decrease as the person becomes sleepier - therefore PVT scores are used as a surrogate for sleepiness. However, PVT scoring takes approximately 10 minutes to carry out, and requires the subject's active attention so cannot be used for in-task monitoring of sleepiness.

[0010] WO2005067790 relates to an apparatus for detecting sleep disordered breathing (SDB), cardiac events and/or heart rate variability (HRV) in a subject from a physiological electrocardiogram (ECG) signal. The apparatus includes means for monitoring the ECG signal and means for extracting from the ECG signal parameters indicative of the SDB, cardiac events and/or HRV. The apparatus also includes means utilizing the parameters to detect the SDB, cardiac events and/or HRV. The SDB, cardiac events and/or HRV may be detected in real time, breath by breath and/or post acquisition of the ECG signal. The apparatus may include means for determining a treatment for the SDB, cardiac events and/or HRV. An electromyogram (EMG) signal may be extracted from the ECG signal to provide a marker for distinguishing OSA from CSA. The marker may indicate that treatment levels should be varied to avoid elevated cardiac risk. A method of detecting SDB, cardiac events and/or HRV in the subject is also disclosed.

[0011] US 2006/241708 relates to an apparatus and method for detecting respiratory disturbances based on multiple physiological parameters are provided. The method includes sensing one or more physiological signals, deriving from the sensed signals multiple physiological parameters that change during a respiratory disturbance, computing a probability that the respiratory disturbance is present using the multiple physiological parameters, and detecting the respiratory disturbance if the probability exceeds a predetermined threshold. In some embodiments, the method further includes generating an alert signal or other report in response to a respiratory disturbance detection. In other embodiments, the method further includes triggering the delivery of a therapy in response to a respiratory disturbance detection.

[0012] US 2006/224073 relates to an integrated physiological signal assessing device that integrates electrical signal detecting technology and optical detecting technology to design a sensing interface module for simultaneously measuring ECG signals and PPG signals, and utilizes multiple algorithm processing methods to obtain ECG parameters, such as rhythm of a heart, ST segment, and QRS interval, as well as vascular parameters, such as vascular stiffness index (SI), vascular reflection index (RI), pulse wave velocity (PWV), and pulse oxygen saturation (SpO2), so as to simplify the conventional vascular functions measuring devices, easily understand physiological conditions of a subject, and helpfully apply on diagnosis and prevention of cardiovascular diseases.

Summary

[0013] In its broadest aspect the present invention provides a method of monitoring level of sleepiness in accordance with claim 1, and a system according to claim 10. Advantageous features are defined in the dependent claims.

[0014] The invention enables the monitoring sleepiness level of human subjects in a convenient, non-invasive and low-cost fashion. In particular, the present invention provides the advantage that it requires a minimal number of signals (two signals) that are robust in the home environment to perform sleep state monitoring, and these signals can also be used concurrently for apnoea detection, which is another significant aspect of sleep apnoea diagnostics. In addition, these signals can be acquired in a non-invasive and fully ambulatory manner using relatively low- cost hardware

[0015] The invention has applications to clinical assessment of subjects with suspected sleep apnoea or sleep disorders that disrupt sleep state patterns, such as narcolepsy, monitoring of sleep and sleepiness patterns in healthy subjects, fitness- for-duty tests for sleepiness, sleepiness monitoring in actual work environments such as machinery operation, and driver sleepiness monitoring.

Brief Description of the Drawings

[0016] Embodiments of the present invention will now be described, by way of example, with reference to the accompanying drawings in which:

Figure 1 is a block schematic diagram of a system for estimating sleep states according to a first embodiment of the present invention.

Figure 2 are waveform diagrams showing parameters derived from the ECG (upper waveform) and PPG (lower waveform) which are used in the first embodiment (as well as the other embodiments).

Figure 3 is a diagram illustrating the output of the system of Figure 1 for estimating sleep states.

Figure 4 is a block schematic diagram of a system for estimating sleepiness according to a second embodiment of the present invention.

Figure 5 is an example of the variation in features derived from RR interval, pulse arrival time, and pulse amplitude for an individual in an alert state (left hand column) and a sleepy state (right hand column).

Figure 6 is a block schematic diagram of a system for estimating sleepiness according to a third embodiment of the present invention.

Figure 7 is a graph illustrating an example of detrended fluctuation analysis.

Figure 8 illustrates a wrapper-based search process.

Detailed Description

[0017] Figure 1 is a block schematic diagram of a system for estimating sleep states according to a first embodiment of the present invention. The system comprises a data acquisition apparatus 10 and data processing stages 12, 14 and 16.

[0018] The data acquisition apparatus 10 is a combined Holter monitor and pulse oximeter. The Holter monitor is capable of recording three data channels. In this embodiment two of the channels are used to record two ECG waveforms, and the remaining channel to record the PPG waveform.

[0019] In particular, two channels of ECG (modified lead V5 and modified lead V1) and one channel of finger PPG (index finger of non-dominant hand) are recorded simultaneously. Only one channel of ECG (modified lead V5) out of the two channels recorded is used for this embodiment, the other being recorded to provide redundancy and to allow for the possibility of calculating an ECG-derived respiration signal. The data is stored in flash memory within a portable storage device carried by the subject in a sling pouch or in a pocket, and is transferred offline to the data processing stages 12 to 16 for further analysis. The data processing stages 12 to 16 can be implemented by a suitably programmed computer. Alternatively, the portable device can have processing capability so that real-time monitoring can be performed.

[0020] It will be noted that this arrangement avoids the subject having to be connected to a bulky recording system. This is in contrast to the current technique of monitoring sleep in a hospital which requires multiple cables to be attached to the subject, these cables terminating at the other end in a bulky recording system. In that arrangement the subject is 'tied' to the recording system for the entire night, as to even go to the washroom would require a technician to remove and subsequently reattach all the cables. In the present embodiment the subject is fully ambulatory.

[0021] In the pre-processing stage 12, various parameters are derived from the ECG and PPG. In the feature extraction stage 14, various features suitable for classifying sleep states are extracted from the various parameters derived in stage 12. Finally, in the classification stage 16, a subset of features is fed into a classifier model to obtain estimated sleep states.

[0022] Figure 2 are waveform diagrams showing parameters derived in the pre-processing stage 12 from the ECG (upper waveform) and PPG (lower waveform). Four parameters, namely RR interval, pulse amplitude, pulse arrival time and respiration are derived from the ECG and PPG signals. The first three are defined based on characteristic points on the waveforms, shown as small circles in Figure 2. RR intervals are the time differences between successive QRS peaks, which can be detected using conventional methods such as Hilbert-transformation with thresholding. To derive pulse amplitude, the PPG is high-pass filtered at 0.05 Hz to remove a very low frequency baseline and then normalised to unit median pulse amplitude as raw PPG values varies considerably between subjects depending on physiological factors such as body position and technical factors such as probe application pressure. Pulse amplitude is then calculated as the beat by beat trough to peak amplitude, and peaks and troughs can be detected using conventional methods such as derivative with thresholding. Pulse arrival time is calculated as the time interval between the R peak on the ECG and the point with maximum gradient on the systolic edge of the PPG. Respiration is obtained by band-pass filtering the PPG between 0.06 and 0.5 Hz.

[0023] In the feature extraction stage 14 the following features are calculated:

(a) PPG spectral spread. This is the Shannon entropy of the power spectral density of the PPG signal, calculated for consecutive thirty-second epochs. This feature is useful for identifying movement associated with wakefulness as the power spectral density of PPG waveforms when subjects are not moving are characterised by a concentration of spectral power around the heart rate and its first few higher harmonics. In contrast, spectral power is more evenly spread out for waveforms contaminated by artefact.

(b) PPG pulse amplitude. This is the mean of the pulse amplitude, calculated for ten-minute epochs sliding at thirty-second intervals. This feature is useful for identifying peripheral vasoconstriction associated with REM sleep, which causes a decrease in pulse amplitude.

(c) Detrended Fluctuation Analysis (DFA). DFA is a technique from statistical physics useful for determining long-term correlation in non-stationary time series. DFA was computed on ten-minute epochs of the RR interval, pulse amplitude and pulse arrival time, sliding at thirty-second intervals. For each epoch, the DFA process is:

i. The time series (of length N) is first demeaned and integrated to get y[k].

ii. It is then divided into segments each of size n (Figure 7).

iii. It is then piece-wise detrended according to the segments (Figure 7) to get $y[k]-y_n[k]$.

iv. F is then computed as the root mean square of $y[k]-y_n[k]$, i.e.

$$F[n] = \sqrt{\frac{1}{N}\sum_{k=1}^{N}(y[k]-y_n[k])^2}$$

v. The above is repeated for different values of n to obtain F[n].

vi. The log transform is then taken to produce the fluctuation function G[n], i.e. G[n] = $\log_{10}$(F[n]).

Another feature that can be obtained is the scaling exponent, which is the slope of the line obtained by regressing G[n] on $\log_{10}$n. In prior art, Penzel et al suggested the scaling exponents obtained from RR intervals are different between sleep stages. Here we found the values G[n] to be a better feature for identifying deep sleep.

(d) Respiratory rate variability. This is the difference between instantaneous respiratory frequency and a baseline respiratory frequency. Instantaneous respiratory frequency is calculated using two-minute, non-overlapping epochs of the PPG-derived respiration signal by taking the frequency with maximum spectral power between 0.15 - 0.4 Hz. Baseline respiratory frequency is calculated in the same way using ten-minute, non-overlapping epochs. This feature is useful for identifying deep sleep as respiratory frequency tend to be highly regular during these periods.

(e) Time and Frequency Analysis. This includes time and frequency domain descriptors of variability in the RR interval, pulse amplitude and pulse arrival time. Examples include standard deviation and spectral power in the low-frequency band.

(f) Multi-Scale Entropy (MSE). MSE is a statistical physics technique useful for revealing changing complexity across different scale factors in complex time series. MSE was computed on ten-minute epochs of the RR interval, pulse amplitude and pulse arrival time, sliding at thirty-second intervals. For each epoch, the MSE process is as follows:

i. The time series (of length N) is first linearly detrended to get x[k].
ii. For a particular scale factor τ, y is then computed by taking the running mean of τ consecutive, non-overlapping values of x[k], i.e.

$$y^{(\tau)}[p] = \frac{1}{\tau}\sum_{k=(p-1)\tau+1}^{p\tau} x[k]$$

where $1 \leq p \leq N/\tau$.
iii. The above is repeated for different values of τ to obtain $y^{(\tau)}[p]$.
iv. Sample entropy is then computed for each $y^{(\tau)}[p]$. For a given time series, its sample entropy is given by:

$$SE = \ln(A/B)$$

where A is the total count of m-point matches, and B is the total count of m+1 point matches. A m-point match occurs when another set of m-points is within a range of $\pm$ r of it. For example, m can be 1 and r can be 15 % of the standard deviation of the time series.

[0024] In the classification stage 16, sleep state estimates (wakefulness, REM, non-REM) are obtained as follows:
(a) Feature Selection. Preferably, the features described are calculated for the entire recording, with one feature vector (made up of all the features) describing each thirty-second epoch. A subset of the features can then selected using feature selection methods in conjunction of a training data set. The feature subset that optimises a certain performance measure, such as classification accuracy, is selected. For example, a wrapper-based search engine as depicted in Figure 8 can be employed for this purpose. Briefly, this is an iterative procedure that takes in the entire feature set and outputs a subset of it that optimises a certain performance measure, such as classification accuracy. The modules of this engine are:

i. Feature Set Search. All possible feature subset combinations are systematically evaluated if technically feasible. Otherwise, a search algorithm such as best-first search is used to systematically evaluate feature subsets.

ii. Feature Set Evaluation. This module evaluates each feature subset generated by the Feature Set Search module, and returns its performance estimate. Evaluation can be performed by cross-validation methods such as leave one subject out cross validation, where for each subject, data from all other subjects are used for training, and data from that subject in question is used for testing.

iii. Epoch Classification. This module uses training data to train a classification model, such as a linear discriminant model, and uses the trained model to classify testing data. The module then returns the classification results.

The following table presents a list of example features that can be generated by the feature selection process, to be used subsequently for distinguishing sleep states.

No.	Parameter	Feature
1	PPG	PPG spectral spread
2	RR interval	DFA G[181]
3	PPG	Pulse amplitude
4	Pulse arrival time	Percentage of successive values differing by > 50 ms
5	Pulse arrival time	Normalised low-frequency spectral power (0.04 - 0.15 cycles/ interval)
6	Pulse amplitude	DFA scaling exponent
7	Pulse arrival time	MSE (scale: 8 beats)
8	PPG	Respiratory rate variability

(b) Linear Discriminants. The selected feature subset is extracted to form consecutive feature vectors, each describing a thirty-second epoch. The features are then supplied to a linear discriminant classifier model, which produces probabilities of each epoch being associated with wakefulness, REM sleep or non-REM sleep.
(c) Post-processing. The probabilities are then smoothed to reduce epoch to epoch variability and then adjusted using heuristic rules based on normal sleep physiology in the population with suspected sleep apnoea. These adjustments include setting the probability for REM sleep to zero for the first 60 minutes of the recording, multiplying by a window that increases linearly from 0 to 1 from 60 to 100 minutes of the recording. Another adjustment is to set the probability for non-REM sleep to zero for the first ten minutes of the recording.
(d) Maximum A posteriori classification. The epochs are then classified into wakefulness, REM sleep or non-REM sleep epochs by assigning them to the class with the maximum adjusted probabilities.
(e) Heuristic correction. The classifications are then adjusted using heuristic rules, including reclassifying sections of non-REM sleep shorter than three minutes which are preceded and followed by REM sleep to REM sleep. Another adjustment is to reject short, isolated REM blocks of at most two-minute duration, and to reclassify these epochs to the class with next highest probability. Another adjustment is to reclassify as wake, short isolated sleep blocks of at most one-minute duration centred on a ten-minute block consisting entirely of wake.

[0025] Figure 3 gives an example of the classification output by comparing it with the output obtained from standard in-laboratory procedures (polysomnography). (a) Top: Polysomnography-scored sleep stages, Bottom: Apnoea events (High = event). (b) Top: Polysomnography-scored sleep stages collapsed to Wake, REM and Sleep states, Bottom: Corresponding estimated sleep states (Dots indicate epochs that were heuristically corrected). Classification accuracy was 72.3 %, and corresponding Cohen’s kappa, which considers accuracy after discounting agreement by chance, was 0.47.

[0026] Figure 4 is a block schematic diagram of a system for estimating sleepiness according to a second embodiment of the present invention. The system comprises a data acquisition apparatus 10 and data processing stages 12, 14’ and 16’. Apparatus 10 and stage 12 are the same as the corresponding components of the first embodiment.

[0027] In the feature extraction stage 14’, the following features are derived from the ECG and PPG signals: PPG spectral spread, respiratory rate variability, PPG pulse amplitude, time and frequency analysis, detrended fluctuation analysis and multi-scale entropy. The features are calculated in the same way as described in relation to Figure 1, except that in this embodiment these features are calculated on one-minute, non-overlapping epochs of data.

[0028] In the classification stage 16', a subset of features associated with each epoch is first selected using feature selection techniques. The process is conducted in the same way as described in relation to Figure 1. This subset of features is then fed into a linear discriminant classification model, which is trained to distinguish between the alert and sleepy states. The classification model produces and outputs the probabilities of each epoch being associated with a sleepiness score. A priori information (such as time of day) may be used in calculating the discriminant values for the one minute epoch. Epochs of different length (e.g., from 10 seconds to hours) could also be used in assessing sleepiness.

[0029] Figure 5 provides an example of how the features derived from RR interval, pulse arrival time, and pulse amplitude vary for an individual in an alert state (left hand column) and a sleepy state (right hand column). The general decrease in variability in the RR interval and pulse arrival time and the general increase in variability in pulse amplitude can be observed qualitatively. Differences in mean levels of heart rate and pulse amplitude can also be observed.

[0030] Figure 6 is a block schematic diagram of a system for estimating sleepiness according to a third embodiment of the present invention in which an objective estimate of sleepiness is obtained based on agreement with psychomotor vigilance test (PVT) scores. The system comprises a data acquisition apparatus 10 and data processing stages 12, 14" and 16". Apparatus 10 and stage 12 are the same as the corresponding components of the first embodiment.

[0031] In the feature extraction stage 14", the following features are derived from the ECG and PPG signals: PPG spectral spread, respiratory rate variability, PPG pulse amplitude, time and frequency analysis, detrended fluctuation analysis and multi-scale entropy. The features are calculated in the same way as described in relation to Figure 1, except that in this embodiment these features are calculated on ten-minute, non-overlapping epochs of data.

[0032] In the sleepiness estimation stage 16", a subset of features associated with each epoch is first selected using feature selection techniques such as stepwise regression. Briefly, in stepwise regression, features are systematically evaluated in terms of a performance measure such as partial correlation with PVT scores, and features with statistically significant partial correlation with PVT scores are selected.

[0033] The following table presents a list of example features that can be generated by the feature selection process, to be used subsequently for estimating PVT scores.

No	Parameter	Feature
1	RR Interval	Heart rate
2	RR Interval	Spectral power in low-frequency band (0.04 - 0.15 cycles/interval)

[0034] The selected feature subset is then fed into a multiple linear regression model, which is trained to provide estimates of PVT scores based on a linear combination of the feature subset. The regression model can also use a priori information (such as time of day) in calculating the estimated PVT score for the ten minute epochs.

Experimental Results

Sleep state monitoring

[0035] 48 subjects representing the entire range of apnoea severity (Table I) were randomly recruited from patients referred to the Sleep Disorders Unit at St. Vincent's University Hospital, Ireland, for evaluation of suspected sleep apnoea.

Table I: Subject characteristics (mean ± standard deviation, range)	
Male : Female	42 : 6
Age (years)	49 ± 10 (28 - 73)
Body Mass Index (kg/m^2)	31 ± 6 (21 - 49)
Apnea Hypopnea Index (hr^{-1})	25 ± 32 (0 - 171)
Epworth Sleepiness Scale	11 ± 6 (0 - 23)

[0036] All subjects underwent standard overnight diagnostic testing for sleep apnoea (polysomnography). ECG and PPG measurements were simultaneously taken using the system described above for sleep state monitoring. Post-polysomnography, experienced sleep technologists performed standard Rechtschaffen and Kales sleep-staging and scoring of respiratory events. Table II summarises the subjects' sleep stage characteristics.

Table II: Sleep stage characteristics obtained from polysomnography	
Sleep State	Proportion of total time in bed (%)
Wake	23 ± 14 (5 - 75)
REM	14 ± 7 (0 - 29)
Non-REM	62 ± 11 (21 - 79)

[0037] The available records were sorted by the subjects' Apnoea-Hypopnea Index (obtained from polysomnography) and assigned alternately to either the training or validation set, yielding training and validation sets of 24 subjects each. This method for splitting the data was used to control for the possible influence of apnoea severity on sleep state estimation.

[0038] The system described above was trained using the training set and tested on the validation set. Table III summarises the training and validation classification performance. As shown, performances on the training and validation data set were in close agreement, indicating the robustness of the classifier. Overall, a classification accuracy of 73.5 ± 7.7 % (Cohen's kappa = 0.49 ± 0.12) was achieved. To separately quantify the performance contribution of the linear discriminant classifier model and the heuristic corrections, Table III also presents the results without heuristic corrections. As expected, the heuristic corrections were useful, but the bulk of performance was contributed by the classifier model.

Table III: Sleep state estimation performance		
	Training Set	Validation Set
With Heuristics Correction		
Accuracy (%)	72.8 ± 8.2	74.1 ± 7.3
Kappa	0.48 ± 0.13	0.50 ± 0.12
Without Heuristics Correction		
Accuracy (%)	71.0 ± 8.7	72.4 ± 7.8
Kappa	0.45 ± 0.13	0.47 ± 0.12

[0039] There was also no significant correlation between classification performance and apnoea severity (r = -0.03, p = 0.85), indicating that the performance of the classifier was limited by factors other than apnoea severity.

[0040] Table IV presents the overall confusion matrix combining results from the training and validation data set. Based on the confusion matrix, overall positive and negative predictive value pairs for each of the sleep states were as follows: Wake (64.1 ± 12.9 %, 88.7 ± 9.8 %), REM (50.8 ± 23.6 %, 94.5 ± 4.5 %) and Sleep (83.2 ± 11.9 %, 67.6 ± 10.0 %).

Table IV: Confusion matrix for sleep state estimation					
		Reference (Polysomnography)			
		Wake	REM	Sleep	Total
Estimate (Proposed System)	Wake	5601	501	2813	8915
	REM	603	3644	2666	6913
	Sleep	2395	1220	18710	22325
	Total	8599	5365	24189	38153

Sleepiness monitoring

[0041] 15 young adults (5 M 10 F, aged 22 ± 3 years, BMI 20.2 ± 2.7 kg/m^2) with no known medical conditions were recruited. All subjects reported normal circadian and sleeping habits, and provided informed consent. Subjects identified a period of alertness and sleepiness each with respect to their normal routine and carried out the same experiment twice on the same day. All subjects chose the morning and afternoon, with a separation of 5.0 ± 1.6 hours in between experiments, and had been awake for about 2.7 and 7.7 hours respectively when the experiments were conducted.

[0042] The experiment consists of two main tasks, performed consecutively in the sitting position. The first task was to watch a ten-minute video, and the second task was to perform a ten-minute Psychomotor Vigilance Test (PVT). Physiological measurements (including ECG, PPG, EEG, respiration and galvanic skin response) were taken throughout the video and PVT tasks.

[0043] The system described above for sleepiness monitoring was developed and tested on this set of data. Using a subset of features that are derived from the ECG and PPG, the classifier model was able to distinguish between alert and sleepy epochs recorded during both the video and PVT task with an accuracy of 72 % ± 15 % (Cohen's kappa = 0.43 ± 0.31). Performance was only slightly worse for classifying epochs from the PVT task (70 % ± 21 %, Cohen's kappa = 0.40 ± 0.42) compared to the video task (73 % ± 15 %, Cohen's kappa = 0.47 ± 0.30), indicating that the classification algorithm is robust for classifying data recorded during different mental situations. Furthermore, using subject-specific classifiers, classification accuracies of 100 % (Cohen's kappa = 1) could be achieved for every subject. Certain features were consistently useful across subjects; however, to achieve full classification accuracy, different additional feature subsets were required for some subjects.

Claims

1. A method of monitoring level of sleepiness, comprising:

simultaneously recording a person's electrocardiogram (ECG) and photoplethysmogram (PPG),
deriving at a data processor a plurality of parameters from both the recorded ECG and PPG data, and
providing an output indicative of a level of sleepiness based upon an analysis of a plurality of features that are determined from the plurality parameters and that relate to characteristics of the level of IF sleepiness, wherein the plurality of parameters are analysed by extracting from the plurality of parameters a plurality of features suitable for classifying level of sleepiness, and feeding a subset of the plurality of features into a classifier to obtain an estimate of the level of sleepiness.

2. The method claimed in claim 1, wherein the ECG and PPG are recorded using a recording apparatus wearable in an ambulatory manner.

3. The method claimed in claim 2, wherein the recording apparatus comprises a combination of a Holter monitor and a pulse oximeter.

4. The method claimed in claim 1, wherein the plurality of parameters include at least one of RR interval, pulse amplitude, pulse arrival time and respiratory rate.

5. The method claimed in claim 1 3 , wherein the features include at least one of PPG spectral spread, PPG pulse amplitude, respiratory rate variability, detrended fluctuation analysis, time and frequency analysis and multi-scale entropy.

6. The method claimed in claim 1, comprising assigning levels of sleepiness to specific epochs of time of greater than 10 seconds in duration.

7. The method of claim 1, further comprising obtaining an objective estimate of sleepiness based on an agreement with phychomotor vigilance test (PVT) scores.

8. The method of claim 1, wherein each of the plurality of parameters is derived from one of the ECG or the PPG data, and wherein the output indicative of a level of sleepiness is based upon an analysis of at least a subset of the derived plurality of parameters.

9. The method of claim 8, wherein the one or more processors are configured to derive an additional parameter from both the recorded ECG and PPG data, and wherein the output indicative of level of sleepiness is based upon an analysis of parameters that includes the additional parameter.

10. A system for monitoring level of sleepiness, comprising:

an apparatus for simultaneously recording a subject's electrocardiogram (ECG) and photoplethysmogram (PPG), and
a data processor for deriving a plurality of parameters from both the recorded ECG and PPG data, and providing

an output indicative of a level of sleepiness based upon an analysis of a plurality of features that are determined from the plurality parameters and that relate to characteristics of the level of sleepiness, wherein the plurality of parameters are analysed by extracting from the plurality of parameters a plurality of features suitable for classifying level of sleepiness, and feeding a subset of the plurality of features into a classifier to obtain an estimate of the level of sleepiness.

11. The system claimed in claim 10, wherein the recording apparatus is wearable in ambulatory manner.

12. The system claimed in claim 10, wherein the recording apparatus comprises a combination of a Holter monitor and a pulse oximeter.

13. The system of claim 10, wherein the data processor is configured to derive each of the plurality of parameters from one of the ECG or the PPG data, and to provide an output indicative of a level of sleepiness based upon an analysis of at least a subset of the derived plurality of parameters.

14. The system of claim 13, wherein the data processor is configured to derive an additional parameter from both the recorded ECG and PPG data, and to provide an output indicative of level of sleepiness based upon an analysis of parameters that includes the additional parameter.

Patentansprüche

1. Verfahren zum Überwachen des Schläfrigkeitsgrades, umfassend:

simultanes Aufzeichnen des Elektrokardiogramms (EKG) und Photoplethysmogramms (PPG) einer Person,
Ableiten, an einem Datenprozessor, einer Vielzahl von Parametern aus sowohl den aufgezeichneten EKG- als auch PPG-Daten und
Bereitstellen einer auf einen Schläfrigkeitsgrad hinweisenden Ausgabe basierend auf einer Analyse einer Vielzahl von Merkmalen, die aus der Vielzahl von Parametern bestimmt werden und die sich auf Eigenschaften des Schläfrigkeitsgrades beziehen, wobei die Vielzahl von Parametern durch das Extrahieren einer Vielzahl von Merkmalen aus der Vielzahl von Parametern, die zum Klassifizieren des Schläfrigkeitsgrades geeignet sind, und das Speisen einer Untergruppe der Vielzahl von Merkmalen in einen Klassifikator analysiert werden, um eine Schätzung des Schläfrigkeitsgrades zu erhalten.

2. Verfahren nach Anspruch 1, wobei das EKG und PPG unter Verwendung einer Aufzeichnungsvorrichtung, die auf eine ambulante Weise tragbar ist, aufgezeichnet werden.

3. Verfahren nach Anspruch 2, wobei die Aufzeichnungsvorrichtung eine Kombination aus einem Holter-EKG und einem Pulsoximeter umfasst.

4. Verfahren nach Anspruch 1. wobei die Vielzahl von Parametern mindestens eines von RR-Intervall, Pulsamplitude, Pulsankunftszeit und Atemfrequenz beinhaltet.

5. Verfahren nach Anspruch 1, wobei die Merkmale mindestens eines von PPG-Spektralspreizung, PPG-Pulsamplitude, Atemfrequenzvariabilität, trendbereinigender Fluktuationsanalyse, Zeit- und Frequenzanalyse und Multiskalen-Entropie beinhalten.

6. Verfahren nach Anspruch 1, umfassend das Zuordnen von Schläfrigkeitsgraden zu bestimmten Zeiträumen mit einer Dauer von mehr als 10 Sekunden.

7. Verfahren nach Anspruch 1, ferner umfassend das Erhalten einer objektiven Schläfrigkeitsschätzung basierend auf einer Übereinstimmung mit Ergebnissen eines psychomotorischen Vigilanztests (PVT).

8. Verfahren nach Anspruch 1, wobei jeder der Vielzahl von Parametern von den EKG- oder den PPG-Daten abgeleitet wird und wobei die auf einen Schläfrigkeitsgrad hinweisende Ausgabe auf einer Analyse mindestens einer Untergruppe der abgeleiteten Vielzahl von Parametern basiert.

9. Verfahren nach Anspruch 8, wobei der eine oder die mehreren Prozessoren konfiguriert sind, um einen zusätzlichen

Parameter aus sowohl den aufgezeichneten EKG- als auch PPG-Daten abzuleiten, und wobei die auf einen Schläfrigkeitsgrad hinweisende Ausgabe auf einer Analyse von Parametern basiert, die den zusätzlichen Parameter einschließt.

10. System zum Überwachen des Schläfrigkeitsgrades, umfassend:

eine Vorrichtung zum simultanen Aufzeichnen des Elektrokardiogramms (EKG) und Photoplethysmogramms (PPG) eines Individuums und
einen Datenprozessor zum Ableiten einer Vielzahl von Parametern aus sowohl den aufgezeichneten EKG- als auch PPG-Daten und Bereitstellen einer auf einen Schläfrigkeitsgrad hinweisenden Ausgabe basierend auf einer Analyse einer Vielzahl von Merkmalen, die aus der Vielzahl von Parametern bestimmt werden und die sich auf Eigenschaften des Schläfrigkeitsgrades beziehen, wobei die Vielzahl von Parametern durch das Extrahieren einer Vielzahl von Merkmalen aus der Vielzahl von Parametern, die zum Klassifizieren des Schläfrigkeitsgrades geeignet sind, und das Speisen einer Untergruppe der Vielzahl von Merkmalen in einen Klassifikator analysiert werden, um eine Schätzung des Schläfrigkeitsgrades zu erhalten.

11. System nach Anspruch 10, wobei die Aufzeichnungsvorrichtung auf eine ambulante Weise tragbar ist.

12. System nach Anspruch 10, wobei die Aufzeichnungsvorrichtung eine Kombination aus einem Holter-EKG und einem Pulsoximeter umfasst.

13. System nach Anspruch 10, wobei der Datenprozessor konfiguriert ist, um jeden der Vielzahl von Parametern aus den EKG- oder den PPG-Daten abzuleiten, und um basierend auf einer Analyse mindestens einer Untergruppe der abgeleiteten Vielzahl von Parametern eine auf einen Schläfrigkeitsgrad hinweisende Ausgabe bereitzustellen.

14. System nach Anspruch 13, wobei der Datenprozessor konfiguriert ist, um einen zusätzlichen Parameter aus sowohl den aufgezeichneten EKG- als auch PPG-Daten abzuleiten, und um basierend auf einer Analyse von Parametern, die den zusätzlichen Parameter einschließt, eine auf einen Schläfrigkeitsgrad hinweisende Ausgabe bereitzustellen.

Revendications

1. Méthode de surveillance du niveau de somnolence comprenant les étapes qui consistent à :

enregistrer simultanément l'électrocardiogramme (ECG) et le photopléthysmogramme (PPG) d'une personne,
déduire, au niveau d'une unité de traitement de données, plusieurs paramètres à partir des éléments d'information tirés à la fois des ECG et PPG enregistrés et
produire une donnée de sortie indicatrice d'un niveau de somnolence sur la base d'une analyse de plusieurs attributs qui sont déterminés à partir des plusieurs paramètres et qui sont liés à des caractéristiques du niveau de somnolence, où les plusieurs paramètres sont analysés en extrayant des plusieurs paramètres plusieurs attributs qui se prêtent à une classification du niveau de somnolence et en introduisant un sous-ensemble des plusieurs attributs dans un classifieur pour obtenir une estimation du niveau de somnolence.

2. Méthode selon la revendication 1, où les ECG et PPG sont enregistrés au moyen d'un appareil d'enregistrement portable en ambulatoire.

3. Méthode selon la revendication 2, où l'appareil d'enregistrement comprend une combinaison d'un moniteur Holter et d'un oxymètre de pouls.

4. Méthode selon la revendication 1, où les plusieurs paramètres incluent au moins un des suivants : intervalle RR, amplitude de l'onde de pouls, temps d'arrivée de l'onde de pouls et fréquence respiratoire.

5. Méthode selon la revendication 1, où les attributs incluent au moins un des suivants : étendue spectrale du PPG, amplitude du PPG de l'onde de pouls, variabilité de la fréquence respiratoire, analyse de fluctuation redressée, analyse temporelle et fréquentielle et entropie multi-échelles.

6. Méthode selon la revendication 1, qui comprend l'affectation de niveaux de somnolence à des périodes de temps spécifiques d'une durée supérieure à 10 secondes.

7. Méthode de la revendication 1, qui comprend en outre l'obtention d'une estimation objective de la somnolence sur la base d'une concordance avec les scores à un test de vigilance psychomotrice (PVT).

8. Méthode de la revendication 1, où chacun des plusieurs paramètres est déduit des éléments d'information tirés soit des ECG, soit des PPG et où la donnée de sortie indicatrice d'un niveau de somnolence repose sur une analyse d'au moins un sous-ensemble des plusieurs paramètres déduits.

9. Méthode de la revendication 8, où les une ou plusieurs unités de traitement sont configurées pour fournir un paramètre supplémentaire déduit des éléments d'information tirés à la fois des ECG et PPG enregistrés et où la donnée de sortie indicatrice d'un niveau de somnolence repose sur une analyse de paramètres qui incluent le paramètre supplémentaire.

10. Système de surveillance du niveau de somnolence comprenant :

un appareil permettant d'enregistrer simultanément l'électrocardiogramme (ECG) et le photopléthysmogramme (PPG) d'un sujet et
une unité de traitement des données pour déduire plusieurs paramètres à partir des éléments d'information tirés à la fois des ECG et PPG enregistrés et produire une donnée de sortie indicatrice d'un niveau de somnolence sur la base d'une analyse de plusieurs attributs qui sont déterminés à partir des plusieurs paramètres et qui sont liés à des caractéristiques du niveau de somnolence, où les plusieurs paramètres sont analysés en extrayant des plusieurs paramètres plusieurs attributs qui se prêtent à une classification du niveau de somnolence et en introduisant un sous-ensemble des plusieurs attributs dans un classifieur pour obtenir une estimation du niveau de somnolence.

11. Système selon la revendication 10, où l'appareil d'enregistrement est portable en ambulatoire.

12. Système selon la revendication 10, où l'appareil d'enregistrement comprend une combinaison d'un moniteur Holter et d'un oxymètre de pouls.

13. Système de la revendication 10, où l'unité de traitement des données est configurée pour déduire chacun des plusieurs paramètres à partir des éléments d'information tirés soit des ECG, soit des PPG et fournir une donnée de sortie indicatrice d'un niveau de somnolence sur la base d'une analyse d'au moins un sous-ensemble des plusieurs paramètres déduits.

14. Système de la revendication 13, où l'unité de traitement des données est configurée pour fournir un paramètre supplémentaire déduit à partir des éléments d'information tirés à la fois des ECG et PPG enregistrés et produire une donnée de sortie indicatrice d'un niveau de somnolence sur la base d'une analyse de paramètres qui incluent le paramètre supplémentaire.

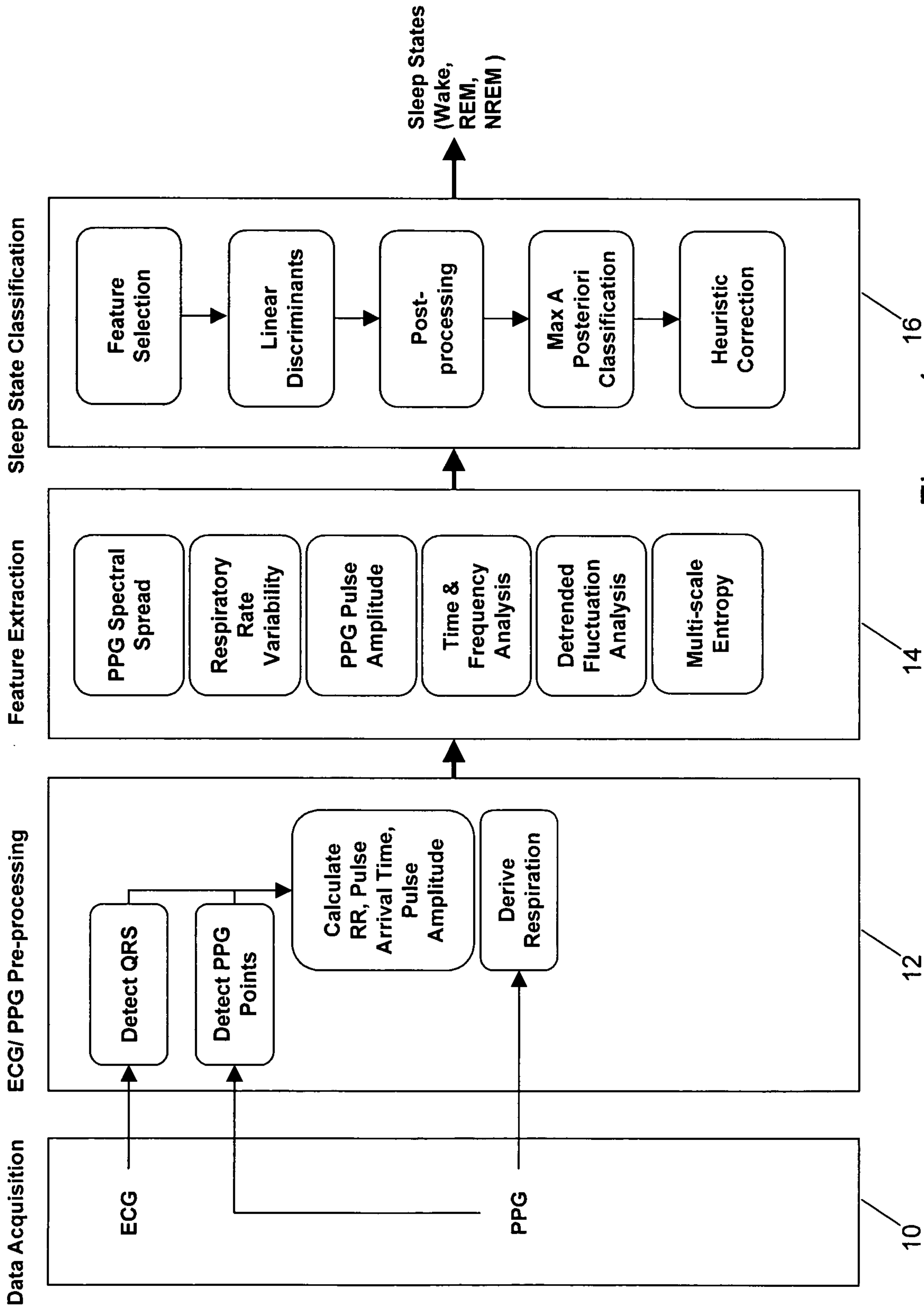

Data Acquisition
ECG
PPG
10
ECG/ PPG Pre-processing
Detect QRS
Detect PPG Points
Calculate RR, Pulse Arrival Time, Pulse Amplitude
Derive Respiration
12
Feature Extraction
PPG Spectral Spread
Respiratory Rate Variability
PPG Pulse Amplitude
Time & Frequency Analysis
Detrended Fluctuation Analysis
Multi-scale Entropy
14
Sleep State Classification
Feature Selection
Linear Discriminants
Post-processing
Max A Posteriori Classification
Heuristic Correction
16
Sleep States (Wake, REM, NREM)

Figure 1

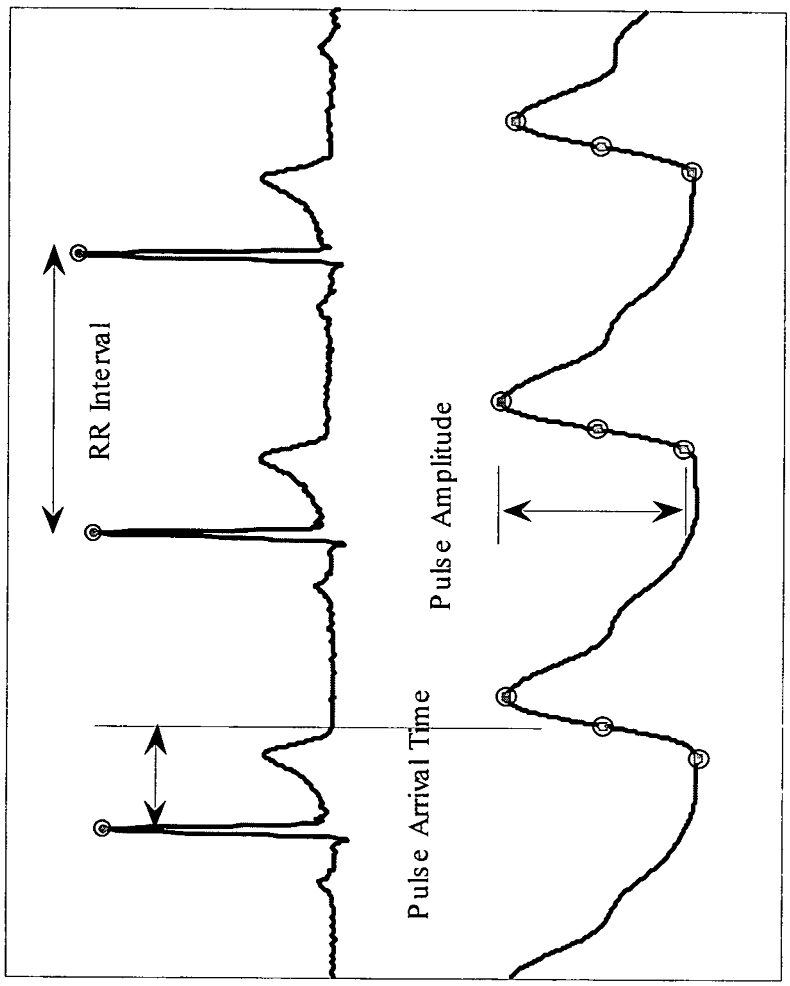


Figure 2

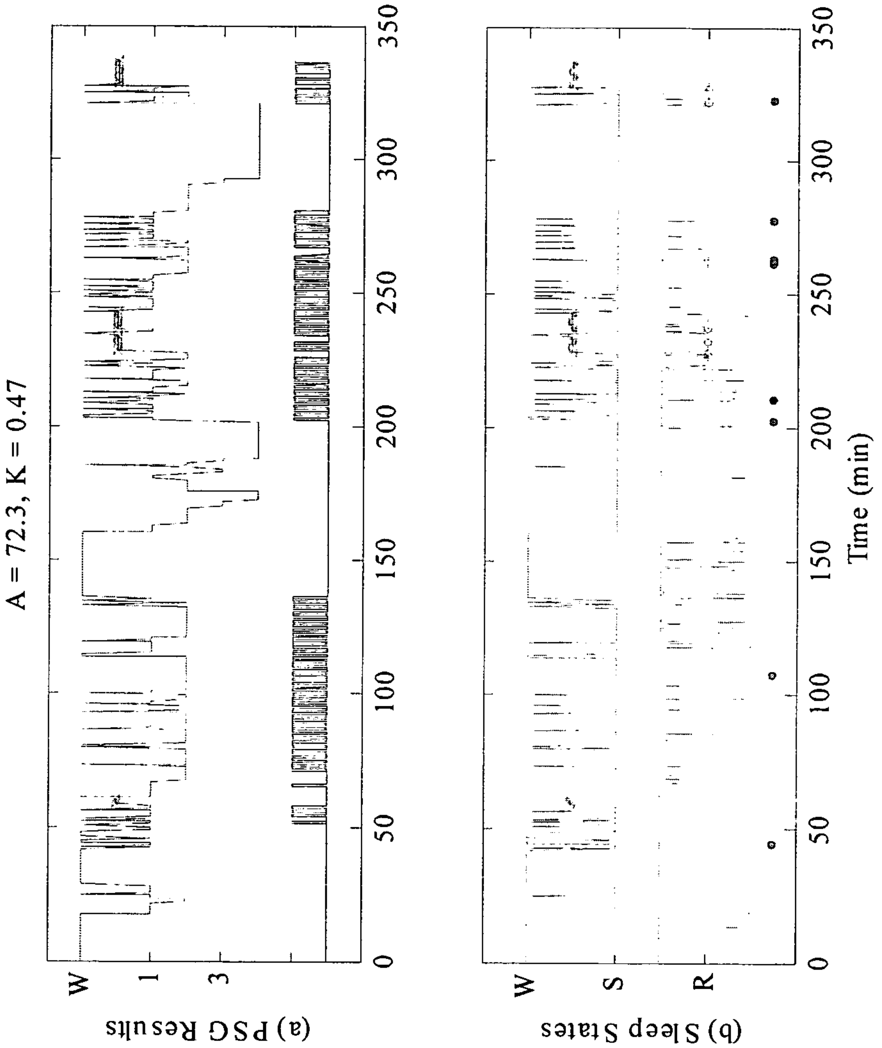

A = 72.3, K = 0.47
(a) PSG Results
W
1
3
(b) Sleep States
W
S
R
0
50
100
150
200
250
300
350
Time (min)

Figure 3

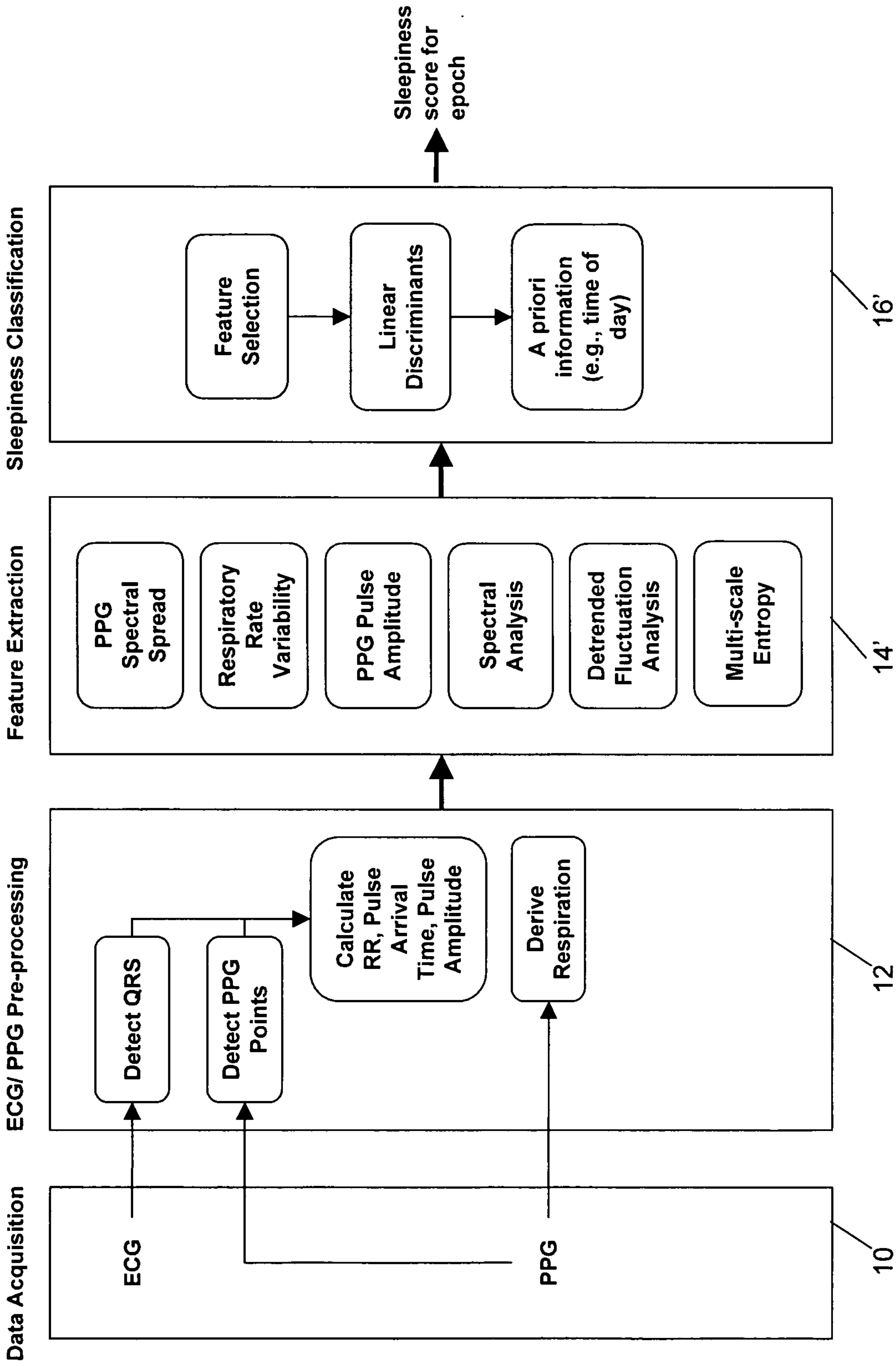

Data Acquisition
ECG
PPG
10
ECG/ PPG Pre-processing
Detect QRS
Detect PPG Points
Calculate RR, Pulse Arrival Time, Pulse Amplitude
Derive Respiration
12
Feature Extraction
PPG Spectral Spread
Respiratory Rate Variability
PPG Pulse Amplitude
Spectral Analysis
Detrended Fluctuation Analysis
Multi-scale Entropy
14'
Sleepiness Classification
Feature Selection
Linear Discriminants
A priori information (e.g., time of day)
16'
Sleepiness score for epoch

Figure 4

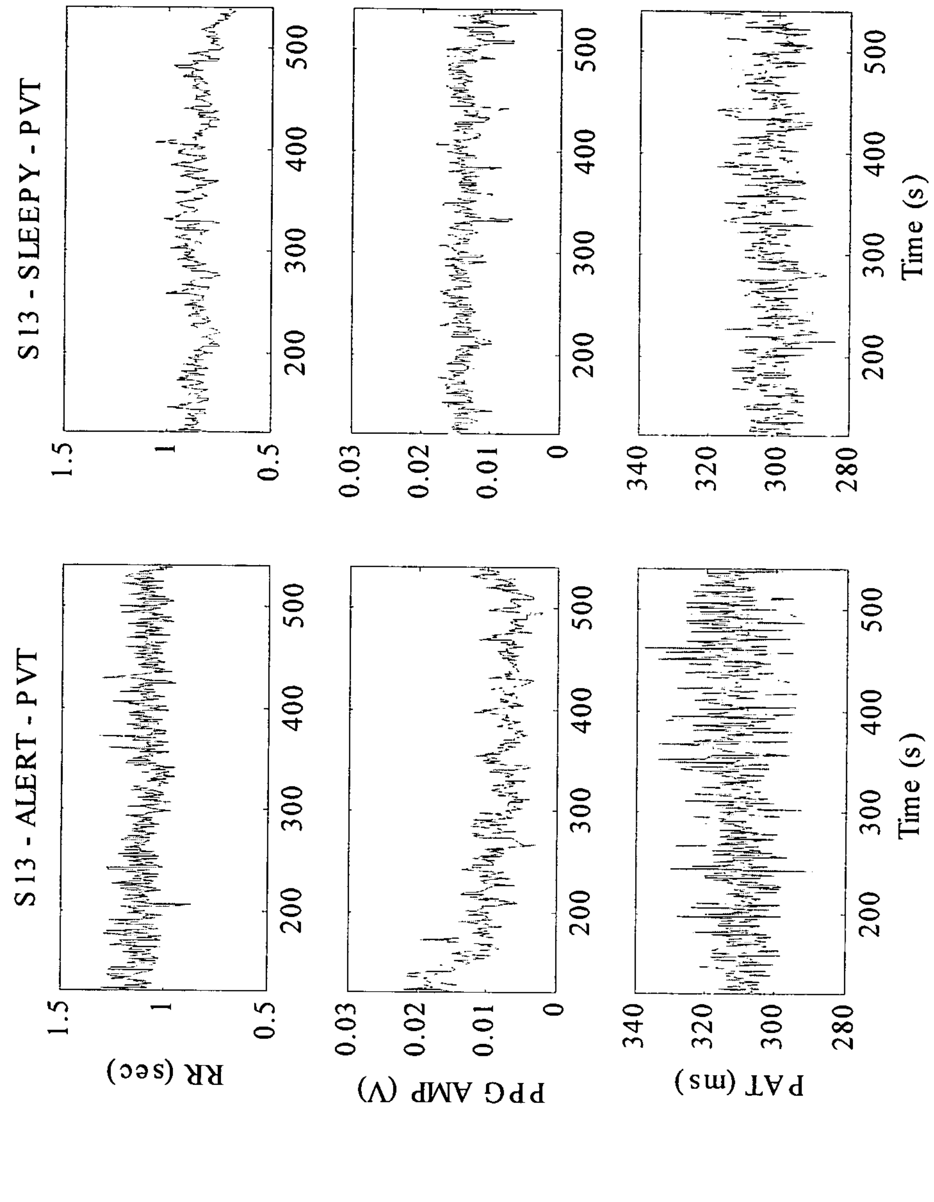

S13 - ALERT - PVT
S13 - SLEEPY - PVT
RR (sec)
PPG AMP (V)
PAT (ms)
Time (s)
Time (s)
1.5
1
0.5
0.03
0.02
0.01
0
340
320
300
280
200
300
400
500

Figure 5

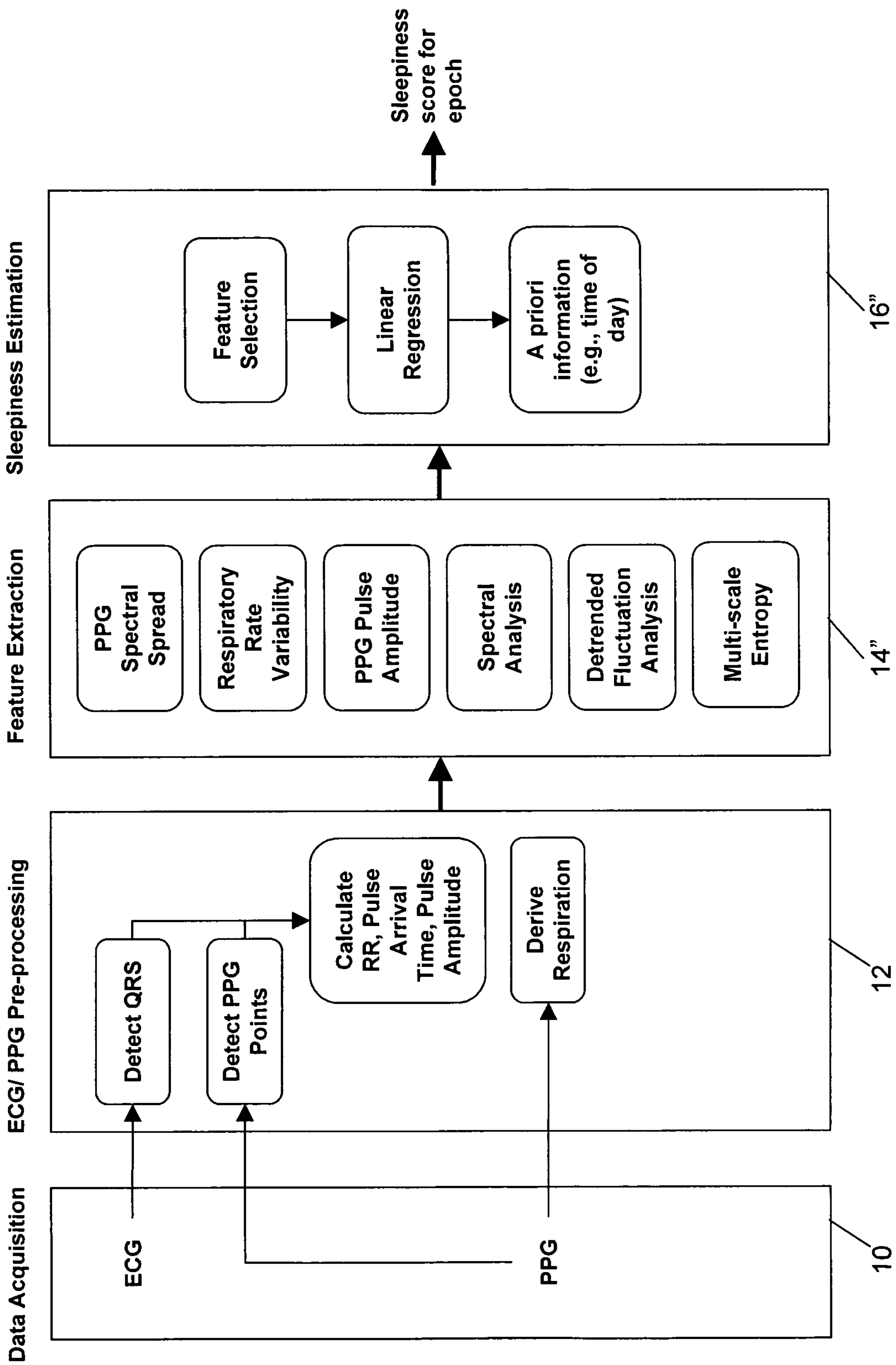
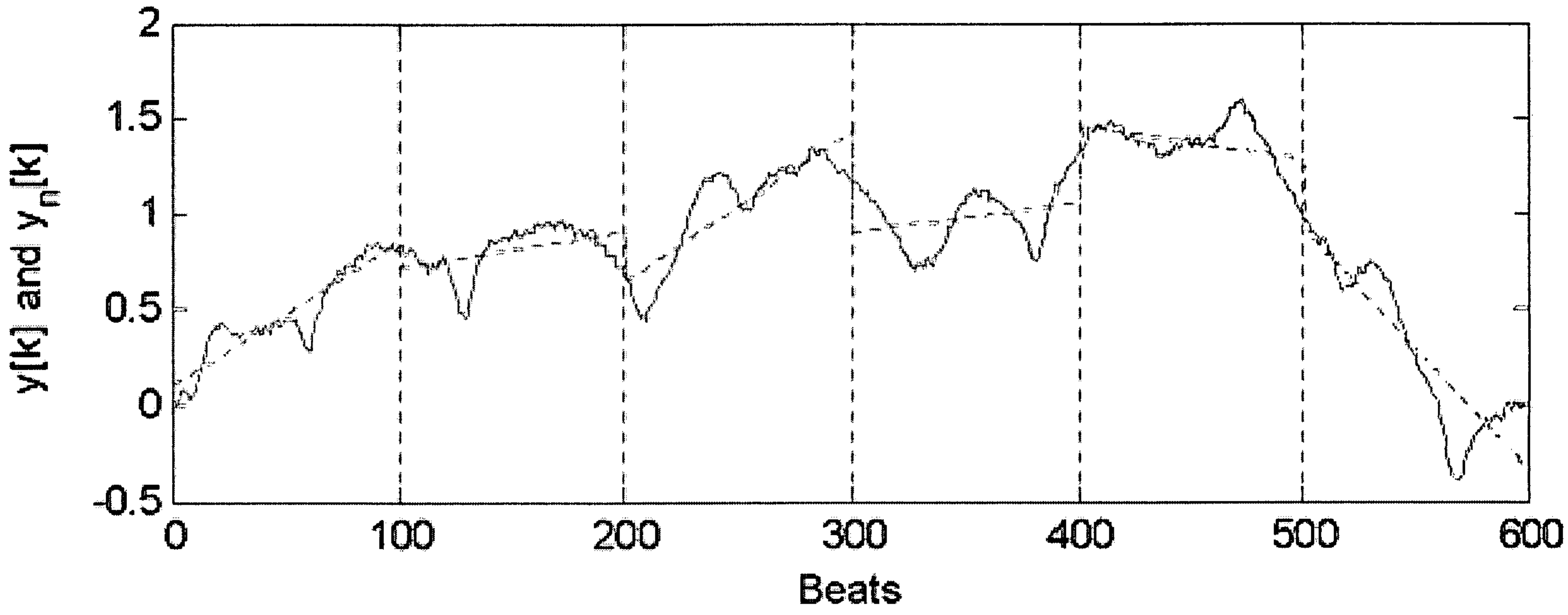

Data Acquisition
ECG
PPG
10
ECG/ PPG Pre-processing
Detect QRS
Detect PPG Points
Calculate RR, Pulse Arrival Time, Pulse Amplitude
Derive Respiration
12
Feature Extraction
PPG Spectral Spread
Respiratory Rate Variability
PPG Pulse Amplitude
Spectral Analysis
Detrended Fluctuation Analysis
Multi-scale Entropy
14”
Sleepiness Estimation
Feature Selection
Linear Regression
A priori information (e.g., time of day)
16”
Sleepiness score for epoch

Figure 6



Example of DFA for n = 100.

Solid line: y[k], demeaned and integrated RR intervals.
Dotted line: $y_n[k]$, piece-wise least squares fit of y[k].

Figure 7

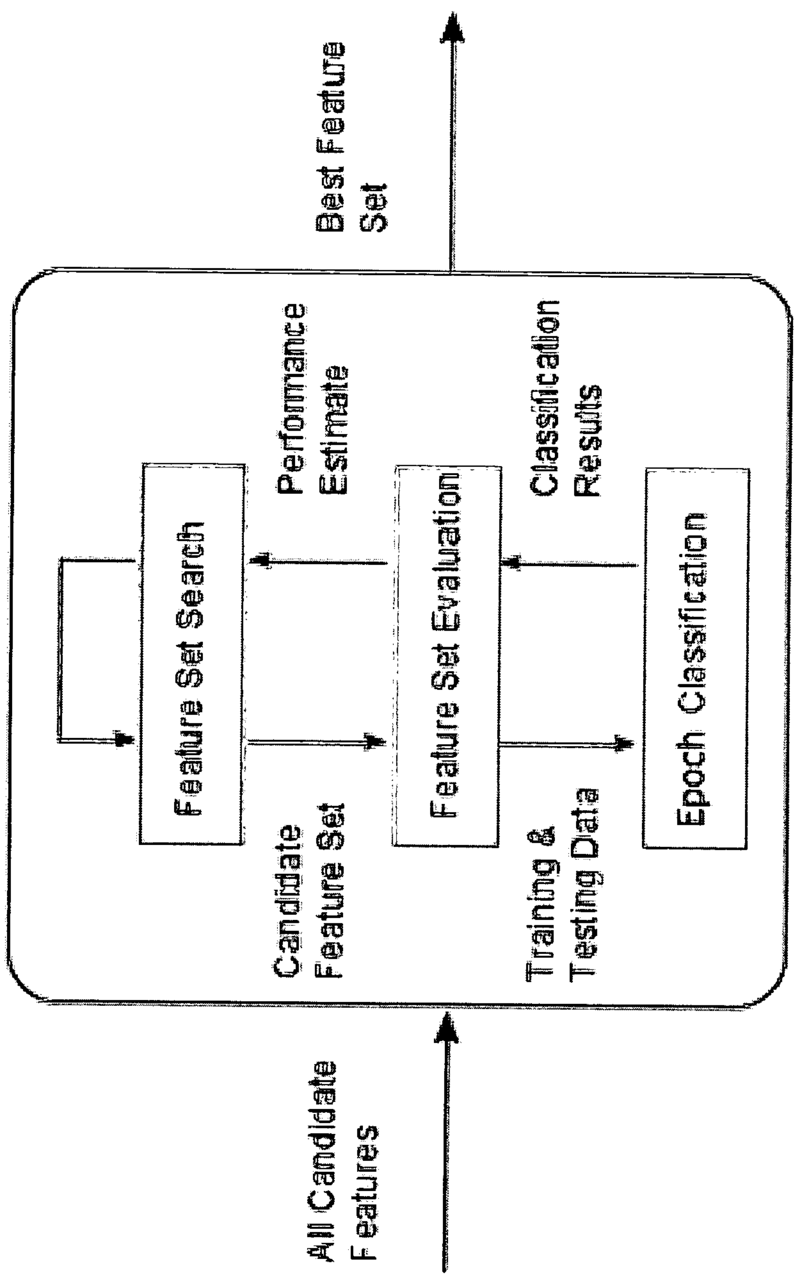

All Candidate Features
Candidate Feature Set
Training & Testing Data
Feature Set Search
Feature Set Evaluation
Epoch Classification
Performance Estimate
Classification Results
Best Feature Set

Figure 8

REFERENCES CITED IN THE DESCRIPTION

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Patent documents cited in the description

- WO 2005067790 A **[0010]**
- US 2006241708 A **[0011]**
- US 2006224073 A **[0012]**

专利名称(译)	用于监视睡意的方法和系统		
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申请号	EP2008785480	申请日	2008-08-11
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代理机构(译)	FRKELLY		
优先权	S20070595 2007-08-21 IE		
其他公开文献	EP2185063A1		
外部链接	Espacenet		

摘要(译)

监视睡眠的方法包括同时记录人的心电图（ECG）和光电容积描记图（PPG），从记录的数据导出多个参数，并基于参数的分析提供指示睡眠特性的输出。 ECG和PPG可以使用设备记录，该设备是Holter监视器和脉搏血氧计的组合，其可以以可移动的方式穿戴。

$$F[n]=\sqrt{\frac{1}{N}\sum_{k=1}^{N}\left(y[k]-y_n[k]\right)^2}$$