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(54) **DETECTION OF SLEEP DISORDERED BREATHING USING CARDIAC AUTONOMIC RESPONSES**

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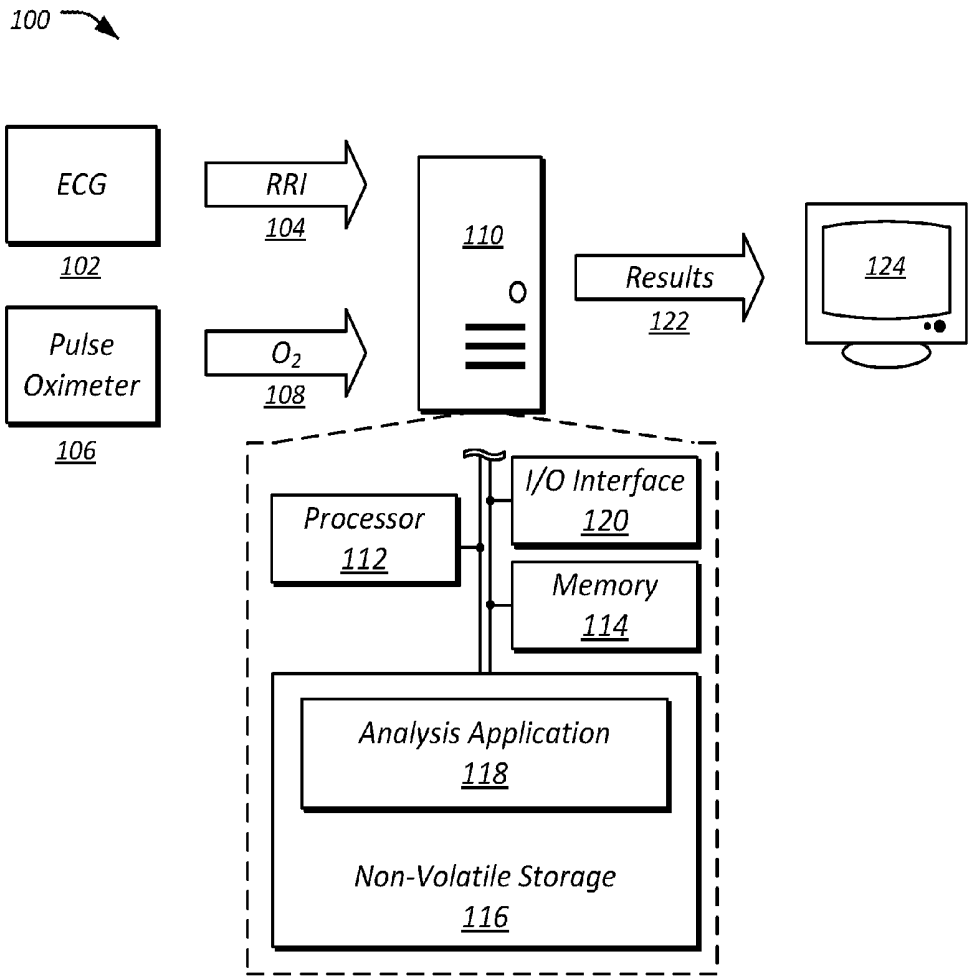
(57) **ABSTRACT**

A memory stores R-R interval (RRI) data collected from a patient over a time interval and oxygen saturation (SaO2) data collected from the patient over the time interval. A processor is programmed to analyze the SaO2 data to identify desaturation events, analyze the RRI data to identify dips, utilize the dips to construct a RRI dip index measure of RRI dips per unit time over the time interval, determine a number of desaturations above a predefined threshold, determine an oxygen desaturation index (ODI), and utilize the RRI dip index and the ODI to provide results indicative of a risk of sleep-disordered breathing (SDB) for the patient.



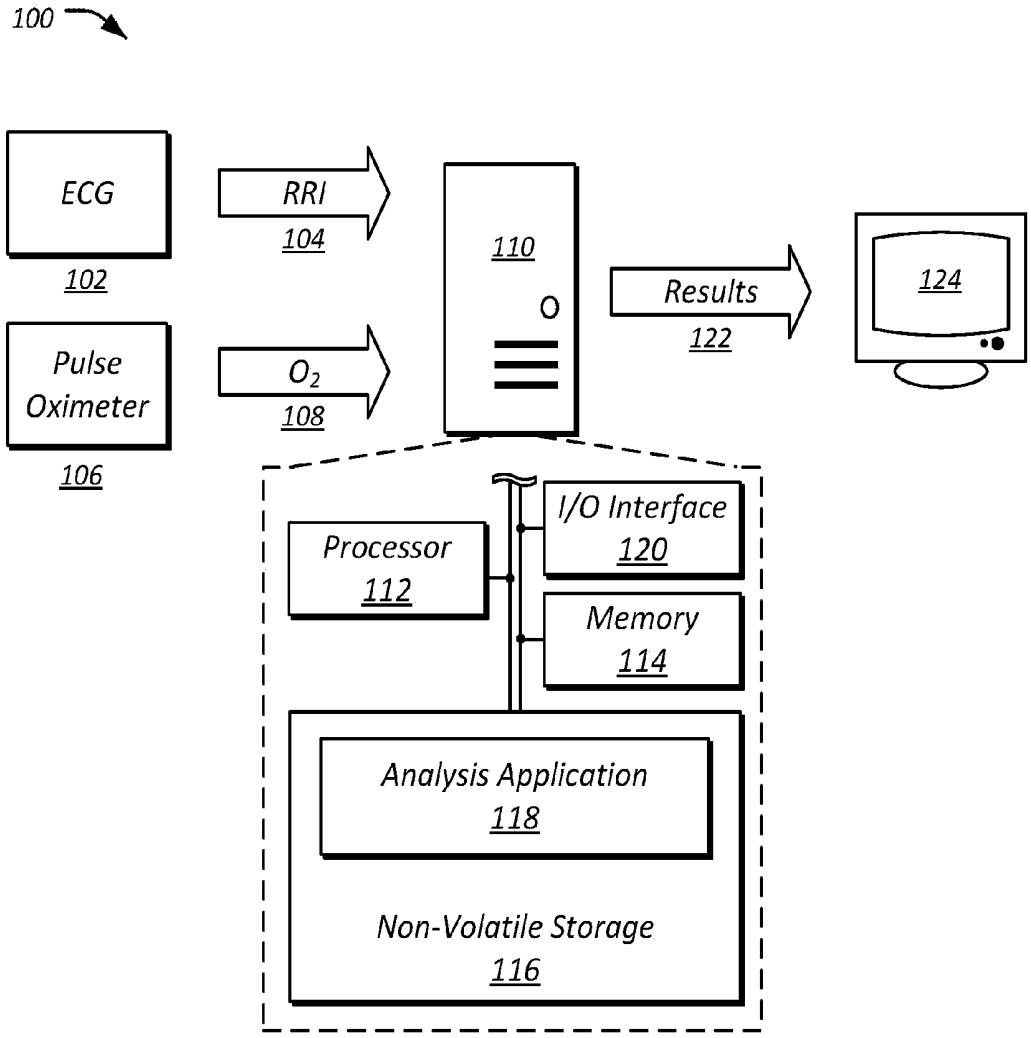

100
ECG
102
RRI
104
Pulse Oximeter
106
O_2
108
110
Results
122
124
Processor
112
I/O Interface
120
Memory
114
Analysis Application
118
Non-Volatile Storage
116

FIG. 1

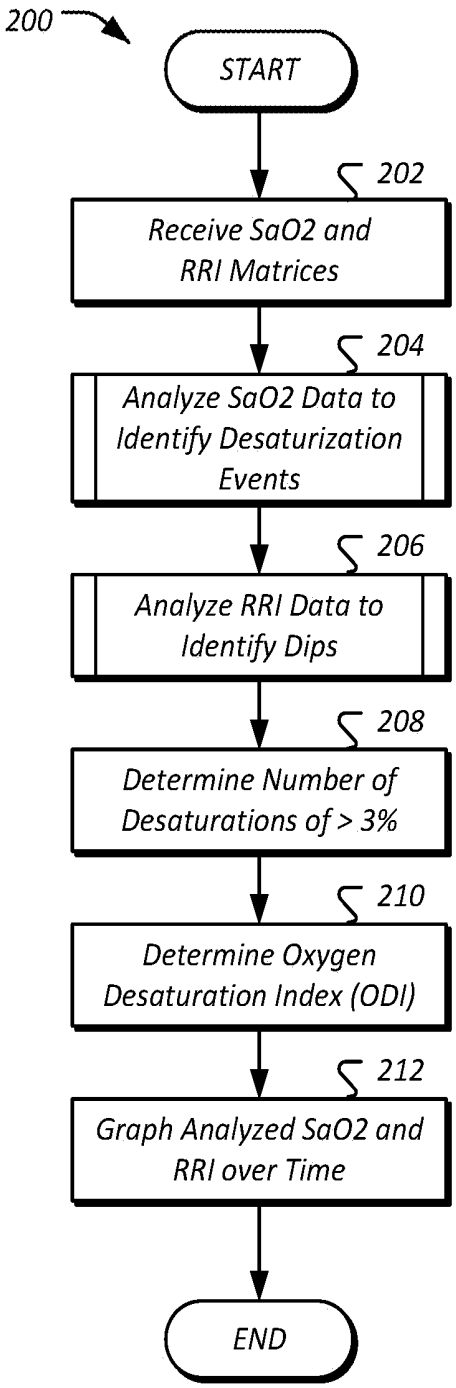

200
START
202
Receive SaO2 and RRI Matrices
204
Analyze SaO2 Data to Identify Desaturization Events
206
Analyze RRI Data to Identify Dips
208
Determine Number of Desaturations of > 3%
210
Determine Oxygen Desaturation Index (ODI)
212
Graph Analyzed SaO2 and RRI over Time
END

FIG. 2

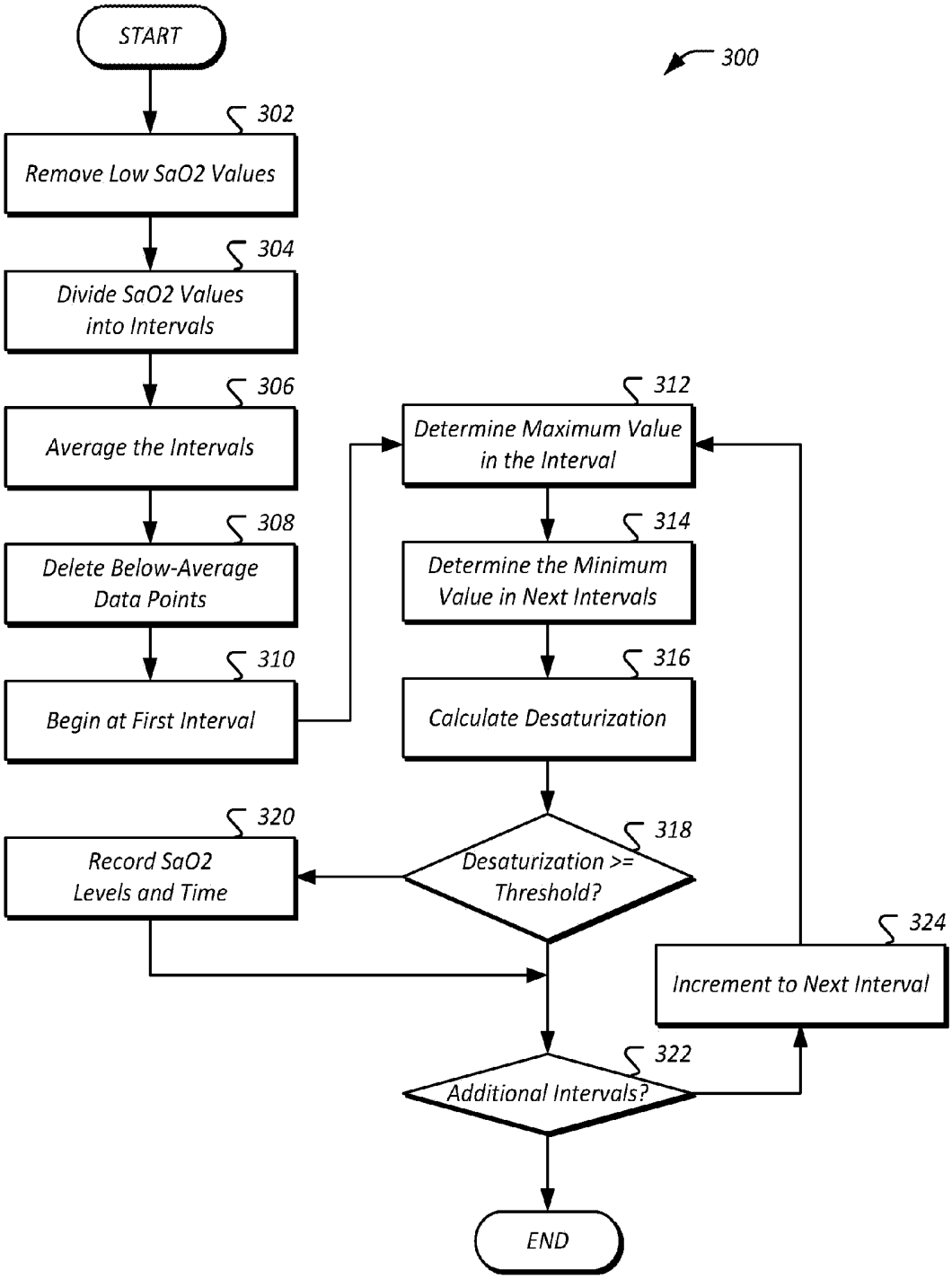

START
300
302
Remove Low SaO2 Values
304
Divide SaO2 Values into Intervals
306
Average the Intervals
308
Delete Below-Average Data Points
310
Begin at First Interval
312
Determine Maximum Value in the Interval
314
Determine the Minimum Value in Next Intervals
316
Calculate Desaturization
318
Desaturization >= Threshold?
320
Record SaO2 Levels and Time
322
Additional Intervals?
324
Increment to Next Interval
END

FIG. 3

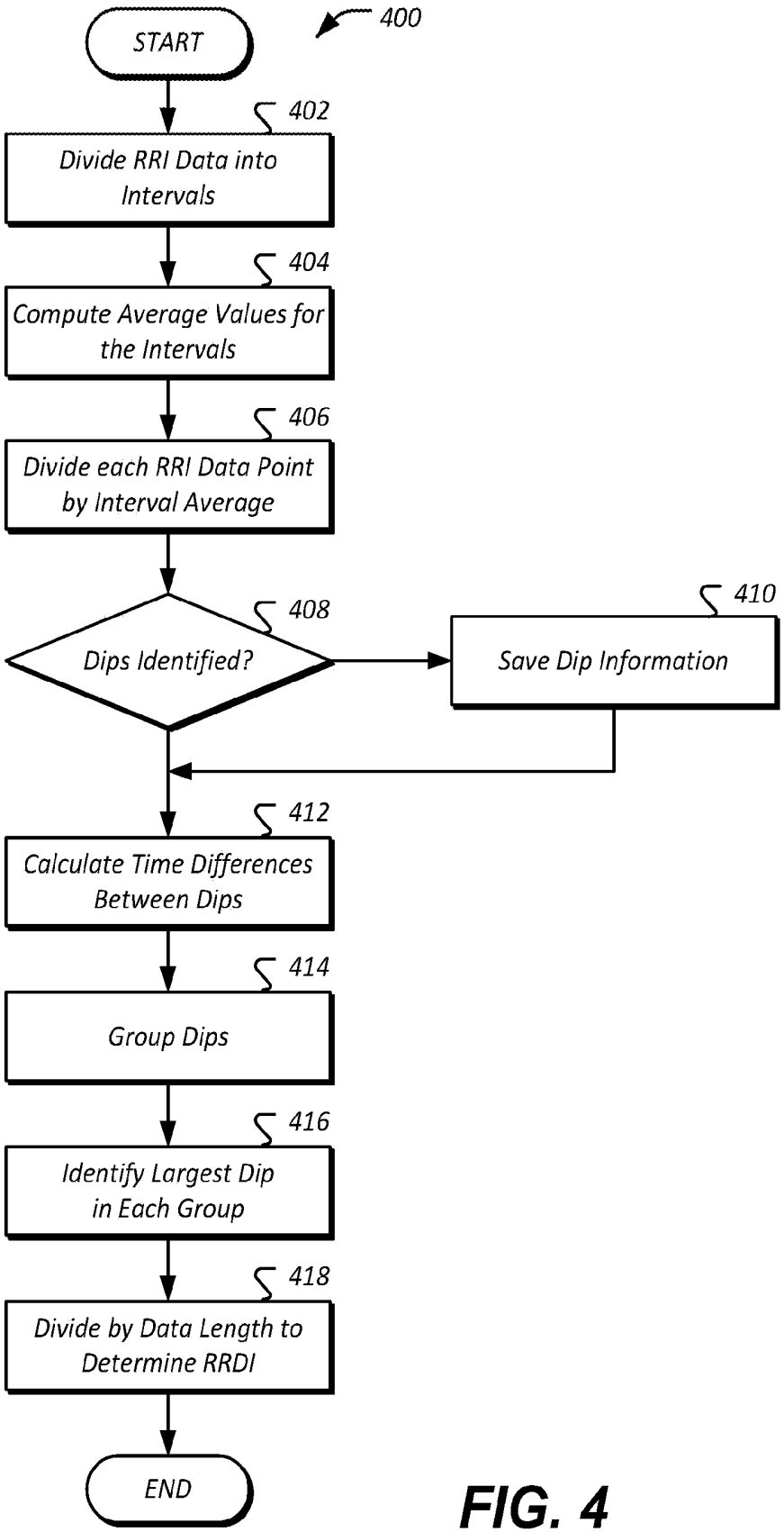

400
START
402
Divide RRI Data into Intervals
404
Compute Average Values for the Intervals
406
Divide each RRI Data Point by Interval Average
408
Dips Identified?
410
Save Dip Information
412
Calculate Time Differences Between Dips
414
Group Dips
416
Identify Largest Dip in Each Group
418
Divide by Data Length to Determine RRDI
END

FIG. 4

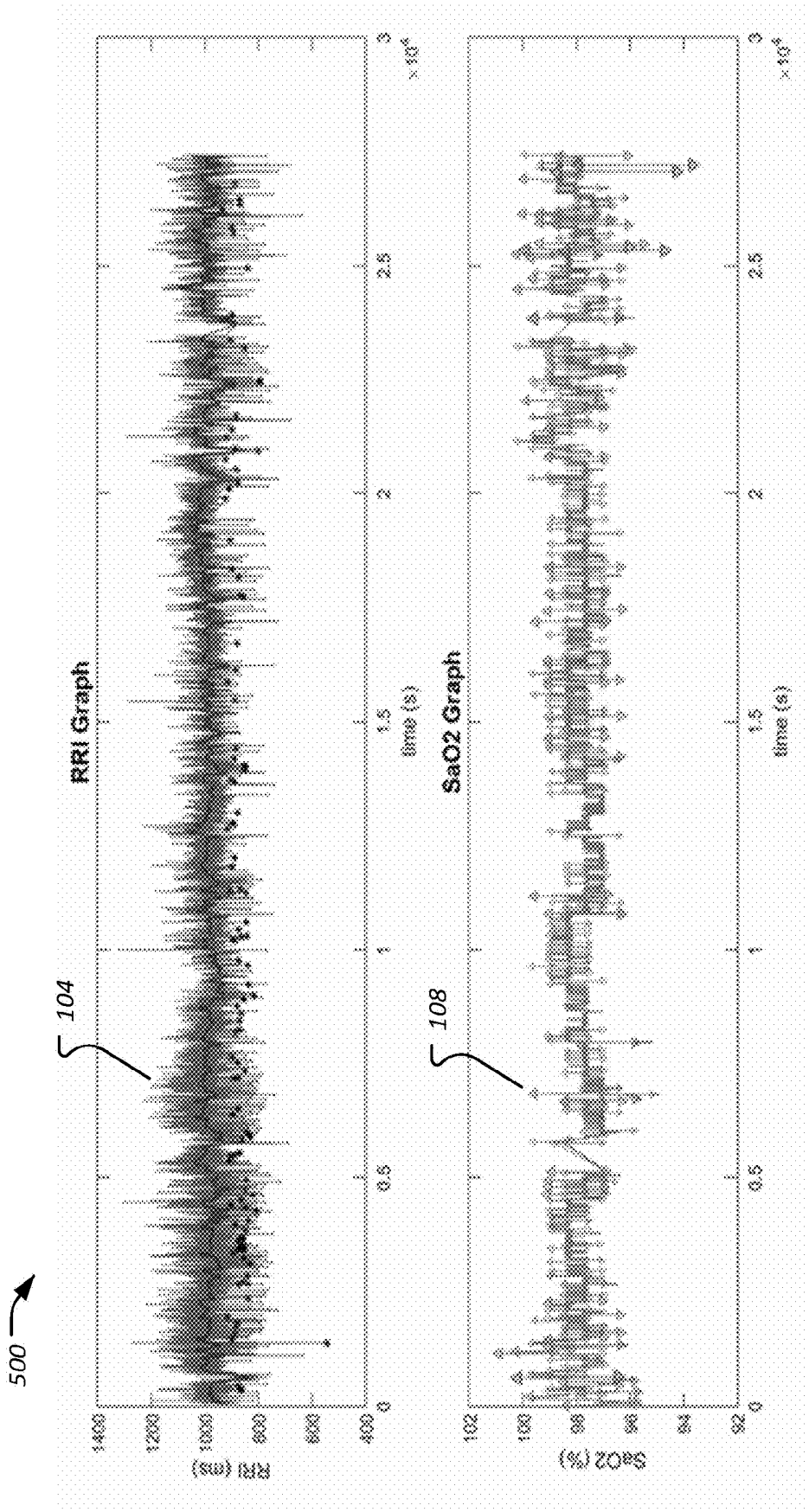

500
104
108
RRI Graph
SaO2 Graph
RRI (ms)
SaO2 (%)
time (s)
time (s)
1400
1200
1000
800
600
400
102
100
98
96
94
92
0
0.5
1
1.5
2
2.5
3
×10^4

FIG. 5

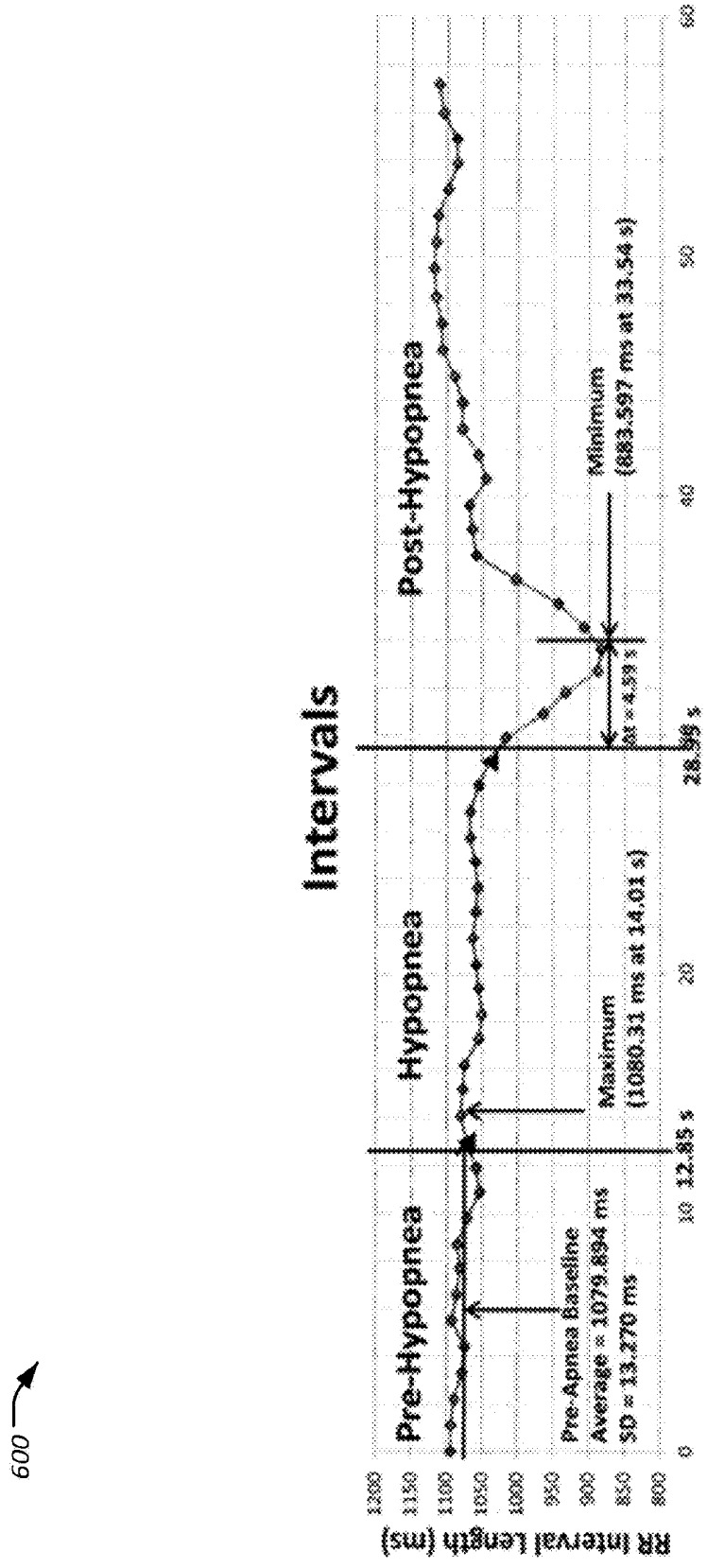

600
Intervals
RR interval length (ms)
1200
1150
1100
1050
1000
950
900
850
800
0
10
20
30
40
50
60
Pre-Hypopnea
Hypopnea
Post-Hypopnea
12.85 s
28.39 s
Pre-Apnea Baseline
Average = 1079.894 ms
SD = 13.270 ms
Maximum
(1080.31 ms at 14.01 s)
Minimum
(883.597 ms at 33.54 s)
Δt = 4.53 s

FIG. 6

700

	CVD Events	Hazard Ratio (95% CI) p-value			
	N (%)	Adjusted for age, BMI, and gender	Adjusted for age, BMI, gender and AHI categories (<5, 5-15 >15)	Adjusted for age, BMI, gender and AHI categories (<5, 5-15 >15), Diabetes, HTN, Stroke, and Smoking	Adjusted for age, BMI, gender and AHI categories (<5, 5-15 >15), Diabetes, HTN, Stroke, Smoking, Average HR, %TST It 90% SaO2
Continuous RRDI (10-unit increment)	26/571 (5)	**1.17 (1.07, 1.28) 0.0003**	**1.19 (1.09, 1.29) 0.0001**	**1.20 (1.10, 1.31) <0.0001**	**1.21 (1.10, 1.32) <0.0001**
RRDI Category					
<20	7/284 (2)	REF	REF	REF	REF
20-40	10/190 (5)	2.47 (0.92, 6.61) 0.072	**2.77 (1.00, 7.65) 0.050**	2.43 (0.86, 6.83) 0.093	**3.01 (1.01, 8.95) 0.048**
>40	9/97 (9)	**3.84 (1.38, 10.71) 0.0102**	**4.62 (1.63, 13.14) 0.0037**	**4.87 (1.72, 13.80) 0.0029**	**5.96 (2.01, 17.60) 0.0013**
p-trend		**0.008**	**0.0033**	**0.0026**	**0.0010**

FIG. 7

DETECTION OF SLEEP DISORDERED BREATHING USING CARDIAC AUTONOMIC RESPONSES

CROSS-REFERENCE TO RELATED APPLICATIONS

[0001] This application claims the benefit of U.S. provisional application Ser. No. 62/395,634 filed Sep. 16, 2016, the disclosure of which is hereby incorporated in its entirety by reference herein.

STATEMENT REGARDING FEDERALLY SPONSORED RESEARCH OR DEVELOPMENT

[0002] This invention was made with government support under Contract Nos. VA 11K2CX000547 and I01CX001040 awarded by the United States Department of Veterans Affairs. The Government has certain rights to the invention.

TECHNICAL FIELD

[0003] Aspects of the disclosure generally relate to detection of sleep-disordered breathing using cardiac-autonomic responses.

BACKGROUND

[0004] Sleep-disordered breathing (SDB) is associated with significant adverse health consequences such as hypertension (HTN) and cardiovascular disease (CVD). These consequences may, in some cases, be prevented with nasal continuous positive airway pressure (CPAP) therapy.

[0005] Sleep-disordered breathing (SDB) is characterized by the occurrence of recurrent episodes of apnea and hypopnea, resulting in oxyhemoglobin desaturation and sleep fragmentation. Apneic episodes are identified by the absence of flow, independent of immediate physiologic consequences. In contrast, the qualitative nature of clinical polysomnography precludes identification of hypopnea based on ventilatory parameters alone. The original definition of hypopnea in Gould's study included flow reduction associated with an oxyhemoglobin desaturation. Thus, all definitions of hypopnea are based on physiologic consequences of decreased alveolar ventilation, namely decreased flow, oxyhemoglobin desaturation, and transient cortical arousal.

[0006] Criteria for airflow reduction have also been variable across different studies, ranging from perceptible qualitative decrease in oral-nasal flow to 50% drop from baseline. Scoring of hypopnea according to the most recent American Academy of Sleep Medicine (AASM) scoring manual requires the presence of physiologic consequences, namely 3% desaturation and/or or cortical arousal. A common limitation of all definitions of hypopnea is that the magnitude of oxyhemoglobin desaturation depends on individual "host factors" such as body weight and baseline pulmonary function. Similarly, the presence of carboxyhemoglobin may shift the oxyhemoglobin dissociation curve to the left and hence dampen the magnitude of oxyhemoglobin desaturation in current smokers.

[0007] The Sleep Heart Health Study investigated the effect of varying the level of hypopnea-related oxyhemoglobin desaturation on the association between SDB and prevalent cardiovascular disease. Specifically, the frequency of hypopneas defined by a threshold of oxyhemoglobin desaturation of 4% or more was associated with cardiovascular disease, while lesser degree of desaturation or cortical arousal were not associated with cardiovascular disease based on self-report. However, there are other studies that have examined the immediate cardiovascular response to episodes of decreased flow, independent of the magnitude of desaturation or electroencephalogram (EEG) cortical arousal, and found conflicting results. While Ayappa et al. found less effect on heart rate (HR) increase immediately after non-apneic and mild reduction in flow, found that non-apneic events were associated more consistently with increased HR.

SUMMARY

[0008] A new method of detecting heart accelerations during sleep that can improve the accuracy of diagnosing SDB without the need for EEG or a desaturation threshold. The method may utilize an automatic detection of heart rate accelerations obtained during sleep study that can be translated into an executable program or a plug □ in for sleep scoring software and can be used in any sleep study across the world. As explained in detail below, the algorithm can predict long term prognosis and incidence of cardiovascular diseases (such as heart attack, heart failure, or need for the cardiac procedures) and cardiovascular-related mortality.

[0009] In one or more illustrative embodiments, a system identifies risk of sleep-disordered breathing (SDB) from heart rate data without using electroencephalogram data or a desaturation threshold. In the system, a memory stores R-R interval (RRI) data collected from a patient over a time interval and oxygen saturation (SaO2) data collected from the patient over the time interval. A processor is programmed to analyze the SaO2 data to identify desaturation events, analyze the RRI data to identify dips, utilize the dips to construct a RRI dip index measure of RRI dips per unit time over the time interval, determine a number of desaturations above a predefined threshold, determine an oxygen desaturation index (ODI), and utilize the RRI dip index and the ODI to provide results indicative of a risk of sleep-disordered breathing (SDB) for the patient.

[0010] In one or more illustrative embodiments, a method for identifying a risk of sleep-disordered breathing (SDB) from heart rate data without using electroencephalogram data or a desaturation threshold includes receiving R-R interval (RRI) data collected from a patient over a time interval; dividing the RRI data into equal segments of a predefined time period length; dividing each data point of the RRI data by an average RRI value calculated for the segment in which the data point is included; if a ratio of the data point to the average RRI value is less than a predefined percentage, identifying the data point as being a dip; constructing a RRI dip index measure of RRI dips per unit time over the time interval; and utilizing the RRI dip index to provide results indicative of the risk of sleep-disordered breathing (SDB) for the patient.

[0011] In one or more illustrative embodiments, non-transitory computer-readable medium comprising instructions for identifying a risk of sleep-disordered breathing (SDB) from heart rate data without using electroencephalogram data or a desaturation threshold, that, when executed by a processor, cause the processor to receive R-R interval (RRI) data collected from a patient over a time interval; divide the RRI data into equal segments of a predefined time period length; divide each data point of the RRI data by an average RRI value calculated for the segment in which the data point is included; if a ratio of the data point to the

average RRI value is less than a predefined percentage, identify the data point as being a dip; construct a RRI dip index measure of RRI dips per unit time over the time interval; and utilize the RRI dip index to provide results indicative of the risk of sleep-disordered breathing (SDB) for the patient.

BRIEF DESCRIPTION OF THE DRAWINGS

[0012] FIG. **1** illustrates an example system for analyzing whether a patient has SDB;

[0013] FIG. **2** illustrates an example process for determining whether a patient has SDB according to analysis of SaO2 data and analysis of R-R interval (RRI) data;

[0014] FIG. **3** illustrates further details of the analysis of the SaO2 data to identify desaturation events;

[0015] FIG. **4** illustrates further details of the analysis of the RRI data to identify dips;

[0016] FIG. **5** illustrates an example graphical illustration of results of the process for determining whether a patient has SDB;

[0017] FIG. **6** illustrates an example RRI data response to a representative non-apneic event; and

[0018] FIG. **7** illustrates example data of adjusted time to event Cox proportional hazard models for RRDI predicting incidence of CVD events.

DETAILED DESCRIPTION

[0019] As required, detailed embodiments of the present invention are disclosed herein; however, it is to be understood that the disclosed embodiments are merely exemplary of the invention that may be embodied in various and alternative forms. The figures are not necessarily to scale; some features may be exaggerated or minimized to show details of particular components. Therefore, specific structural and functional details disclosed herein are not to be interpreted as limiting, but merely as a representative basis for teaching one skilled in the art to variously employ the present invention.

[0020] Sleep-disordered breathing (SDB) is strongly linked to cardiovascular morbidity and mortality. SDB traditionally include apneic and non-apneic respiratory events (RE) if associated with desaturation or arousals. However SDB encompasses a spectrum of respiratory abnormalities that could disrupt normal physiology.

[0021] Current technology in detecting and diagnosing sleep-related respiratory events is based either on full polysomnography, which requires in-laboratory testing, or on portable home sleep studies (HST). The HST method varies in level of complexity and data acquisition. Most HST combine pulse oxymetry and respiratory effort. However, a majority of respiratory events (e.g., hypopnea) can be missed if not followed by significant desaturation (e.g., equal to or more than 4%). According to the recommended scoring criteria of the American Academy of Sleep Medicine (AASM), hypopnea is defined as a drop of at least 30% of airflow associated with desaturation (equal to or more than 3%) and/or arousal. Respiratory events such apnea and hypopnea lead to sympathetic activation following each event that can lead to brief tachycardia as a result of arousal and/or desaturation.

[0022] As explained in detail below, using single lead electrocardiography (ECG) without electroencephalogram (EEG) monitoring, systems and methods may calculate an index correlated to severity of sleep disordered breathing. Using the index, severity of sleep disordered breathing may be determined to provide an estimate of the patient's long term outcome. For instance, the index may be used to identify patients with increased risk of adverse cardiovascular outcome, such as heart attack, heart failure, cardiac procedure, or cardiac death.

[0023] FIG. **1** illustrates an example system **100** for analyzing whether a patient has SDB.

[0024] The system includes an electrocardiography (ECG) device **102** configured to create RRI data **104**, and a pulse oximeter **106** configured to create oxygen saturation (SaO2) data **108**. The system **100** further includes a computing device **110** having a processor **112**, a memory **114**, a non-volatile storage **116**, and an input/output interface **120**. The analysis application **118** may be an application included on the storage **116** of the computing device **110**. The computing device **110** receives the RRI data **104** and the oxygen saturation data **108** (e.g., via a wired or wireless transceiver), and executes the analysis application **118** to create results **122**. The results **122** may be provided to a display **124** for review. It should be noted that the system **100** is merely one example, and systems including more, fewer, and/or different components may be used. For example, while the analysis application **118** is illustrated as a component of a standalone computer, in other examples the analysis application **118** may be implemented in software, firmware, and/or hardware in a medical device, and/or integrated into a non-diagnostic consumer device such as an application executed by a user's smartphone.

[0025] Cardiac autonomic disturbances during sleep, such as R-R interval (RRI), can serve as a predictor of CVD in patients with SDB. As explained below, increased RRI dip index (RRDI) during sleep is associated with increased CVD or death related to CVD. Accordingly, the analysis application **118** includes instructions that, when loaded into the memory **114** and executed by the processor **112**, cause the computing device **110** to utilize the RRI data **104** and the SaO2 data to determine results **122** indicative of whether or not a patient has SDB. Specific examples of these instructions are described in detail with reference to the processes below.

[0026] FIG. **2** illustrates an example process **200** for determining whether a patient has SDB according to analysis of SaO2 data **108** and analysis of RRI data **104**. As discussed in detail, the analysis application **118** detects sleep disordered breathing using ECG tracing and beat-to-beat heart rate variability. Respiratory events are typically followed by a drop in RRI and a desaturation. Accordingly, the analysis application **118** analyzes changes in R-R interval (RRI) length (heart rate) and desaturations during sleep.

[0027] At **202**, the analysis application **118** receives the SaO2 data **108** and RRI data **104**. In an example, the data may be received from the ECG **102** and pulse oximeter **106** from a connected patient. In other examples, the SaO2 data **108** and RRI data **104** may be received from storage, e.g., having been collected from a previous recording of patient ECG tracing and beat-to-beat heart rate variability. In some examples, the analysis application **118** may perform preprocessing of the RRI data **104**. This preprocessing may be done to clean the data for further processing. As some examples, the preprocessing may include normalizing heights of the raw RRI values, removing short artifacts, and adding missing beats, if necessary. In other examples, the analysis

application **118** may receive RRI data **104** in which the raw RRI values have been manually reviewed for consistency. In some examples, one aspect of cleaning of the RRI data **104** includes removing indexed RRI data points from the RRI data **104**. This removal may be utilized later in determining the total amount of RRI data **104** that was processed.

[0028] At **204**, the analysis application **118** analyzes the SaO2 data **108** to identify desaturation events. Further aspects of the analysis are illustrated with reference to the process **300** of FIG. **3**. Referring to FIG. **3**, at **302** the analysis application **118** removes low SaO2 data **108** values. (e.g., those that are less than 50%). These values may be removed because these are likely to be artifacts, as values this low are rare or indicative of other health-related issues. In other examples, the threshold percentage for removal could be even higher, e.g., 60%, 70%, or even 80%. At **304**, the analysis application **118** divides the SaO2 data **108** values into intervals (e.g., one second intervals). At **306**, the analysis application **118** determines an average value for each of the intervals. At **308**, the analysis application **118** deletes data points from the SaO2 data **108** that are more than a predefined amount below the average (e.g., that are 0.1% smaller than the average in an example). These removals may also be done to remove data artifacts, although this removal may not necessarily be directly tied to a specific physiological effect.

[0029] The analysis application **118** then cycles through the intervals. At **310**, the analysis application **118** begins at the first interval. At **312**, the analysis application **118** determines the maximum value in the next set of intervals (e.g., the minimum value across the next 60 intervals in an example). For instance, the analysis application **118** may review through the next samples of data until the time of the reviewed data is at least 60 intervals in length greater than the timestamp of the current maximum value (or the maximum amount available if less data than 60 intervals remains) to find a minimum. It should be noted that the use of a timeframe of 60 intervals is only one example, and other values, such as 30 or 90 times the interval length may be used. The analysis application **118** also calculates the desaturation for the interval at **316**. For example, the analysis application **118** may subtract the maximum value of the interval from the minimum value identified for the set of intervals. If at **316** the analysis application **118** determines that the desaturation is at least a predefined value (e.g., 1%), the analysis application **118** proceeds to **320** to record or mark the SaO2 levels and time information for later processing. After **318** or **320**, the analysis application **118** proceeds to **322** to determine whether additional intervals remain. If so, the analysis application **118** transitions to **324** to increment to the next interval, and to operation **312** to continue cycling through the intervals. If no further intervals remain, the process **300** ends and flow returns to the process **200**.

[0030] Referring back to FIG. **2**, at **206** the analysis application **118** analyzes the RRI data **104** to identify "dips." As explained in greater detail with reference to FIG. **4**, at **402** the analysis application **118** divides the RRI data **104** into segments (e.g., one minute segments) and at **404** the analysis application **118** calculates the average RRI value for each segment. The analysis application **118** at **406** analyzes each point of the RRI data **104** and divides it by the average RRI value calculated for the segment in which the RRI data **104** point belongs. If the analysis application **118** determines at **408** that this ratio is less than a predefined threshold value, (e.g., 90%), at **410** the analysis application **118** stores or marks the interval index, RRI length, time at which the RRI length was found, and the ratio for further processing. It should be noted that 90% is merely one example, and other thresholds may additionally or alternately be determined, for example, 85%, 80%, 75%, 70%, 65% or 60% as some other possibilities. In cases where additional thresholds are used, the analysis application **118** may provide indices for each. Regardless, RRI values for which the ratio is less than the predefined threshold value may be referred to as "dips."

[0031] At **412**, the analysis application **118** calculates time differences between the dips. The analysis application **118** analyzes these dips in chronological order and places them into groups at **414**. The analysis application **118** may optionally perform filtering of the dips to remove standalone dips. Standalone dips may refer to dips flanked on both sides by an RRI ratio above the predefined threshold (e.g., above the 90%). Such dips may be removed as they do not contribute to a greater trend of decreasing or increasing RRI ratio. Regardless of whether the filtering is performed, the analysis application **118** creates a group and places all dips in it until the analysis application **118** identifies a pair of dips separated by more than a predefined time interval (e.g., ten seconds in an example, although greater or lesser time periods may be used). If so, the analysis application **118** creates a new group for the separated dip. The analysis application **118** analyzes and groups all of the "dips" in this manner. Using the determined groups, at **416** the analysis application **118** identifies the largest dip (i.e., the one with the smallest ratio) in each group and notes these as the biggest dips per group.

[0032] At **418**, the analysis application **118** divides the number of the biggest dips in the overall data file by the total time length of the file to determine the RRDI (RR Interval Dips Index). The RRDI may refer to a measure of the overall events per unit time, e.g., per hour in some examples. As mentioned above, one aspect of cleaning of the RRI data **104** may include removing indexed data points for artifact data from the RRI data **104**. When determining the RRDI, the analysis application **118** may detect when intervals have been removed if there is a skip in the index column (for example, for the indices [1, 2, 3, 5, 6], index 4 was skipped). The analysis application **118** may, accordingly, determine an amount of time elapsed between the pairs of data points flanking each skipped data point, sums these amounts of time, and subtracts the sum from the total length of the study. This difference may be referred to as the "corrected time." The analysis application **118** may, accordingly, use the corrected time as the total time length in determining the overall RRDI. After **418**, the process **400** ends and flow returns to the process **200**.

[0033] Generally, an increased RRDI measure may correlate to an increased risk of adverse cardiovascular outcome, such as heart attack, heart failure, cardiac procedure, or cardiac death. Accordingly, the RRDI measure may be compared against a cutoff value to determine whether the patent whose data is being analyzed should be flagged for follow-up screening. This cutoff value may be scaled according to various factors, such as patient age, gender, weight, or other demographic or health risk information (e.g., smoker vs. non-smoker).

[0034] Referring back to FIG. **2**, at **208** the analysis application **118** determines a number of desaturations that

are greater than or equal to a predefined amount (e.g., greater than 3%). At **210**, the analysis application **118** calculates the oxygen desaturation index (ODI), which refers to a measure of the number of events identified at **208** over time. For instance, the ODI may refer to an hourly index of the number of 3% events per hour. At **212**, using the RRI data **104**, the SaO2 data **108**, and the information marked or stored above, the analysis application **118** generates the results **122**. These results **122** may be provided to the display **124**.

[0035] FIG. **5** illustrates an example graphical illustration **500** of the results **122** of the process **200** for determining whether a patient has SDB. As shown in the illustration **500**, the RRI data **104** and the SaO2 data **108** are graphed over time with the same time scale.

[0036] More specifically, the RRI data **104** may be graphed to illustrate the raw data before processing (e.g., shown in gray). The RRI data **104** may also be illustrated with the calculated average (e.g., a minute average computed at operation **306**). This average is shown in black. The dips computed at operation **410** may also be shown, indicated in the illustration as the dark dots for dips to be considered and as the black asterisks for standalone dips that are filtered out.

[0037] Regarding the SaO2 data **108**, the raw data may be displayed along with the relative maximums and minimums. For instance, indications of a first size and/or color (e.g., large and red triangles) may indicate maximums or minimums of 3% or more, indications of a second size and/or color (e.g., medium and purple triangles) may indicate maximums or minimums of 2% to 3%, and indications of a third size and/or color (e.g., small and blue triangles) may indicate maximums or minimums of 1% to 2%. Continuing with the example of triangular indications, upward pointing triangles may refer to relative maximums, while downward pointing may triangles refer to relative minimums.

[0038] FIG. **6** illustrates an example RRI response to a representative non-apneic event. Using the analysis application **118**, the system **100** may more accurately detect respiratory events without EEG monitoring. This detection may be done based on the magnitude of drop in RRI following respiratory event >/=10 from a preceding baseline. Notably, this determination may be made independent of desaturation or arousal on EEG. Accordingly, the system **100** may further allow for automated scoring of sleep studies that were recorded in-laboratory or at home. By simple run of the analysis application **118** using single lead ECG, the system **100** may calculate the RRDI index to estimate severity of sleep disordered breathing and thereby estimate the patient's long term outcome, such as CVD.

[0039] While many of the examples described herein relate to the analysis of ECG data, it should be noted that other sources of heart data may also be used. In an example, instead of RRI data **104**, heart rate data or another type of heart beat information may potentially be used to identify the greatest dips per measure of percent of heart beats.

[0040] FIG. **7** illustrates example data **700** of adjusted time to event Cox proportional hazard models for RRDI predicting incidence of CVD events. CVD events may include, as some examples, heart attack, angioplasty, heart failure, stent, pacemaker, coronary artery disease, bypass surgery, atherosclerosis, or CVD death.

[0041] Regarding the data set, the proportional hazards regression is based on a sample size of 571 persons. Out of an initial set of 1,397 studies of persons, 141 were excluded as having used beta blockers during polysomnography (PSG), while 84 were excluded as having used CPAP on the night of the study. Thus, 1,172 scored PSG studies remained from 745 individuals. Out of these, 70 were excluded as having had no follow-up, while 46 were excluded as having had an event before the PSG. Thus, 629 individuals with PSG data remained. Out of these, 58 individuals were excluded as having used beta blockers at any other time during the study. Accordingly, a remaining sample size of 571 individuals with PSG data were included in the study.

[0042] As shown in the data **700**, 26 out of the 571 individuals displayed continuous RDDI events and experienced a CVD event. Two hundred eighty-four of the 571 individuals had an RRDI index of less than 20, where out of those seven experienced a CVD event (2%). One hundred ninety of the 571 individuals had an RDDI index between 20 and 40, where out of those 10 experienced a CVD event. Ninety-seven of the 571 individuals had an RDDI index of greater than 40, where out of those nine experienced a CVD event (9%).

[0043] As can be seen by the hazard ratios, out of the 26 individuals who experienced a CVD event, the individuals showing continuous RDDI events were 1.17 times more likely to experience a CVD event. For those with an RDDI score of 20-40, the likelihood increases to 2.47 times, and for those with an RDDI score exceeding 40, the likelihood increases to 3.84 times. These likelihoods become even more significant once additional factors such as AHI categories, diabetes, HTN, stroke, smoking, average HR, and % TST is 90% SaO2 are accounted for. Accounting for these additional factors, individuals showing continuous RDDI events were 1.21 times more likely to experience a CVD event. For those with an RDDI score of 20-40, the likelihood increases to 3.01 times, and for those with an RDDI score exceeding 40, the likelihood increases to 5.96 times. Thus, the aforementioned systems and methods of detecting HR accelerations during sleep improve the accuracy of diagnosing SDB without the need for EEG or desaturation thresholds. Accordingly, the systems and methods allow for automated scoring of sleep studies that can be recorded in the laboratory or at home.

[0044] Computing devices described herein, such as the computing device **110**, generally include computer-executable instructions, where the instructions may be executable by one or more computing devices such as those listed above. Computer-executable instructions may be compiled or interpreted from computer programs created using a variety of programming languages and/or technologies, including, without limitation, and either alone or in combination, Java™, C, C#, C++, Visual Basic, Java Script, Perl, MatLab, etc. In general, a processor (e.g., a microprocessor) receives instructions, e.g., from a memory, a computer-readable medium, etc., and executes these instructions, thereby performing one or more processes, including one or more of the processes described herein. Such instructions and other data may be stored and transmitted using a variety of computer-readable media.

[0045] While exemplary embodiments are described above, it is not intended that these embodiments describe all possible forms of the invention. Rather, the words used in the specification are words of description rather than limitation, and it is understood that various changes may be made without departing from the spirit and scope of the

invention. Additionally, the features of various implementing embodiments may be combined to form further embodiments of the invention.

What is claimed is:

1. A system for identifying a risk of sleep-disordered breathing (SDB) from heart rate data without using electroencephalogram data or a desaturation threshold, comprising:

a memory storing R-R interval (RRI) data collected from a patient over a time interval and oxygen saturation (SaO2) data collected from the patient over the time interval; and

a processor programmed to

analyze the SaO2 data to identify desaturation events,

analyze the RRI data to identify dips,

utilize the dips to construct a RRI dip index measure of RRI dips per unit time over the time interval,

determine a number of desaturations above a predefined threshold,

determine an oxygen desaturation index (ODI), and

utilize the RRI dip index and the ODI to provide results indicative of the risk of sleep-disordered breathing (SDB) for the patient.

2. The system of claim **1**, wherein the RRI data is received from an electrocardiography (ECG) device, and the SaO2 data is received from a pulse oximeter device.

3. The system of claim **1**, wherein the processor is further programmed to:

divide the RRI data into equal segments of a predefined time period length;

divide each data point of the RRI data by an average RRI value calculated for the segment in which the data point is included; and

if a ratio of the data point to the average RRI value is less than a predefined percentage, identify the data point as being one of the dips.

4. The system of claim **3**, wherein the processor is further programmed to, for each identified dip, identify an interval index of the dip, an RRI length of the dip, a time at which the RRI length was found, and the ratio of the data point to the average RRI value.

5. The system of claim **3**, wherein the time period length is one minute.

6. The system of claim **3**, wherein the predefined percentage is 90%.

7. The system of claim **3**, wherein the processor is further programmed to:

chronologically place dips into a group until a pair of dips in the group are separated by more than a predefined group time interval;

responsive to the pair of dips being separated by more than a predefined time interval, create a new group for continuing the chronological placement of dips; and

for each group, identify a dip having the smallest ratio in each group; and

compute a respiratory-related RRI drops value as a count of the dips having the smallest ratio in each group.

8. The system of claim **7**, wherein the predefined group time interval is ten times the time period length.

9. The system of claim **8**, wherein the predefined group time interval is ten minutes.

10. A method for identifying a risk of sleep-disordered breathing (SDB) from heart rate data without using electroencephalogram data or a desaturation threshold, comprising:

receiving R-R interval (RRI) data collected from a patient over a time interval;

dividing the RRI data into equal segments of a predefined time period length;

dividing each data point of the RRI data by an average RRI value calculated for the segment in which the data point is included;

if a ratio of the data point to the average RRI value is less than a predefined percentage, identifying the data point as being a dip;

constructing a RRI dip index measure of RRI dips per unit time over the time interval; and

utilizing the RRI dip index to provide results indicative of the risk of sleep-disordered breathing (SDB) for the patient.

11. The method of claim **10**, wherein the time period length is one minute.

12. The method of claim **10**, wherein the predefined percentage is 90%.

13. The method of claim **10**, further comprising:

chronologically placing dips into a group until a pair of dips in the group are separated by more than a predefined group time interval;

responsive to the pair of dips being separated by more than a predefined time interval, create a new group for continuing the chronological placement of dips; and

for each group, identify a dip having the smallest ratio in each group; and

compute a respiratory-related RRI drops value as a count of the dips having the smallest ratio in each group.

14. The method of claim **13**, wherein the predefined group time interval is ten times the time period length.

15. A non-transitory computer-readable medium comprising instructions for identifying a risk of sleep-disordered breathing (SDB) from heart rate data without using electroencephalogram data or a desaturation threshold, that, when executed by a processor, cause the processor to:

receive R-R interval (RRI) data collected from a patient over a time interval;

divide the RRI data into equal segments of a predefined time period length;

divide each data point of the RRI data by an average RRI value calculated for the segment in which the data point is included;

if a ratio of the data point to the average RRI value is less than a predefined percentage, identify the data point as being a dip;

construct a RRI dip index measure of RRI dips per unit time over the time interval; and

utilize the RRI dip index to provide results indicative of the risk of sleep-disordered breathing (SDB) for the patient.

16. The medium of claim **15**, wherein the time period length is one minute.

17. The medium of claim **15**, wherein the predefined percentage is 90%.

18. The medium of claim **15**, further comprising instructions that, when executed by the processor, cause the processor to:

chronologically place dips into a group until a pair of dips in the group are separated by more than a predefined group time interval;

responsive to the pair of dips being separated by more than a predefined time interval, create a new group for continuing the chronological placement of dips; and

for each group, identify a dip having the smallest ratio in each group; and

compute a respiratory-related RRI drops value as a count of the dips having the smallest ratio in each group.

19. The medium of claim **18**, wherein the predefined group time interval is ten times the time period length.

* * * * *

专利名称(译)	使用心脏自主神经反应检测睡眠呼吸紊乱		
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摘要(译)

存储器存储在一段时间间隔内从患者收集的R-R间隔（RRI）数据和在该时间间隔内从患者收集的氧饱和度（SaO2）数据。处理器被编程以分析SaO2数据以识别去饱和事件，分析RRI数据以识别倾角，利用倾角构建在该时间间隔内每单位时间的RRI倾角的RRI倾角指数测量，确定高于预定义的阈值，确定氧饱和度指数（ODI），并利用RRI浸浴指数和ODI来提供指示患者睡眠呼吸紊乱风险（SDB）的结果。