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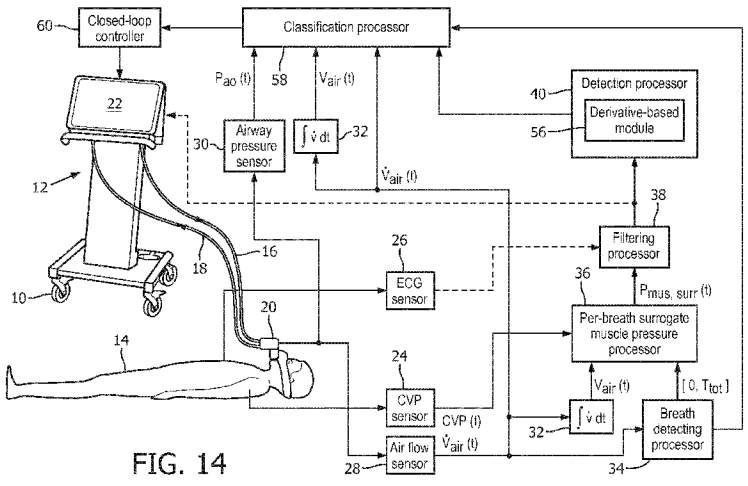

FIG. 14

(57) Abstract: A respiratory monitoring apparatus (10) includes a central venous pressure sensor (24) configured to measure a central venous pressure (CVP) signal of a patient. At least one processor (32, 34, 36, 38, 40, 42, 44, 58) is programmed to process the CVP signal to generate respiratory information for the patient by operations including: segmenting the CVP signal based on detected breath intervals; calculating a surrogate muscle pressure signal from the segmented CVP signal; and filtering the surrogate muscle pressure signal to remove a cardiac activity component a cardiac activity component of the surrogate respiratory muscle pressure signal.

WO 2017/140500 A1

ENHANCEMENT OF RESPIRATORY PARAMETER ESTIMATION AND ASYNCHRONY DETECTION ALGORITHMS VIA THE USE OF CENTRAL VENOUS PRESSURE MANOMETRY

FIELD

The following relates to the medical therapy arts, respiratory therapy arts, medical ventilation arts, and related arts.

BACKGROUND

Respiratory monitoring is performed for diagnosing respiratory ailments and in support of respiratory therapies such as mechanical ventilation. Characterization of the respiratory effort exerted by the patient is of particular importance for optimizing ventilator settings for various support modes, such as pressure support ventilation (PSV). The goal is to provide just sufficient support to maintain effective respiration without over-supporting the patient which can lead to atrophy effects, lung injury, increased difficulty in eventually weaning the patient off the ventilator, under-supporting the patient which can lead to excessive muscle fatigue, or other deleterious effects.

Respiratory effort may be variously quantified. The basic parameter is usually referred to as respiratory muscle pressure $P_{mus}(t)$, that is, the pressure exerted on the lungs by the patient's diaphragm and chest musculature. Work of Breathing (WoB) may be computed from the volume integral of $P_{mus}(t)$ (i.,e. $WOB = \int P_{mus}(t)dV$), or the time integral of the product of $P_{mus}(t)$ and flow (i.e., $WOB = \int P_{mus}(t)\dot{V}(t)dt$) over a single breath, while Power of Breathing (PoB) may be computed from the volume integral of $P_{mus}(t)$, or the time integral of the product of $P_{mus}(t)$ and flow over a unit time (e.g., per minute, thus encompassing several breaths). Thus, characterizing the respiratory muscle pressure, $P_{mus}(t)$, is a key step in monitoring respiratory effort.

Known approaches for assessing respiratory muscle pressure include invasive and non-invasive techniques. For example, a non-invasive technique, called the End-Inspiratory Pause maneuver, is used to assess respiratory system resistance and elastance by blocking the airway at the end of the inspiratory phase. $P_{mus}(t)$ can then be calculated via the use of the Equation of Motion of the Lungs, and the measured airway pressure and air flow. This approach

relies on certain assumptions that may not be valid in all circumstances, and also is clinically problematic as it interrupts (albeit briefly) life-sustaining respiration. In another example, an invasive technique involves the placement of a balloon-tipped catheter into a patient's esophagus. Esophageal pressure has been shown to be a close proxy of intrapleural pressure and it is used to compute the patient's P_{mus}. Other approaches rely upon fltting airway pressure and air flow to an Equation of Motion of the Lungs relating these values and parameterized by respiratory system parameters such as respiratory system resistance, R_{rs} and respiratory system compliance C_{rs} or elastance E_{rs}. These approaches also generally rely upon some simplifying assumptions on the patient's true $P_{mus}(t)$ profile in order to evaluate the otherwise undetermined set of equations. These simplifying assumptions may again not be valid under all circumstances. Problems particularly arise during patient-ventilator asynchrony episodes in which the patient's respiratory effort is not well-synchronized with the positive airway pressure applied by the mechanical ventilator.

The following provides new and improved apparatuses and methods which overcome the foregoing problems and others.

BRIEF SUMMARY

In accordance with one aspect, a respiratory monitoring apparatus includes a central venous pressure sensor configured to measure a central venous pressure (CVP) signal of a patient. At least one processor is programmed to process the CVP signal to generate respiratory information for the patient by operations including: segmenting the CVP signal to deflne breath intervals; calculating a surrogate respiratory muscle pressure signal from the segmented CVP signal; and flltering the surrogate respiratory muscle pressure signal to remove a cardiac activity component of the surrogate respiratory muscle pressure signal.

In accordance with another aspect, a mechanical ventilation apparatus includes a mechanical ventilator. A central venous pressure sensor is configured to measure a central venous pressure signal of a patient as a function of time. At least one airway sensor is conflgured to measure airway pressure and air flow as a function of time for the patient on the mechanical ventilator. At least one processor is programmed to: receive the central venous pressure signal from the central venous pressure sensor; receive the airway air flow signal as a function of time for the patient from the at least one airway sensor; calculate a surrogate respiratory muscle

pressure signal as a function of time for each breath of the patient; extract at least one respiratory characteristic from the surrogate muscle pressure signal by operations including filtering data indicative of cardiac activity of the patient from the respiratory muscle pressure signal, determining a shape of the surrogate muscle pressure signal and updating settings of a constrained optimization algorithm and/or a parametric optimization algorithm of the mechanical ventilator based on the shape-detected signal.

In accordance with another aspect, a non-transitory storage medium stores instructions readable and executable by one or more microprocessors programmed to perform a method of monitoring breathing patterns of a patient. The method includes: receiving a central venous pressure value from a central venous pressure sensor; receiving values of at least one of airway pressure and airway air flow as a function of time for the patient from at least one airway sensor; segmenting the received values to determine each breath of the patient; calculate a surrogate respiratory muscle pressure signal as a function of time for each breath of the patient; filtering data indicative of cardiac activity of the patient from the surrogate respiratory muscle pressure signal using the cardiac data received from an ECG sensor, if available; extracting a plurality of peaks in the flltered signal, the peaks corresponding to a shape of the flltered signal; and updating settings of a constrained optimization algorithm and/or a parametric optimization algorithm of the mechanical ventilator based on the shape-detected signal.

One advantage resides in improved monitoring for anomalies in patient respiratory effort during mechanical ventilation of a spontaneously respiring patient.

Another advantage resides in detecting an asynchrony in patient respiratory effort by filtering the cardiac activity of the patient from a respiratory signal.

Another advantage resides in detecting such an asynchrony in patient respiratory effort without determining the patient respiratory muscle pressure $P_{mus}(t)$.

Another advantage resides in automatically adjusting settings of a ventilator responsive to a detected asynchrony.

Another advantage resides in improving estimation of respiratory mechanics from constrained optimization/parametric optimization techniques by using the appropriate monotonicity constraints and timing of the true muscle pressure..

Further advantages of the present invention will be appreciated to those of ordinary skill in the art upon reading and understand the following detailed description. It will be

appreciated that any given embodiment may achieve none, one, more, or all of the foregoing advantages and/or may achieve other advantages.

BRIEF DESCRIPTION OF THE DRAWINGS

The invention may take form in various components and arrangements of components, and in various steps and arrangements of steps. The drawings are only for purposes of illustrating the preferred embodiments and are not to be construed as limiting the invention.

FIGURE 1 shows several intrapleural pressure graphical profiles, $P_{pl}(t)$, with respect to the actual muscle pressure profiles, $P_{mus}(t)$, for different types of breaths.

FIGURE 2 shows several right atrial pressure profiles, $P_{ra}(t)$, (P_{ra} is equivalent to CVP signal) in reference to the intrapleural pressure for the breaths shown in FIGURE 1.

FIGURE 3 shows candidate nominal (synchronous) P_{mus} proflles subject to monotonicity constraints and linear piecewise constraints.

FIGURE 4 shows a sample P_{mus} proflle for double inspiratory effort and expiratory effort.

FIGURE 5 shows a schematic representation of respiratory mechanics and the heart.

FIGURE 6 shows an electrical analogue of the respiratory apparatus and central veins.

FIGURE 7 shows actual and surrogate muscle effort signals during a regular inspiratory effort.

FIGURE 8 shows actual and surrogate muscle effort signals during a double inspiratory effort.

FIGURE 9 shows actual and surrogate muscle effort signals during an expiratory effort.

FIGURE 10 shows a schematic of a proposed ventilator apparatus in accordance with one aspect of the present disclosure.

FIGURE 11A shows a graph of right atrial pressure corresponding to a breath with double inspiratory effort.

FIGURE 11B shows a graph of right atrial pressure corresponding to a breath with expiratory effort.

FIGURE 12A shows a graph of filtered surrogate muscle pressure proflles along with peak detection for a breath with double inspiratory effort.

FIGURE 12B shows a graph of filtered surrogate muscle pressure proflles along with peak detection for a breath with expiratory effort.

FIGURE 13A shows segments of surrogate muscle pressure signal with positive monotonicity, negative monotonicity, and constant value for the filtered signal of FIGURE 12A.

FIGURE 13B shows segments of surrogate muscle pressure signal with positive monotonicity, negative monotonicity, and constant value for the filtered signal of FIGURE 12B.

FIGURE 14 shows a schematic of a proposed ventilator apparatus in accordance with another aspect of the present disclosure.

FIGURE 15 shows example graphs of different type of patient-ventilator asynchronies.

FIGURE 16 shows a flow chart of an exemplary method of use for the ventilator apparatus of FIGURE 10.

FIGURE 17 shows a flow chart of an exemplary method of use for the ventilator apparatus of FIGURE 14.

DETAILED DESCRIPTION

In the following, improved respiratory system monitoring approaches are disclosed which leverage measured central venous pressure (CVP) to provide improved assessment of respiratory activity. In particular, the disclosed approaches recognize that CVP reflects the deflections caused by the activity of the respiratory muscles in the intrapleural pressure, $P_{pl}(t)$, which is the pressure in the thoracic cavity. More particularly, the right atrial pressure, $P_{ra}(t)$, correlates well with intrapleural pressure, $P_{pl}(t)$, and CVP is a surrogate for the right atrial pressure, $P_{ra}(t)$, as the CVP signal's measurement site is on the thoracic veins, located close to (right before) the right atrium. Cardiopulmonary modeling disclosed herein shows these relationships. Conceptually, the venous system (e.g. the superior and inferior vena cavae) return blood from the body into the right atrium, thus providing a physiological basis for relating P_{ra} and CVP. Further, a relationship between intrapleural pressure, $P_{pl}(t)$ and respiratory muscle pressure, $P_{mus}(t)$, may be expressed (up to a constant term) as follows: $P_{mus}(t)=P_{pl}(t)-E_{cw}V_{air}(t)$ where E_{cw} is the chest wall elastance and $V_{air}(t)$ is the lung inflation volume (computable as a

time integral of airway air flow). In embodiments disclosed herein, this approximate relation is typically used, although it is contemplated to further account for secondary factors such as chest wall resistance and/or dependence of E_{cw} on the lung inflation volume $V_{air}(t)$. Substituting CVP as a close proxy for the intrapleural pressure leads to the relationship of a surrogate muscle pressure $P_{mus,\ surr}(t)=CVP(t)-E_{cw}V_{air}(t)$. Advantageously, CVP is already monitored in many critical care settings as a component of cardiac and/or cardiovascular system monitoring in patients with cardiac or coronary ailments. By contrast, the intrapleural pressure $P_{pl}(t)$ and right atrial pressure $P_{ra}(t)$ are not typically monitored in critical care settings, and instruments for such monitoring are not readily available.

In some embodiments, the foregoing may be used to get a surrogate respiratory muscle pressure, $P_{mus,surr}(t)$, from measured CVP(t) and airway air flow. It will be appreciated that the surrogate muscle pressure signal that is computed using CVP may differ from the true P_{mus} for all clinical conditions due to different factors, like cardiac activity, that affect the CVP waveform per se. In some embodiments, given the approximate nature of the underlying relationships, only the shape of the $P_{mus}(t)$ waveform is estimated from this relation – but this waveform shape information is recognized herein to be of significant value in improving respiratory system estimation in the presence of complicating factors such as patient-ventilator asynchrony. Hence, in embodiments described herein, CVP is used to get a surrogate muscle pressure signal ($P_{mus,surr}(t)$). This $P_{mus,surr}(t)$ signal is then used to get shape information and timing of the true $P_{mus}(t)$ signal. Subsequently, this information is used to modify already developed estimation techniques, e.g. CO and PO (these use airway pressure and air flow measurements only), so that the underlying true $P_{mus}(t)$ is more accurately estimated in the case of anomalous patient respiratory activity relative to the ventilatory support (asynchrony).

In general, approaches disclosed herein use measured CVP(t) to compute a surrogate P_{mus} ($P_{mus,surr}$). In doing so, the signal (either CVP or $P_{mus,surr}$) is filtered to remove cardiogenic pulses due to the beating heart. The cardiogenic component may be identified using an external electrocardiogram (ECG) signal, or may be identified by analysis of the measured CVP(t) signal on the basis that the heart rate is a periodic signal with a typical frequency of ~60-150 beats/min whereas respiration is typically on the order of 4-20 breaths/min. In some embodiments, the airway air flow and/or the CVP(t) signal is analyzed to segment breath intervals further assisting in the CVP and/or $P_{mus,surr}$ signal processing.

Physiological patient variables, like pressures, flows, heart rate and respiratory rate, can offer signiflcant advances in the diagnosis and tracking of diseases. For instance, arterial blood pressure (ABP) of a patient is nearly ubiquitously monitored in hospitals and is indicative of the cardiac afterload and the stress developed in the ventricular wall. Another commonly measured signal is central venous pressure of a patient. CVP is primarily used by the medical community as an index of cardiac preload, which reflects the ability of the heart to generate sufficient pressure to induce blood flow. CVP offers an indication of the interaction between the cardiac function and the circulatory apparatus as portrayed by the well-known Frank-Starling curves. Therefore, CVP monitoring, in addition to the commonly measured ABP, is considered to offer physicians valuable insight on the dynamics of the cardiovascular apparatus, especially in the intensive care unit (ICU).

As recognized herein, in addition to the aforementioned cardiovascular-related information that physicians can attain when CVP monitoring is available at the bedside, the CVP waveform itself also demonstrates deflections that are associated with patient's respiratory activity. In particular, the thoracic veins, the site at which CVP is commonly measured, are located inside the thoracic cavity and thus are subject to the intrapleural pressure P_{pl}, which is the pressure between the lungs and the thoracic wall. As demonstrated herein by cardiopulmonary simulations, the intrapleural pressure exhibits prominent swings due to either spontaneous respiration (no external support) or external mechanical ventilation support. In the former case, the patient's respiratory effort, as expressed by muscle pressure (P_{mus}), the equivalent pressure of the force exerted by the respiratory muscles, pulls the diaphragm downwards and expands the thoracic wall, causing the P_{pl} to decrease. During muscle relaxation, elastance of the chest wall, e.g. characterized by elastance parameter E_{cw}, causes intrapleural pressure to return to its resting value. In the case of a mechanically ventilated patient, for example in pressure control ventilation (PCV) mode, the mechanically ventilated patient shows P_{pl} with positive swings that follow the delivered volume profile. Moreover, in partially-assisted mechanical ventilation modes, like in pressure support ventilation (PSV), where the patient and ventilator share the work performed on the respiratory apparatus, P_{pl} contains both negative and positive swings depending on the balance between these two sources.

In simulation results reported herein, cardiopulmonary (CP) system modeling was used to demonstrate various relationships and correlations underlying the disclosed respiratory

monitoring techniques utilizing CVP measurements. The CP model used for these simulations is described in Albanese et al., "An Integrated Mathematical Model of the Human Cardiopulmonary System: Model Development", *Am. J. Physiol. - Hear. Circ. Physiol.*, p. ajpheart.00230.2014, Dec. 2015 (available online at http://www.ncbi.nlm.nih.gov/pubmed/26683899 or http://ajpheart.physiology.org/content/early/2015/12/14/ajpheart.00230.2014). This is an integrated cardiopulmonary model that mathematically describes the interactions between the cardiovascular and respiratory (i.e. pulmonary) systems along with their main short-term control mechanisms, and incorporates cardiovascular circulation, respiratory mechanics, tissue and alveolar gas exchange, and short-term neural control mechanisms acting on the cardiovascular and the respiratory functions. The CP system model can be utilized to simulate both normal CP behavior and CP behavior under the influence of various pathology conditions.

Sample simulated pressure and air flow waveforms for two consecutive breaths are depicted in FIGURE 1. The effort exerted by an active (i.e., non-sedated) patient during spontaneous respiration or under PSV mode was simulated via P_{mus} profiles that resemble the equivalent muscle pressure derived from experimental patient data. FIGURE 1 illustrates that intrapleural pressure exhibits negative swings when the patient is active and positive deflections while the ventilator supports the delivery of air into the respiratory apparatus. P_{ao} is the pressure at the patient's airway opening, or at the ventilator's Y-juncture, while flow and volume are indicative of the air flow being delivered to the lungs either due to the external ventilator support or due to the activity of the patient. It will be appreciated that volume is a direct integral of the flow and is reset to zero at a ventilator at the beginning of every breath.

As shown in FIGURE 1, the steady state P_{pl} has a negative value. At the end of each breath, the transpulmonary pressure (defined as alveolar pressure (i.e., inside) minus P_{pl} (i.e., outside) pressure, needs to be positive in order for the lungs to be inflated (i.e., alveoli not collapsed). For instance, at a normal spontaneous breath, the transpulmonary pressure is around 5 cmH_2O and since the airway pressure is zero, the pleural pressure P_{pl} is equal to -5 cmH_2O. This end-expiratory pleural pressure P_{pl} is thus associated to the Functional Residual Capacity (FRC) of the lungs and it is affected by the external (airway) end-expiratory pressure (PEEP). For instance, if PEEP value of PSV and PCV breaths is different than zero, the end-expiratory pleural pressure is larger than -5 cmH_2O.

Referring to FIGURE 2, a qualitative demonstration of the relationship between central venous and intrapleural pressure waveforms is attained by plotting these two signals along with P_{mus}. All signals are simulated for the different breath types shown in FIGURE 1 (i.e., (a) spontaneous breaths, (b) PSV, and (c) PCV modes). In the simulation studies shown in FIGURE 2, the right atrial pressure (P_{ra}) waveform instead of CVP is shown. Venous side catheterization (the catheter is sometimes referred to as central line catheter), which provides the CVP waveform in the clinical setting, aims to capture the dynamic behaviour of the right atrium and thus the measured CVP is expected to be a close proxy of P_{ra}. It will be appreciated that a CVP central line sensor is not the only way to obtain CVP signal information. Any means for such measurement are suitable to obtain CVP pressure values. Some CVP sensors are low pressure sensors and hence are prone to distortions in their outputs due to bulk patient movement

In addition to the deflections caused by the respiratory activity, the right atrial pressure and thus the measured CVP waveform include cyclic oscillations pertaining to the cardiovascular function (i.e., the cardiogenic signal component, as indicated by the black circle in FIGURE 2).

The CVP signal contains deflections due to dynamics arising either inside or outside the particular vessel or structure that serves as the measuring point. Cardiac oscillations are of the former type and are owing to the function of the heart and the circulatory apparatus. They can be attributed to the propagation of blood flow through the vasculature, back to the right side of the heart, or to wave deflections stemming from the contractile heart chambers (i.e., the right atrium and ventricle). Of the latter type, breathing patterns (either spontaneous or mechanically supported) affect the intravenous pressure by causing deflections whose magnitude and direction depend on the external intrapleural pressure and the vessel's stiffness.

Algorithms, such as a constrained optimization (CO) algorithm and/or a parametric optimization (PO) algorithm, that estimate the respiratory apparatus mechanics (e.g., resistance, elastance, and the like) and the effort exerted by the patient's respiratory muscles (typically quantified as P_{mus}) by solving an Equation of Motion of the Lungs rely either on monotonicity constraints on the underlying respiratory muscle pressure P_{mus} waveform, or on certain assumptions of a shape of the respiratory muscle pressure P_{mus} profile, in order to overcome the typically underdetermined nature of the problem. For example, it can be assumed that, in a CO procedure, a P_{mus} profile within a breath consists of a region of negative

monotonicity, which extends up to the point with the minimum value, and a region of positivity monotonicity that is, in turn, followed by another region of constant pressure. For instance, a sample P_{mus} profile that follows these monotonicity constraints is shown in the left hand graph of FIGURE 3. In another example, such as a PO approach, it is assumed that P_{mus} has morphological characteristics similar to CO but the piecewise regions follow certain pre-configured profiles, like linear (shown in the right-hand graph of FIGURE 3), parabolic, or constant. PO searches over a range of possible P_{mus} waveforms that differ in terms of shape, timing, and magnitude and selects the one that gives the optimal estimation results as far as the airway pressure fitting error is concerned.

The aforementioned assumptions on the morphological characteristics of P_{mus} are satisfied for an appreciably large range of normal inspiratory effort profiles; however, there exist a significant number of cases, especially in diseased states and/or under poorly configured ventilator settings, where the muscle pressure does not comply with these constraints. Such cases could include, but are not limited to, double inspiratory efforts or forced expiratory efforts, similar to the ones shown in FIGURE 4. Under these circumstances, the algorithmic performance of CO and PO is expected to degrade considerably. However, if the overall shape of the muscle pressure profile is known *a priori*, both algorithms can be modified accordingly and thus tailored to each particular breathing pattern. For instance, if a double inspiratory effort is detected, appropriate monotonicity, or piecewise, constraints can replace the default ones, so as to improve the estimation results not only in terms of P_{mus}, but also of the respiratory apparatus resistance and elastance estimates. To this end, information about the shape of P_{mus} via the use of CVP measurements, as disclosed herein, can provide for a wider applicability of CO and PO estimation techniques within the clinical environment.

In another respiratory monitoring task, an accurate assessment of the initiation and termination of the patient's respiratory activity has been proved to be a major challenge. Proper and synchronous triggering and cycling off of each mechanically supported breath in accordance with the patient's demands can lead to benefits such as significant reduction of the work of breathing, shorter duration of hospitalization due to higher chances of weaning success and therefore lower healthcare costs. To this end, accurate detection of patient-ventilator asynchrony is desired. Conventionally, airway pressure and air flow measurements are used to determine the type and severity of the asynchrony and then provide the healthcare practitioner

with appropriate corrective actions or automatically and optimally adjust relevant ventilator settings. In embodiments disclosed herein, the CVP waveform is also used for assessing asynchrony, as CVP provides a signal distinct from conventional respiratory measurements (e.g. airway pressure and flow) that reflects the intrapleural swings and hence the breathing effort.

As demonstrated by CP simulation results such as those described herein with reference to FIGURES 1 and 2, there is a correlative relationship between the intrapleural pressure (P_{pl}) and central venous pressure (CVP). In particular, various breathing patterns represented by the muscle pressure waveform across ventilation modes or patient conditions result in different intrapleural pressure waveforms, and thus correlated central venous pressure profiles. Based on this observation, the following advantageously provides a way, by using the CVP signal, to perform respiratory monitoring tasks such as: (1) appropriately modify the monotonicity constraints in a CO algorithm, or select the category of the pre-deflned profllles of P_{mus} in a PO algorithm; and (2) enhance the asynchrony detection and classification algorithms.

A schematic representation of the heart and lungs within the thoracic cavity is shown in FIGURE 5. In this simplifled figure, the respiratory apparatus (i.e. lungs) is represented by a single elastic alveolar compartment (i.e., balloon) with intra-alveolar pressure, P_{al}, and a resistive pathway (i.e., airways, e.g. the trachea). Both the alveoli and heart reside within the chest wall (i.e., thoracic cavity) and thus are subject to the intrapleural pressure, P_{pl}, which, in turn, depends on both the external airway pressure, P_{ao}, and the muscle pressure, P_{mus}. In the heart, the focus is drawn on the right atrium with pressure P_{ra} that is fllled with blood from the venules via the thoracic veins, primarily the superior and inferior vena cavae. As the right atrium is located inside the thoracic cavity, changes in the intrapleural pressure P_{pl} impact the right atrial pressure P_{ra}, and vice versa. Because these pressure transfers depend on the elastic properties of the vascular tissue and the shape of the vessel, the value of the vessel's elastance indicates how attenuated these changes will be.

The electrical analogue corresponding to the above schematic representation is depicted in FIGURE 6. The resistance and elastance elements of the airways/lungs are denoted as R_{aw} and E_L respectively, whereas the elastance of the chest wall is denoted as E_{cw}. The additional resistance, R_{cw}, that accounts for energy dissipation within the chest wall is often omitted due to the relatively low friction of the tissues. For instance, the CP model, used for the simulation results, neglects R_{cw} and thus the intrapleural pressure is calculated as $P_{pl} = P_{mus} +$

$E_{cw}V_{air}$, where V_{air} is the volume of air delivered into the lungs and computed as the time integral of flow, $\dot{V}_{air}$ (a nominal value of E_{cw} is 10 cmH_2O/L). CVP is the pressure within the thoracic (central) veins and E_v is the parameter that reflects the elastic properties of the veins due to their material properties and geometry (i.e. shape).

According to the conservation of mass principle, the change in volume of the central venous compartment, as accounted for by the elastance element, E_v, is equal to the difference of the blood flow entering and exiting the corresponding spatial location. Hence, the following first-order ordinary differential equation (ODE) can be derived:

$$\frac{dV_{CVP}}{dt} = Q_{in} - Q_{out} \Rightarrow \frac{1}{E_v}\left(C\dot{V}P - \dot{P}_{pl}\right) = Q_{from\ venules} - Q_{to\ right\ heart}$$

$$\Rightarrow C\dot{V}P - \dot{P}_{pl} = E_v\left(Q_{from\ venules} - Q_{to\ right\ heart}\right). \qquad \text{Equation 1}$$

One of the properties of the veins is their ability to act as a capacitance reservoir and store a signiflcant amount of blood volume. This phenomenon is attributed to their high compliance value that depends on the state of venous tone and is altered by the sympathetic stimulation. It is then reasonable to assume that venous compliance is large, or $E_v \cong 0$ (a typical value for E_v is 0.012 cmH_2O/L). Using this approximation, a surrogate signal for the intrapleural pressure can be derived,

$$C\dot{V}P \cong \dot{P}_{pl} \Rightarrow \int_0^t C\dot{V}P(\tau)d\tau \cong \int_0^t \dot{P}_{pl}(\tau)d\tau \Rightarrow CVP(t) - CVP(0) \cong P_{pl}(t) - P_{pl}(0)$$

$$\Rightarrow P_{pl}(t) \cong CVP(t) - CVP(0) + P_{pl}(0).$$

Equation 2

As P_{pl} is associated with the muscle effort via the chest wall mechanical properties (neglecting R_{cw}), it can then be deemed possible to express a surrogate $P_{mus}(t)$ signal by using the $CVP(t)$ according to Equation 2,

$$P_{mus}(t) = P_{pl}(t) - E_{cw}V_{air}(t) \overset{(2)}{\Rightarrow} P_{mus}(t) \cong CVP(t) - E_{cw}V_{air}(t) + P_0,$$

where $P_0 = P_{pl}(0) - CVP(0)$ is a constant term. Equation 3

Equation 3 thus provides for calculation of a surrogate respiratory muscle pressure $P_{mus,surr}(t)$, or at least its waveform, given measured CVP(t) and $V_{air}(t)$, the latter being obtained as a time integral of airway air flow.

For a visual comparison of the actual muscle pressure, $P_{mus}(t)$, and the surrogate signal $P_{mus,surr}(t)$ computed via Equation 3, i.e. $P_{mus,surr}(t) = CVP(t) - E_{cw}V_{air}(t) + P_0$, PSV breaths are focused on, as pressure support ventilation is a common mode that allows the patient to actively breathe and share the work of breathing with the machine. It is thus expected that, during pressure support ventilation (PSV), the breathing patterns may signiflcantly differ from breath to breath, based on the patient's clinical condition and the selected ventilator settings. Similarly to the simulation results presented earlier, a simplified version of a cardiopulmonary model can be used to generate $P_{mus}(t)$ and $P_{mus,surr}(t)$ and simulate the corresponding airway pressure, air flow, and volume waveforms for three different breathing patterns: (i) regular inspiratory effort (FIGURE 7), (ii) double inspiratory effort (FIGURE 8), and (iii) expiratory effort (FIGURE 9). It will be appreciated that the CP model generates only the true P_{mus} and then simulates/computes CVP, airway pressure and air flow signals. From this, the surrogate P_{mus} is computed according to the assumption that E_v is approximately zero. In FIGURES 7-9, the surrogate muscle pressure (i.e., the solid line in the bottom graph of each figure) computed via the central venous pressure (or the right atrial pressure in the case of the simulation studies presented herein) behave similarly to the actual $P_{mus}(t)$ (i.e., the dashed line in the bottom graph of each flgure). One difference is that higher frequency oscillations are observed in the surrogate signal that are not present in the actual respiratory muscle pressure signal – these higher frequency oscillations are cardiogenic oscillations due to the beating heart. The cardiogenic oscillations can signiflcantly affect the derived surrogate signal $P_{mus,surr}(t)$ and it is thus desirable to be filtered out. Appropriate filtering could potentially include the use of electrocardiogram (ECG) signals for a more accurate identification of the cardiovascular-induced swings, or identifying the cardiogenic oscillations as periodic pulses in the CVP matching a known "reasonable" pulse rate range, e.g. 60-150 beats per minute in a typical healthy adult.

Although mechanical ventilation (MV) therapy has been used in the ICU for many years, it is still far from being optimal. Particularly, patient-ventilator asynchrony is one of the main issues associated with the use of MV in patients who are not completely sedated/paralyzed and are able to develop spontaneous respiratory efforts. Patient-ventilator

asynchrony occurs when the timing of the ventilator cycle is not simultaneous with the timing of the patient's respiratory cycle. High levels of asynchrony are associated with increased work of breathing, longer duration of MV, higher incidence of tracheostomy, weaning failure, longer ICU length of stay and hospitalization, and hence increased healthcare costs and poor patient outcomes.

There are two classes of patient-ventilator asynchrony that can be further divided into a total of 5 different subtypes. Triggering asynchronies refer to a situation in which a beginning of the neural inspiratory period (neural Ti) does not match the beginning of the ventilator inspiratory period (mechanical Ti). Within this class, two subtypes of asynchrony can be identified: ineffective triggering and auto-triggering. Cycling off asynchronies refer to a situation in which the end of the neural Ti does not match the end of the mechanical Ti. Within this class, three subtypes of asynchrony can be identifled: delayed cycling off; early cycling off; and double triggering.

As used herein, the term "ineffective triggering" (and variants thereof) refers to a patient-ventilator asynchrony in which a patient initiates an inspiratory effort that fails to trigger the ventilator.

As used herein, the term "auto triggering" (and variants thereof) refers to a patient-ventilator asynchrony in which the ventilator is triggered without the presence of any voluntary inspiratory effort by the patient.

As used herein, the term "delayed cycling off" (and variants thereof) refers to a patient-ventilator asynchrony in which the ventilator cycles off (i.e. terminates the active delivery of pressure or flow) after the end of the neural Ti.

As used herein, the term "early cycling off" (and variants thereof) refers to a patient-ventilator asynchrony in which the ventilator cycles off (i.e. terminates the active delivery of pressure or flow) before the end of the neural Ti.

As used herein, the term "double triggering" (and variants thereof) refers to a patient-ventilator asynchrony in which the premature termination of the ventilator support generates the occurrence of a double inspiratory cycle within the same respiratory cycle.

With reference to FIGURE 10, an embodiment of a respiratory monitoring apparatus **10** is shown. In some embodiments, the respiratory monitoring apparatus **10** may include a mechanical ventilator **12** conflgured to deliver mechanical ventilation to a patient **14**.

Thus, the respiratory monitoring apparatus **10** may also be referred to as a mechanical ventilation apparatus.

The mechanical ventilation apparatus **10** is used to provide mechanical ventilation to a patient via the mechanical ventilator **12** that delivers air flow and/or pressure in accordance with ventilator settings to a ventilated patient **14** via an inlet air hose **16**. Exhaled air returns to the ventilator **12** via an exhalation air hose **18**. A Y-piece or T-piece **20** (or alternatively a tracheal tube, or in some cases a full-face mask) couples air from the discharge end of the inlet air hose **16** to the ventilated patient **14** during inhalation and couples exhaled air from the ventilated patient **14** into the exhalation air hose **18** during exhalation. Not shown in FIGURE 10 are numerous other ancillary components that may be provided depending upon the ventilation mode and other therapy being received by the ventilated patient **14**. Such ancillary components may include, by way of illustration: an oxygen bottle or other medical-grade oxygen source for delivering a controlled level of oxygen to the air flow, usually controlled by a Fraction of Inspired Oxygen (FiO_2) ventilator setting; a humidifier plumbed into the inlet line **16**; a nasogastric tube to provide the patient **14** with nourishment; and so forth. The mechanical ventilator **12** has a user interface including, in the illustrative example, a touch-sensitive display **22** via which the physician, respiratory specialist, or other medical personnel can visualize the ventilator settings and monitor measured physiological variables (e.g., airway pressure and air flow) and operating parameters of the mechanical ventilator **12**. Additionally or alternatively, the user interface may include physical user input controls (buttons, dials, switches, et cetera), a keyboard, a mouse, audible alarm device(s), indicator light(s), or so forth.

In addition, the patient **14** is monitored by a central venous pressure (CVP) sensor **24** configured to measure a CVP signal of the patient, an optional electrocardiogram (ECG) sensor **26** configured to measure an ECG signal of the patient, an airway flow sensor **28** configured to measure airway air flow as a function of time for the patient on the mechanical ventilator **12**, and, an airway pressure sensor **30** conflgured to measure airway pressure as a function of time for the patient on the mechanical ventilator **12**. The patient may be monitored by other sensors (not shown), such as a respiratory rate sensor, SpO_2 sensor, or so forth. Each of the illustrative sensors **24**, **26, 28, 30** are described in more detail below.

The CVP sensor **24** is configured to measure a CVP signal of the patient **14**. The CVP sensor **24** is inserted into a blood vessel, and more particularly a major vein, near the right

atrium of the heart (i.e., the inferior vena cava). Advantageously, the pressure in the right atrium P_{ra} is correlated with the pressure (P_{pl}) in the pleural cavity, between chest wall and lungs, of the patient and (together with the air flow) to the respiratory muscle pressure via Equation 3, and thus, the CVP pressure signal can be used to extract respiratory information of the patient **14**. To do so, the respiratory monitoring apparatus **10** includes at least one processor that is programmed to generate respiratory information for the patient. For example, the illustrative at least one processor includes an integrating processor **32**, a breath detecting processor **34**, a per-breath surrogate muscle pressure processor **36**, a filtering processor **38**, a detection processor **40**, a per-breath respiratory parameters/variables estimating processor **42**, and a WOB calculator **44**.

The integrating processor **32** computes the air volume $V_{air}(t) = \int \dot{V}_{air}(t)dt$. Further, because the approaches disclosed herein operate on a per-breath basis, the breath detecting processor **34** is configured to detect the onset of inspiration by analyzing the acquired air flow sample stream. Each successive breath is then defined as the interval from the onset of one inspiration period to the onset of the next inspiration period. Each breath identified by the breath analyzer spans a time interval $[0, T_{tot}]$ where time 0 corresponds to the first sample at the onset of the inspiration period and time T_{tot} corresponds to the end of the breath, that is, the last sample just before the beginning of the next breath. The per-breath surrogate muscle pressure processor **36** is programmed to receive: (1) the CVP signal from the CVP sensor **24**; and (2) the volume of air from the integrating processor **32**. For each breath interval $[0, T_{tot}]$ delineated by the breath detecting processor **34**, the per-breath surrogate muscle pressure processor **36** is programmed to segment the CVP and air volume signals into breath intervals (i.e., individual breaths) and calculate the surrogate muscle pressure signal, $P_{mus,surr}(t)$, as a function of time using Equation 3 (reproduced here):

$$P_{mus,surr}(t) = CVP(t) - E_{cw}V_{air}(t) + P_0$$

where t belongs to the breath interval $[0, T_{tot}]$, CVP(t) denotes the CVP signal, E_{cw} denotes a chest wall elastance, V_{air} denotes a lung air volume computed by the integrating processor **32**, and P_0 corresponds to a constant. Determination of the bias term P_0 is not of importance as the true muscle pressure signal is always shifted in order to start from, and end to, a zero value. In addition, in applications for which the P_{mus} waveform shape is of interest (for example to identify monotonically increasing or decreasing regions, double-peaks, or other such dynamic structure), the choice of P_0 value is not of significance.

The per-breath $P_{mus,surr}$ signal is then transmitted to the filtering processor **38**. At this point, the segmented CVP and/or $P_{mus,surr}$ signal could also be displayed on a display **22** of the respiratory monitoring apparatus **10**. FIGURE 11A shows the segmented CVP signal displayed on the display **22** for a breath with double inspiratory effort, while FIGURE 11B shows the segmented CVP signal displayed on the display **22** for a breath with expiratory effort. In both FIGURES 11A and 11B, the right atrial pressure P_{ra} (suitably represented by CVP) has been segmented with the time samples given by the breath detector **34**.

The filtering processor **38** is programmed to receive the per-breath $P_{mus,surr}$ signal from the per-breath surrogate muscle pressure processor **36**. In some embodiments, when the ECG sensor **26** is included, the filtering processor **38** is also programmed to receive an ECG signal from the ECG sensor **26**, and segment the ECG signal into breath intervals according to the output of the breath detector **34**. The filtering processor **38** is programmed to filter the received $P_{mus,surr}$ signal to remove a cardiac activity component of the signal. In some embodiments, when the ECG sensor **26** is not used, the filtering processor **38** is programmed to remove data from the $P_{mus,surr}$ signal indicative of cardiac activity of the patient **14**. For example, cardiogenic oscillations in $P_{mus,surr}$ signal are expected to be substantially periodic in nature with a frequency much higher than the respiratory rate. Thus, the filtering processor **38** can determine which portions of the $P_{mus,surr}$ signal to filter out. In another example, when the ECG sensor **26** is used, the filtering processor **38** is programmed to use the received ECG signal to filter (i.e., "remove") the portions of the $P_{mus,surr}$ signal that are indicative of cardiac activity of the patient. In a variant embodiment, the cardiogenic component can be filtered out from CVP signal first followed by the computation of the surrogate muscle pressure signal.

At this point, the filtered $P_{mus,surr}$ signal could be displayed on the display **22**. FIGURE 12A shows the surrogate P_{mus} signal displayed on the display **22** for a breath with double inspiratory effort, while FIGURE 12B shows the surrogate P_{mus} signal displayed on the display **22** for a breath with expiratory effort. In both FIGURES 12A and 12B, the $P_{mus,surr}$ signal computed by Equation 3 has been filtered to remove the cardiac components of the surrogate signal; small peaks, e.g. at about 421 sec, 422 sec, and 423 sec in FIGURE 12A, are residual cardiogenic signal remaining after the filtering.

It will be appreciated that the generated respiratory information for the patient **14** can include: (1) a surrogate intrapleural pressure signal equated to the segmented and filtered

CVP signal (i.e., the segmented and filtered CVP signal value, see Equation 2); (2) a filtered surrogate respiratory muscle pressure waveform determined for each breath interval from the segmented CVP signal (i.e., $P_{mus,\ surr}$, see Equation 3); and the like (e.g. WoB or PoB). Each of the generated respiratory information can, in some embodiments, be displayed on the display **22.**

In some embodiments, the detection processor **40** is programmed detect or extract features of the calculated surrogate P_{mus} signal to determine a shape of the signal. For example, the detection processor **40** is programmed to detect a plurality of peaks **46** and **48** in the segmented and filtered $P_{mus,surr}$ signal. From the detected peaks **46** and **48**, the detection processor is programmed to generate the respiratory information (e.g., CVP(t), $P_{mus,surr}(t)$, and the like) segments over time intervals delineated by the peaks. The peaks **46** correspond to the positive peaks, and the peaks **48** correspond to negative peaks. The detection processor **40** is programmed to identify the positive peaks **46**, the negative peaks **48**, and the monotonicity of the segments between the peaks, i.e., segments with negative monotonicity **50**, with positive monotonicity **52** and constant value **54.** The shape of the surrogate P_{mus} signal can be used to alter constraints or parameters in a corresponding CO algorithm and/or a PO algorithm incorporated in a per-breath respiratory parameters/variables estimating processor **42**. For example, the physiological knowledge of the shape of the muscle pressure profile can be infused in the respiratory parameters/variables estimating processor **42** in the form of regional constraints on $P_{mus}(t)$. In the CO approach, such monotonic regions are expressed in a set of inequalities and equalities and the desired respiratory system parameters and $P_{mus}(t)$ profile are estimated by a constrained optimization problem whose quadratic cost function is subject to the aforementioned regional constraints. In a different aspect, a PO approach employs simple yet realistic mathematical templates to express the linear piece-wise parameterized $P_{mus}(t)$ over a single breath. The WOB calculator **44** is programmed to process the per-breath estimated $P_{mus}(t)$ from the estimator **42** and programmed to compute a value for the patient's Work of Breathing (or Power of Breathing) according to the equation $WOB = \int P_{mus}(t)\dot{V}(t)dt$ (or $POB = \frac{1}{T}\int_0^T P_{mus}(t)\dot{V}(t)dt$, where T is some chosen time interval preferably encompassing several breaths).

For example, the detection processor **40** can include any suitable peak detection hardware (e.g., a peak detector circuit with a diode and a capacitor) or software (e.g., a Matched Filtration with Experimental Noise Determination algorithm, a vectorized peak detection

algorithm, a least-squares curve-fitting algorithm, an optimization peak detection algorithm, a derivative-based algorithm, or the like). In illustrative embodiments described herein, the detection processor **40** uses a derivative-based module **56** to detect peaks of $P_{mus,surr}(t)$ versus time signal. It will be appreciated that the derivative-based module **56** also includes any suitable algorithms for signal processing processes (e.g., filtering, signal to noise ratio reduction, data smoothing, and the like). As described in more detail below, the derivative-based module **56** is configured to identify one or more anomalies in the breathing pattern based on the peak detection readings, as described in more detail below. The derivative-based module **56** is configured to detect peak values **46, 48** (e.g., "y-axis" values of the $P_{mus,surr}(t)$ versus time signal, as described in more detail below) and the associated time values (e.g., "x-axis values") at which these peaks occur. From the peaks **46, 48**, the shape of the $P_{mus,surr}$ signal can be determined. The detected segments of distinct monotonicity for the $P_{mus,surr}(t)$ signals are shown in FIGURES 13A and 13B for a breath with double inspiratory effort (FIGURE 13A) and a breath with expiratory effort (FIGURE 13B).

FIGURE 14 shows another embodiment of the mechanical ventilation apparatus **10'**, in which the respiratory information derived at least in part from CVP measurements is used to provide open-loop ventilator control guidance or automated closed-loop ventilator control. The mechanical ventilation apparatus **10'** can be configured substantially identically to the mechanical ventilation apparatus **10** of FIGURE 10, except as described below.

The mechanical ventilation apparatus **10'** includes the mechanical ventilator **12** (and associated components), the CVP sensor **24**, the optional ECG sensor **26**, the air flow sensor **28**, the airway pressure sensor **30**, the integrating processor **32**, the breath detecting processor **34**, the per-breath surrogate muscle pressure processor **36**, the filtering processor **38**, the detection processor **40**, the per-breath respiratory parameters/variables estimating processor **42**, and the WOB calculator **44**, and the display **22**, as described above. The mechanical ventilation apparatus **10'** also includes a classification processor **58**, which is described in more detail below.

As described above, the integrating processor **32** computes the time integral of the air flow and the breath detecting processor **34** identifies the onset of the inspiration and defines the breath interval $[0, T_{tot}]$ for each breath. The per-breath surrogate muscle pressure processor **36** is programmed to receive the CVP signal from the CVP sensor **24,** the air volume from the

integrator **32**, and the breath interval from the breath detecting processor **34**. The processor **36** is programmed to segment the CVP and volume signals using the breath interval time instances and compute the per-breath surrogate muscle pressure signal, as described above.

The per-breath $P_{mus,surr}$ signal is transmitted to the filtering processor **38**, where it is being filtered as described above. An optional ECG signal from the ECG sensor **26** can also be used by the filtering processor **38** to improve the filtering process. The filtered per-breath $P_{mus,surr}$ signal is then processed by the detection processor **40** to determine the peaks **46, 48** thereof. These peak-detected signals could be displayed on the display **22**. The peak-detected signal is also transmitted to the classification processor **58.**

The classification processor **58** is programmed to classify in a per-breath basis an asynchrony based on the extracted (i.e., peak-detected) $P_{mus,surr}$ signal, the airway pressure, air flow, and volume signals according to at least one of: no asynchrony; ineffective triggering; auto-triggering; delayed cycling off; early cycling off; and double triggering. FIGURE 15 shows examples of a displayed signal for each type of asynchrony. The classification processor **58** can be configured as an artificial neural network, a Logistic Regression algorithm, a Bayes classification algorithm, and the like.

Referring back to FIGURE 14, the classification processor **58** is configured to receive peak and monotonicity detection readings from the derivative-based module **56** of the detection processor **40**. From these peak and monotonicity detection readings, the classification processor **58** is configured to indicate any anomalous/abnormal breath and determine the type of patient-ventilation asynchrony (e.g., ineffective triggering; auto-triggering; delayed cycling off; early cycling off; and double triggering). The classification processor **58** then "fiags" the asynchrony, and can assign a corresponding indication to the type of asynchrony, as described in more detail below. The indication is then transmitted to, and displayed on, the display **22**.

The classification processor **58** then analyzes the extracted surrogate muscle pressure signal from the detection processor **40** along with airway pressure, air flow, and volume waveforms to determine a type of asynchrony. In the example shown in FIGURES 13A and 13B, the filtered surrogate muscle pressure signal includes multiple peaks, either positive **46,** or negative **48**, and different regions of distinct monotonicity, like negative **50**, positive **52**, or constant value **54**. By using the signals shown in FIGURE 15 as a "template", the classification processor **58** can compare the templates to the actual measured signals of airway pressure and air

flow, and/or use the positions of the peaks **46, 48** and segments of distinct monotonicity **50, 52, 54** in surrogate muscle pressure signal to determine the type of asynchrony. Due to the positioning of the negative and positive peaks **46** and **48** (described above), the classification processor **58** determines that the underlying muscle pressure effort is subject to double inspiratory effort (FIGURE 13A) or expiratory effort (FIGURE 13B). The classification processor **58** then flags the asynchrony type, for instance a possible double triggering asynchrony for FIGURE 13A and a delayed cycling off asynchrony for FIGURE 13B, and sends the indication of the asynchrony (i.e., a numerical value) to the display component **22**, where it is displayed for a medical professional (e.g., a nurse, a doctor, and the like).

In other embodiments, when an asynchrony is detected, the indication and/or the displayed signal of $P_{mus,surr}(t)$ conveys to a medical professional that the asynchrony is occurring. The classification processor **58** is further programmed to suggest a recommendation for a medical professional to adjust the settings of the mechanical ventilator **12** to correct the asynchrony. The recommendation is displayed on the display **22.** The medical professional can then adjust the settings of the ventilator **12** so that the asynchrony no longer occurs. In this manner, the mechanical ventilation apparatus **10'** is an open-loop apparatus. A summary of suitable corrective action(s) for each type of asynchrony is described in Table 1 below.

Asynchrony Type	Corrective Action
Ineffective triggering	1. Decrease trigger threshold 2. Reduce sedation 3. Reduce the potential for intrinsic PEEP: – Decrease tidal volume; – Decrease pressure support; – Increase exhalation time; – Reduce resistance in airways
Auto-triggering	1. Increase trigger threshold 2. Switch from flow to pressure triggering 3. Check for circuit leaks
Delayed cycling off	1. Increase cycling threshold 2. Decrease Ti
Early cycling off	1. Increase Ti 2. Decrease cycling threshold
Double triggering	1. Increase tidal volume 2. Increase sedation 3. Increase Ti 4. Decrease cycling threshold

Table 1

In further embodiments, the mechanical ventilation apparatus **10'** is further programmed to automatically adjust the settings of the mechanical ventilator **12** to correct the asynchrony. To do so, the mechanical ventilation apparatus **10'** includes a closed-loop controller **60**. In some embodiments, the closed-loop controller **60** can be configured as a power of breathing or a work of breathing controller. In such case, integrated into the controller **60** are the per-breath respiratory parameters/variables estimating processor **42** and the WOB/POB calculator **44**. The closed-loop controller **60** is programmed to calculate the patient's power (or

work) of breathing by time integration of the product of the estimated $P_{mus}(t)$ from **42** and air flow and to adjust the ventilator setting based on the difference between the actual and desired power or work of breathing in order to optimally support the patient's spontaneous respiratory effort. Such a closed-loop controller is described in U.S. Patent Publication No. 2015/0059754, which is incorporated in its entirety herein. In embodiments disclosed herein, the indication output by the classification processor **58** is also input to the closed-loop ventilator controller **60**. If the indication indicates a respiratory asynchrony, then the closed loop ventilator controller **60** can take appropriate action, such as maintaining the current ventilator setting in an open-loop fashion, or adjusting ventilator settings based on the detected asynchronous condition, based on the recommendations listed in Table 1. In other embodiments, the controller **60** can be a multiple-input and multiple-output (MIMO) controller that accepts, besides the WOB/POB value, additional physiological variables, such as SpO_2, end-tidal CO_2, and/or mean arterial blood pressure values, and accordingly adjusts multiple ventilator settings, like the pressure support level, the end-expiratory pressure, the triggering and cycling-off sensitivity, and/or the fraction of oxygen in the supplied air.

It will also be appreciated that the various signals and values described herein can be communicated to the various processors **36, 38, 40, 58** and components **12, 22, 42, 44, 60** via a communication network (e.g., a wireless network, a local area network, a wide area network, a personal area network, BLUETOOTH®, and the like). Alternatively, the components **36, 38, 40, 42, 44, 58** and controller **60** may be built into the mechanical ventilator **12** (e.g., executing on a microprocessor or microcontroller of the ventilator **12**) in which case data from the sensors **24, 26, 28, 30** are collected by the ventilator **12** and hence available to the components **36, 38, 40, 42, 44, 58** and controller **60**. In another contemplated embodiment, the algorithms of the processors are implemented on the microprocessor of a patient monitor (not shown) that displays vital signs such as heart rate, respiration rate, blood pressure, or so forth, and the output of these processors **36, 38, 40, 58** and components **42, 44** are suitably displayed on the patient monitor display component.

FIGURE 16 shows a method **100** of improving the respiratory parameter estimation in the case of an anomalous breathing pattern. The method **100** includes receiving a CVP signal, an airway pressure signal, an air flow signal, and an ECG signal of a patient from a corresponding sensor **24, 26, 28, 30 (102)**. The received signals for each breath of the patient are

segmented (**104**). A surrogate signal for a respiratory muscle pressure generated by the patient is calculated for each segmented breath (**106**). Data indicative of cardiac activity of the patient is filtered from the surrogate muscle pressure signal (**108**). Peaks in the filtered signal are extracted (**110**). Regions of positive monotonicity, negative monotonicity, and constant values are defined on the filtered signal (**112**). Default assumptions of the shape of the underlying muscle pressure profile in CO and PO algorithms are modified (**114**). A more accurate estimate of the patient's respiratory muscle effort and the respiratory system's parameters is provided (**116**).

FIGURE 17 shows a method **200** of suggesting or automatically performing a corrective action in regards to the selected ventilator settings upon detecting a patient-ventilator asynchrony event. The method **200** includes receiving a CVP signal, an airway pressure signal, an air flow signal, and an ECG signal of a patient from a corresponding sensor **24, 26, 28, 30 (202).** The received signals are segmented for each breath of the patient (**204**). A surrogate signal for a respiratory muscle pressure generated by the patient is calculated for each segmented breath (**206**). Data indicative of cardiac activity of the patient is filtered from the surrogate muscle pressure signal (**208**). Peaks in the filtered signal are extracted (**210**). Regions of positive monotonicity, negative monotonicity, and constant values are defined on the filtered signal (**212**). An asynchrony is classified based on the overall shape of the muscle pressure signal and the measured airway pressure signal and the air fiow signal (**214**). A recommendation to adjust the settings of a ventilator is suggested, or the settings of the ventilator are automatically adjusted (**216**).

The various data processing components **36, 38, 40, 42, 44, 58** and controller **60** are suitably implemented as a microprocessor programmed by firmware or software to perform the disclosed operations. In some embodiments, the microprocessor is integral to the mechanical ventilator **12**, so that the data processing is directly performed by the ventilator **12**. In other embodiments the microprocessor is separate from the mechanical ventilator **12**, for example being the microprocessor of a desktop computer. The various data processing components **36, 38, 40, 42, 44, 58** and controller **60** of the mechanical ventilator apparatus may also be implemented as a non-transitory storage medium storing instructions readable and executable by a microprocessor (e.g. as described above) to implement the disclosed operations. The non-transitory storage medium may, for example, comprise a read-only memory (ROM),

programmable read-only memory (PROM), flash memory, or other repository of firmware for the ventilator **12**. Additionally or alternatively, the non-transitory storage medium may comprise a computer hard drive (suitable for computer-implemented embodiments), an optical disk (e.g. for installation on such a computer), a network server data storage (e.g. RAID array) from which the ventilator **12** or a computer can download the apparatus software or firmware via the Internet or another electronic data network, or so forth.

The invention has been described with reference to the preferred embodiments. Modifications and alterations may occur to others upon reading and understanding the preceding detailed description. It is intended that the invention be construed as including all such modifications and alterations insofar as they come within the scope of the appended claims or the equivalents thereof.

CLAIMS:

1. A respiratory monitoring apparatus **(10)** comprising:

a central venous pressure sensor **(24)** configured to measure a central venous pressure (CVP) signal of a patient; and

at least one processor **(32, 34, 36, 38, 40, 42, 44, 58)** programmed to process the CVP signal to generate respiratory information for the patient by operations including:

segmenting the CVP signal based on detected breath intervals;

calculating a surrogate respiratory muscle pressure signal from the segmented CVP signal; and

filtering the surrogate respiratory muscle pressure signal to remove a cardiac activity component of the surrogate respiratory muscle pressure signal.

2. The apparatus **(10)** of claim 1, wherein the generated respiratory information includes at least one of:

a surrogate intrapleural pressure signal determined from the segmented and filtered CVP signal.

a surrogate respiratory muscle pressure waveform determined for each breath interval from the segmented and filtered CVP signal and a measured air flow signal integrated to determine an air volume signal.

3. The apparatus **(10)** of either one of claims 1 and 2, further including:

an electrocardiogram (ECG) sensor **(26)** configured to measure an ECG signal;

wherein the at least one processor **(32, 34, 36, 38, 40, 42, 44, 58)** is programmed to perform the filtering using the ECG signal received from the ECG sensor **(26)**.

4. The apparatus **(10)** of any one of claims 1-3, further comprising:

a mechanical ventilator (**12**) configured to deliver mechanical ventilation to the patient;

wherein the at least one processor (**32, 34, 36, 38, 40, 42, 44, 58**) is further programmed to:

receive a start of inhalation mark as a function of time for each breath of the patient from the mechanical ventilator (**12**); and

determine breath intervals of the patient from the start of inhalation marks.

5. The apparatus (**10**) of any one of claims 1-4, further including:

at least one airway sensor (**28, 30**) configured to measure airway air flow as a function of time for the patient on the mechanical ventilator (**12**);

wherein the at least one processor (**32, 34, 36, 38, 40, 42, 44, 58**) is programmed to generate the respiratory information as a function of time using the segmented CVP signal and volume of air as a function of time.

6. The apparatus (**10**) of claim 5, wherein the at least one processor (**32, 34, 36, 38, 40, 42, 44, 58**) is programmed to:

calculate the surrogate respiratory muscle pressure as a function of time from the equation:

$$P_{mus,surr}(t) = CVP(t) - E_{cw}V_{air}(t) + P_0;$$

where $P_{mus,surr}(t)$ denotes surrogate respiratory muscle pressure, CVP(t) denotes the CVP signal, E_{cw} denotes a chest wall elastance, V_{air} denotes a lung air volume computed as an integral of the air flow as a function of time, and P_0 denotes a constant.

7. The apparatus (**10**) of any one of claims 1-6, wherein the at least one processor (**32, 34, 36, 38, 40, 42, 44, 58**) is further programmed to:

detect a plurality of peaks (**46, 48**) in the segmented and filtered surrogate muscle pressure signal; and

generate the respiratory information including a respiratory muscle pressure waveform comprising respiratory muscle pressure waveform segments over time intervals delineated by the peaks.

8. The apparatus (**10**) of claim 7, wherein the at least one processor (**32, 34, 36, 38, 40, 42, 44, 58**) is further programmed to:

update settings of a constrained optimization algorithm and/or a parametric optimization algorithm of the mechanical ventilator (**12**) based on the peak-detected muscle pressure signal.

9. The apparatus (**10**) of any one of claims 1-8, wherein the central venous pressure sensor (**24**) is a central venous pressure central line sensor.

10. A mechanical ventilation apparatus (**10'**), comprising:

a mechanical ventilator (**12**);

at least one airway sensor (**28, 30**) configured to measure airway pressure and air flow as functions of time for the patient on the mechanical ventilator (**12**);

at least one processor (**32, 34, 36, 38, 40, 42, 44, 58**) programmed to:

receive a central venous pressure signal from a central venous pressure sensor (**24**);

receive the air flow signal as a function of time for the patient from the at least one airway sensor (**28, 30**);

calculate a respiratory muscle pressure signal as a function of time for each breath of the patient;

extract at least one respiratory characteristic from the surrogate muscle pressure signal by operations including:

filtering data indicative of cardiac activity of the patient from the respiratory muscle pressure signal;

determining a shape of the respiratory muscle pressure signal; and

updating settings of a constrained optimization algorithm and/or a parametric optimization algorithm of the mechanical ventilator (**12**) based on the shape-detected signal.

11. The apparatus (**10'**) of claim 10, further including:

an electrocardiogram (ECG) sensor (**26**) configured to measure data indicative of cardiac activity of the patient;

wherein the at least one processor (**32, 34, 36, 38, 40, 42, 44, 58**) is further programmed to filter data indicative of cardiac activity of the patient from the segmented signal using the cardiac data received from the ECG sensor (**26**).

12. The apparatus (**10'**) of either one of claims 10 and 11, wherein the at least one processor (**32, 34, 36, 38, 40, 42, 44, 58**) is further programmed to:

receive a start of inhalation mark as a function of time for each breath of the patient and a start of exhalation mark as a function of time for each breath of the patient from the mechanical ventilator (**12**); and

determine a duration of each breath of the patient as a function of time from the start of inhalation and the start of exhalation marks by segmenting the received marks and the air flow signal as a function of time to determine each breath of the patient.

13. The apparatus (**10'**) of any one of claims 10-12, wherein the at least one processor (**32, 34, 36, 38, 40, 42, 44, 58**) is further programmed to:

calculate the signal of a surrogate respiratory muscle pressure as a function of time generated by the patient on the mechanical ventilator (**12**) from the received central venous pressure and air volume signals.

14. The apparatus (**10'**) of claim 13, wherein the at least one processor (**32, 34, 36, 38, 40, 42, 44, 58**) is further programmed to:

calculate a surrogate signal of respiratory muscle pressure as a function of time generated by the patient on the mechanical ventilator (**12**) from the equation:

$$P_{mus,surr}(t) = CVP(t) - E_{cw}V_{air}(t) + P_0;$$

wherein $P_{mus,surr}(t)$ corresponds to surrogate respiratory muscle pressure, CVP corresponds to central venous pressure, E_{cw} corresponds to elastance of a chest wall, V_{air} denotes a lung air volume computed as an integral of the air flow as a function of time, and P_0 corresponds to a constant;

display, on a display (**22**), the calculated value of respiratory muscle pressure.

15. The apparatus (**10'**) of any one of claims 10-14, wherein the at least one processor (**32, 34, 36, 38, 40, 42, 44, 58**) is further programmed to:

extract a plurality of peaks (**46, 48**) in the filtered surrogate muscle pressure signal, the peaks (**42, 44**) corresponding to a shape of the filtered signal.

16. The apparatus (**10'**) of any one of claims 10-15, further including:

a classification processor (**58**) programmed to classify an asynchrony of the extracted signal according to at least one of:

no asynchrony;

ineffective triggering;

auto-triggering;

delayed cycling off;

early cycling off; and

double triggering.

17. The apparatus (**10'**) of claim 16, wherein the at least one processor (**32, 34, 36, 38, 40, 42, 44, 58**) is further programmed to at least one of:

suggest a recommendation for a medical professional to adjust the settings of the mechanical ventilator (**12**) to correct the asynchrony, wherein the recommendation is displayed on the display (**22**); and

automatically adjust the settings of the mechanical ventilator (**12**) to correct the asynchrony.

18 A non-transitory storage medium storing instructions readable and executable by one or more microprocessors (**32, 34, 36, 38, 40, 42, 44, 58**) to perform a method of monitoring breathing patterns of a patient, the method comprising:

receiving a central venous pressure value from a central venous pressure sensor (**24**);

receiving values of at least one of airway pressure and air flow as a function of time for the patient from at least one airway sensor (**28, 30**);

segmenting the received values to determine each breath of the patient;

computing a surrogate muscle pressure signal from the segmented CVP signal;

filtering data indicative of cardiac activity of the patient from the surrogate muscle pressure signal using the cardiac data received from an ECG sensor (**26**);

extracting a plurality of peaks (**46, 48**) in the filtered signalcorresponding to a shape of the filtered signal; and

updating settings of a constrained optimization algorithm and/or a parametric optimization algorithm of the mechanical ventilator (**12**) based on the peak-detected signal.

.19. The non-transitory storage medium of claim 18, wherein the at least one microprocessor (**32, 34, 36, 38, 40, 42, 44, 58**) is further programmed to:

receive a start of inhalation mark as a function of time for each breath of the patient and a start of exhalation mark as a function of time for each breath of the patient from the mechanical ventilator (**12**); and

determine a duration of each breath of the patient as a function of time from the start of inhalation and the start of exhalation marks.

20. The non-transitory storage medium of either one of claims 18 and 19, wherein the at least one microprocessor (**32, 34, 36, 38, 40, 42, 44, 58**) is further programmed to:

calculate a surrogate signal of respiratory muscle pressure as a function of time generated by the patient on the mechanical ventilator (**12**) from the equation:

$$P_{mus,surr}(t) = CVP(t) - E_{cw}V_{air}(t) + P_0;$$

wherein $P_{mus,surr}(t)$ corresponds to surrogate respiratory muscle pressure, CVP corresponds to central venous pressure, E_{cw} corresponds to elastance of a chest wall, V_{air} denotes a lung air volume computed as an integral of the air flow as a function of time, and P_0 corresponds to a constant;

display, on a display (**22**), the calculated value of respiratory muscle pressure.

21. The non-transitory storage medium of any one of claims 18-20, wherein the at least one microprocessor (**32, 34, 36, 38, 40, 42, 44, 58**) is further programmed to:

classify an asynchrony of the extracted signal according to at least one of:

no asynchrony;

ineffective triggering;

auto-triggering;

delayed cycling off;

early cycling off; and

double triggering;

and

at least one of:

suggest a recommendation for a medical professional to adjust the settings of the mechanical ventilator (**12**) to correct the asynchrony, wherein the recommendation is displayed on the display (**22**); and

automatically adjust the settings of the mechanical ventilator (**12**) to correct the asynchrony.

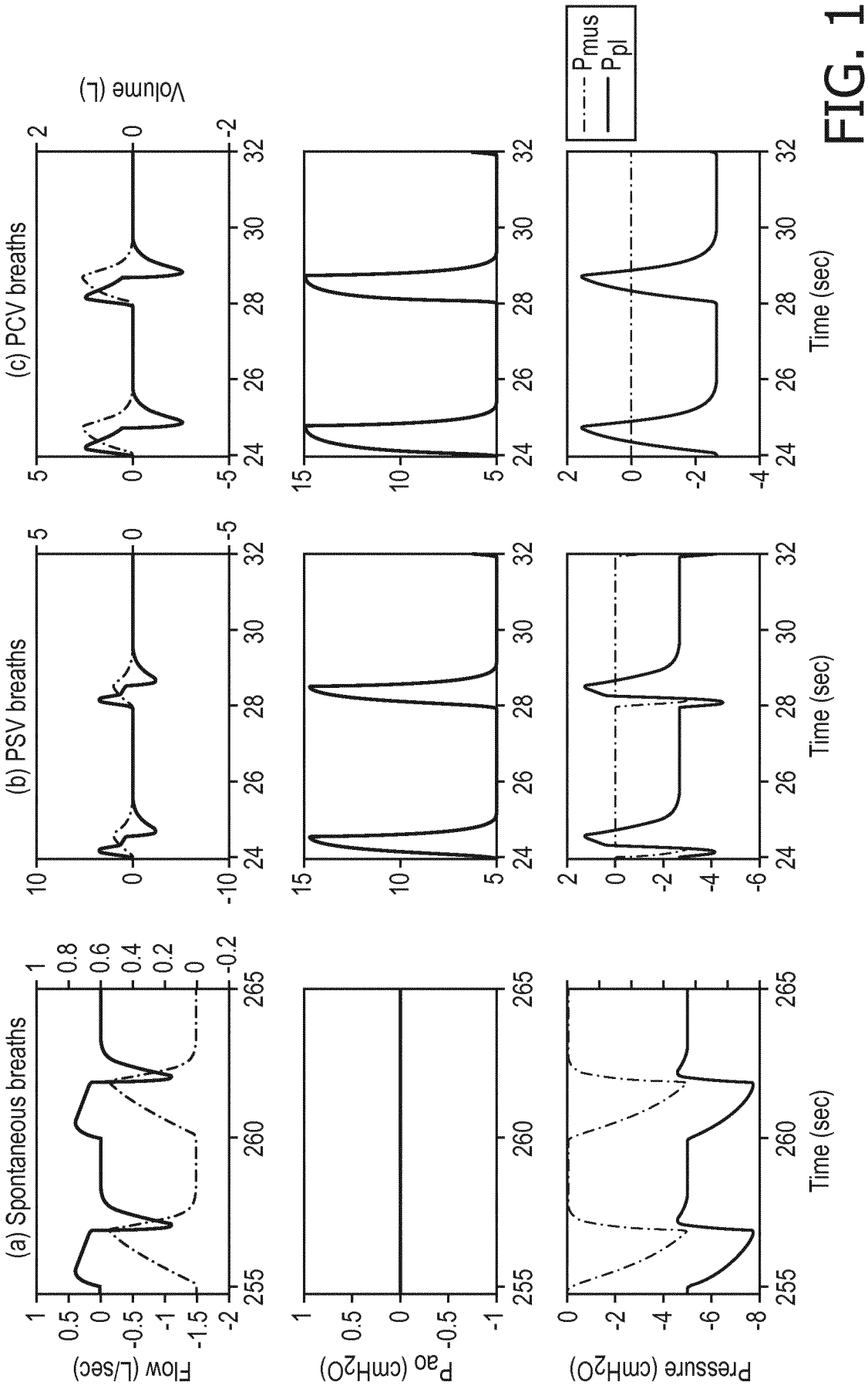
(a) Spontaneous breaths
(b) PSV breaths
(c) PCV breaths
Flow (L/sec)
Volume (L)
P_{ao} (cmH_2O)
Pressure (cmH_2O)
P_{mus}
P_{pl}
Time (sec)
Time (sec)
Time (sec)

FIG. 1

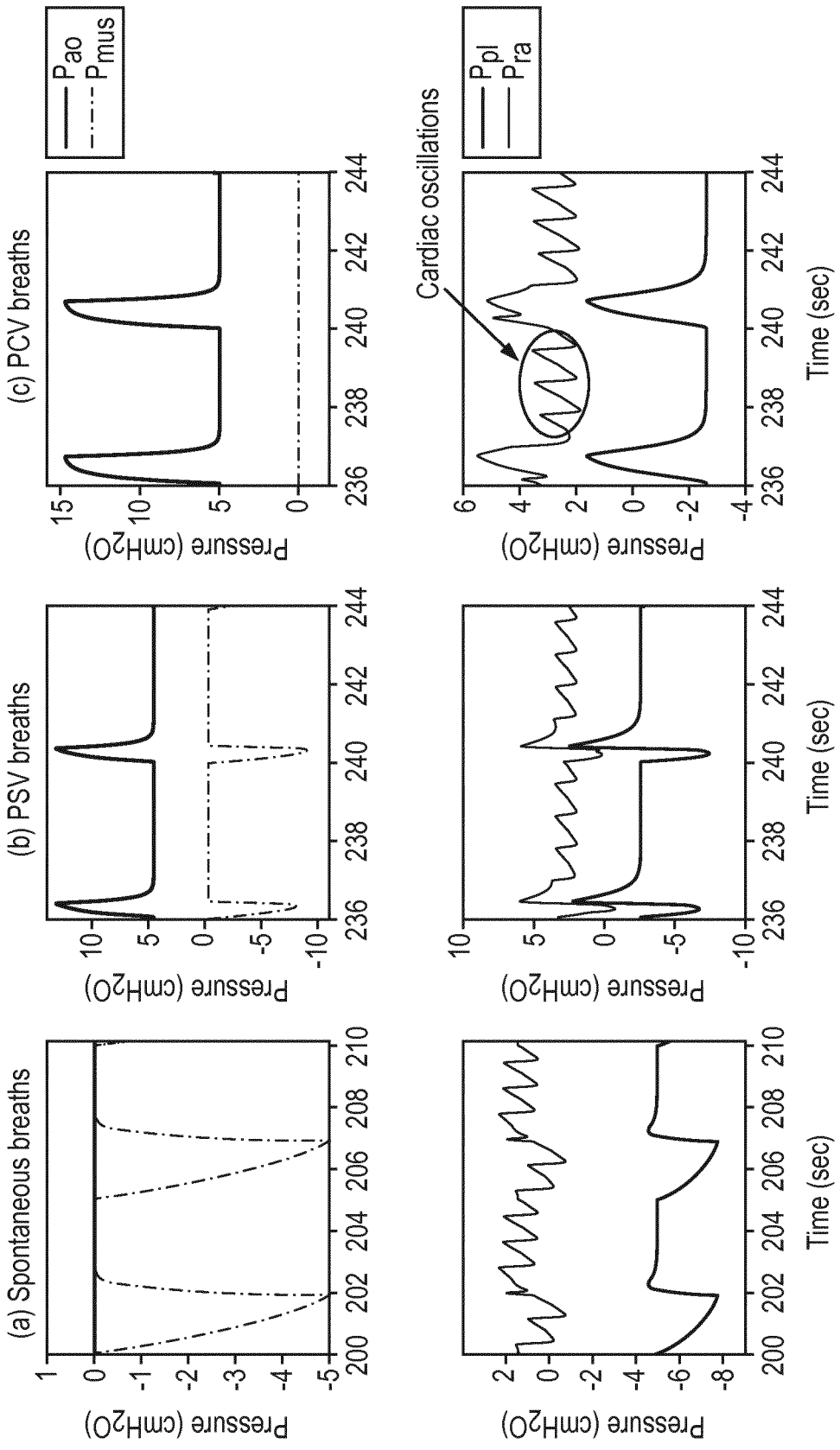
(a) Spontaneous breaths
(b) PSV breaths
(c) PCV breaths
Cardiac oscillations
Pao
Pmus
Ppl
Pra
Pressure (cmH2O)
Time (sec)

FIG. 2

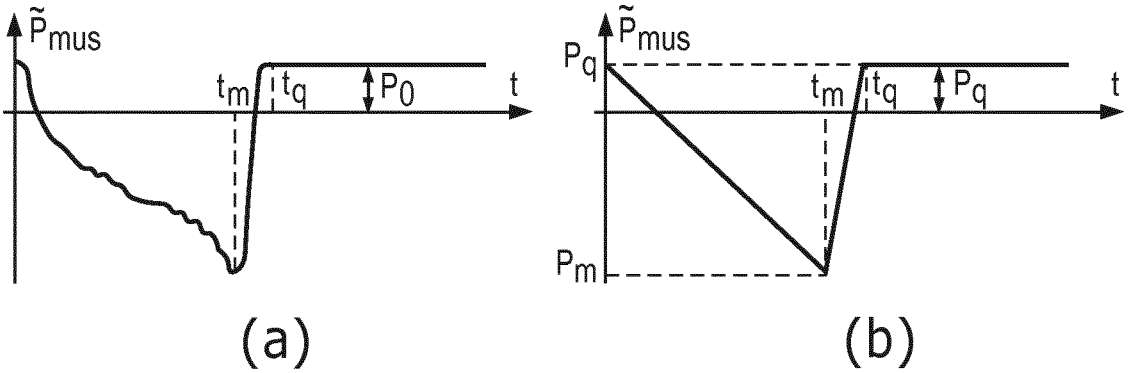
$\tilde{P}_{mus}$
t_m
t_q
P_0
t
$\tilde{P}_{mus}$
P_q
t_m
t_q
P_q
t
P_m
(a)
(b)

FIG. 3

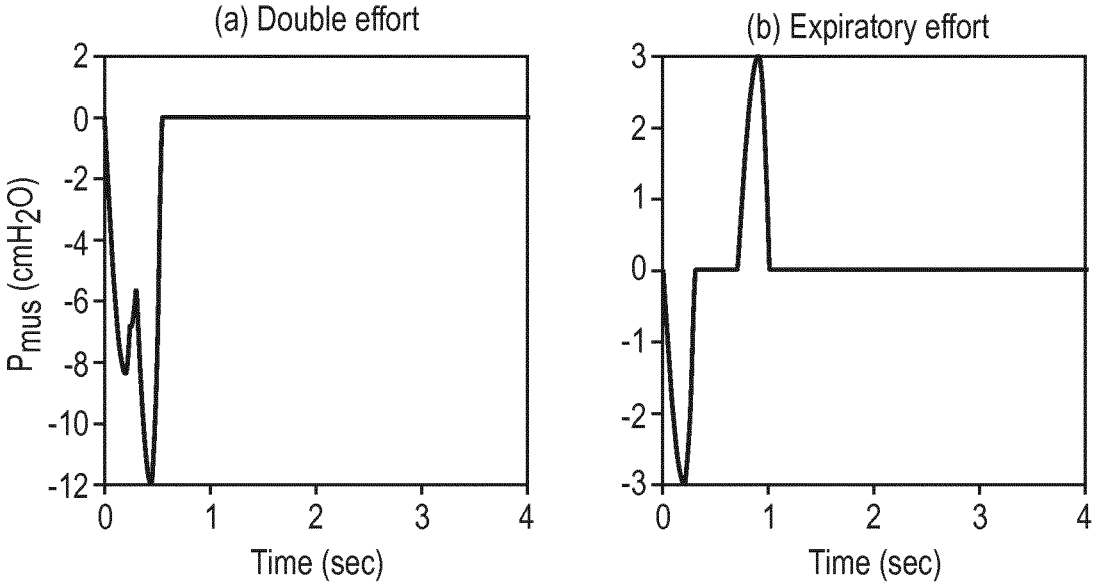
(a) Double effort
P_{mus} (cmH_2O)
2
0
-2
-4
-6
-8
-10
-12
0
1
2
3
4
Time (sec)
(b) Expiratory effort
3
2
1
0
-1
-2
-3
0
1
2
3
4
Time (sec)

FIG. 4

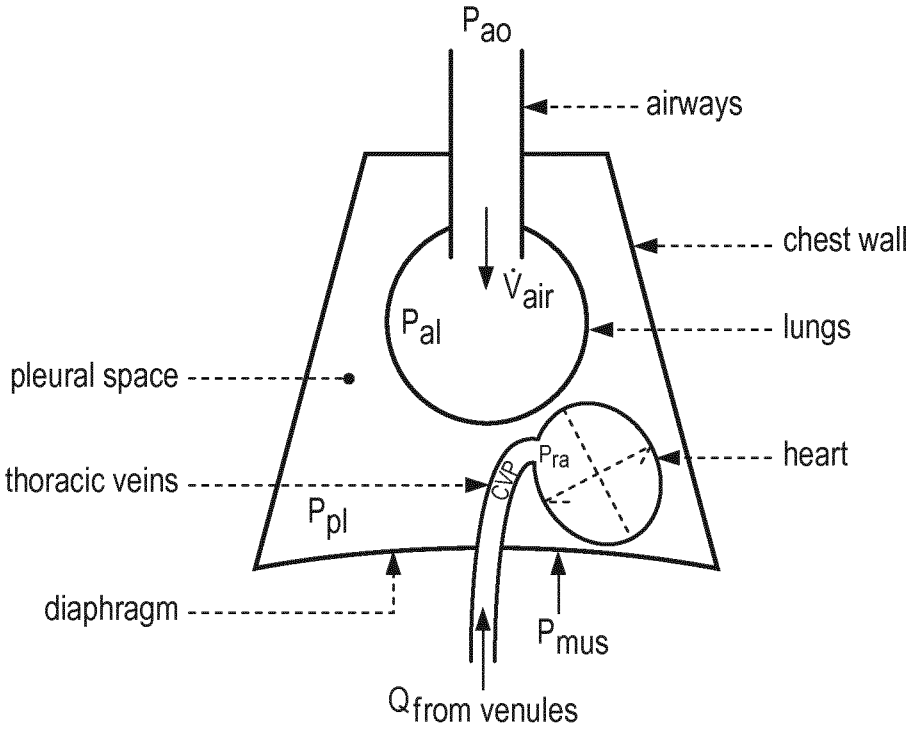
P_{ao}
airways
chest wall
$\dot{V}_{air}$
P_{al}
lungs
pleural space
heart
P_{ra}
CVP
thoracic veins
P_{pl}
diaphragm
P_{mus}
$Q_{from\ venules}$

FIG. 5

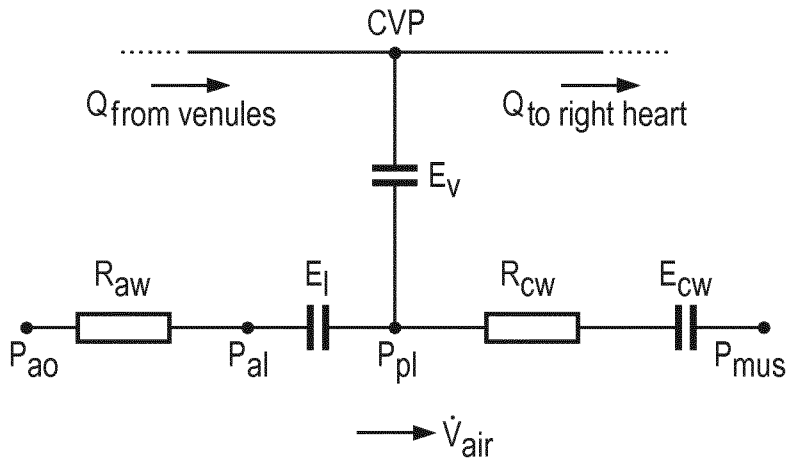
CVP
$Q_{from\ venules}$
$Q_{to\ right\ heart}$
E_v
R_{aw}
E_l
R_{cw}
E_{cw}
P_{ao}
P_{al}
P_{pl}
P_{mus}
$\dot{V}_{air}$

FIG. 6

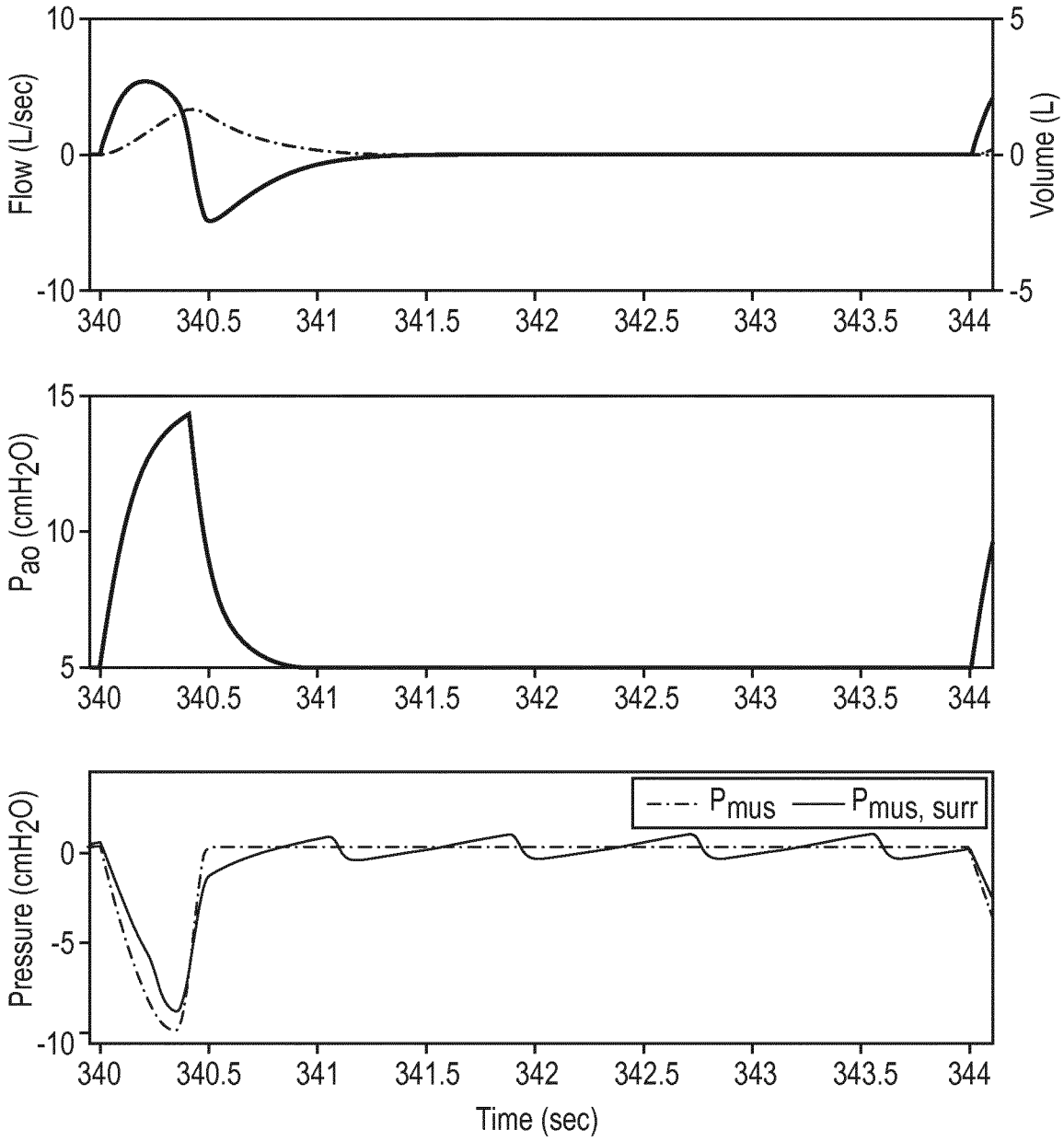
Flow (L/sec)
Volume (L)
10
0
-10
5
0
-5
340
340.5
341
341.5
342
342.5
343
343.5
344
P_{ao} (cmH_2O)
15
10
5
Pressure (cmH_2O)
P_{mus}
$P_{mus, surr}$
Time (sec)

FIG. 7

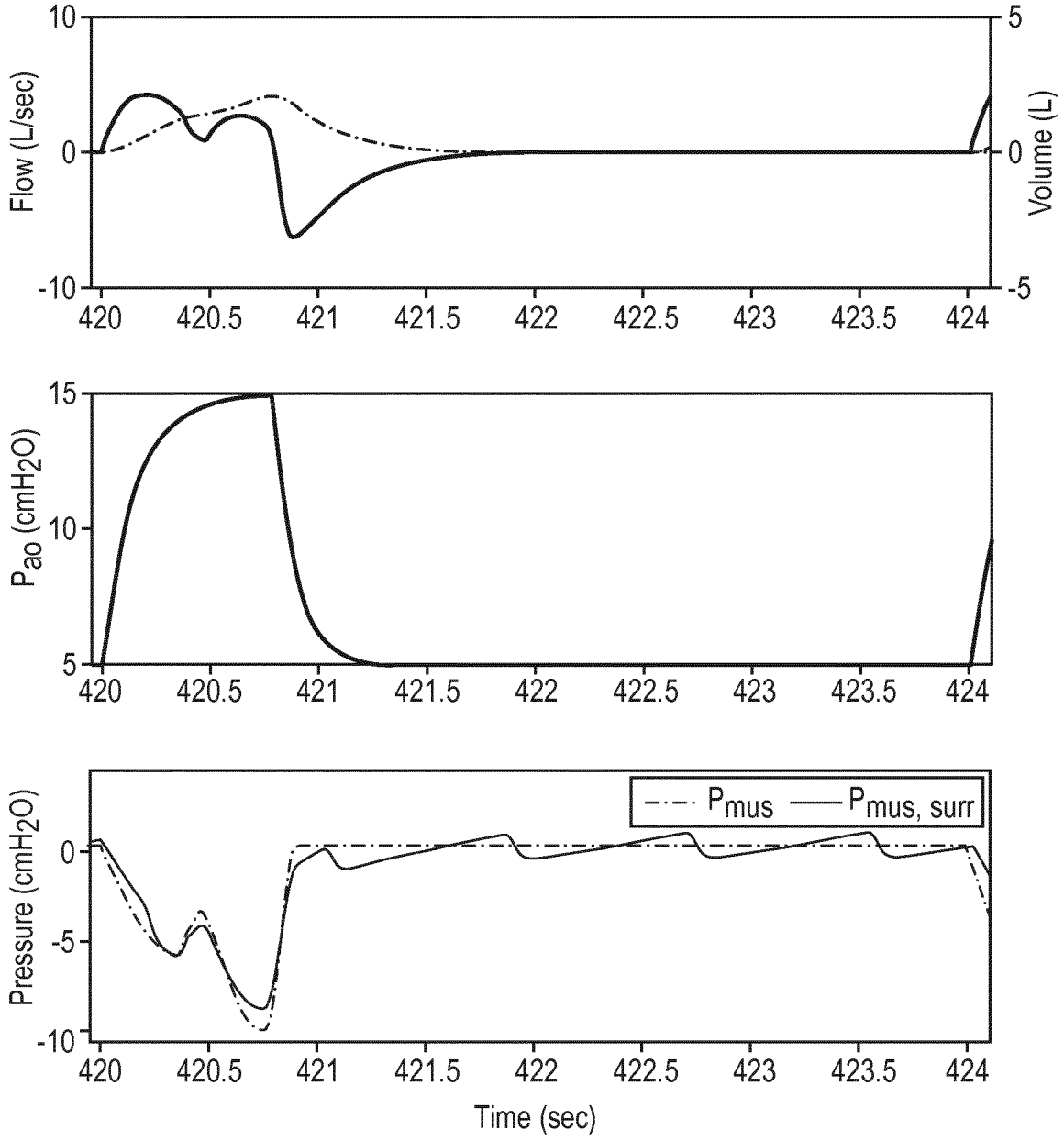
Flow (L/sec)
Volume (L)
10
0
-10
5
0
-5
420
420.5
421
421.5
422
422.5
423
423.5
424
P_{ao} (cmH_2O)
15
10
5
Pressure (cmH_2O)
P_{mus}
$P_{mus, surr}$
Time (sec)

FIG. 8

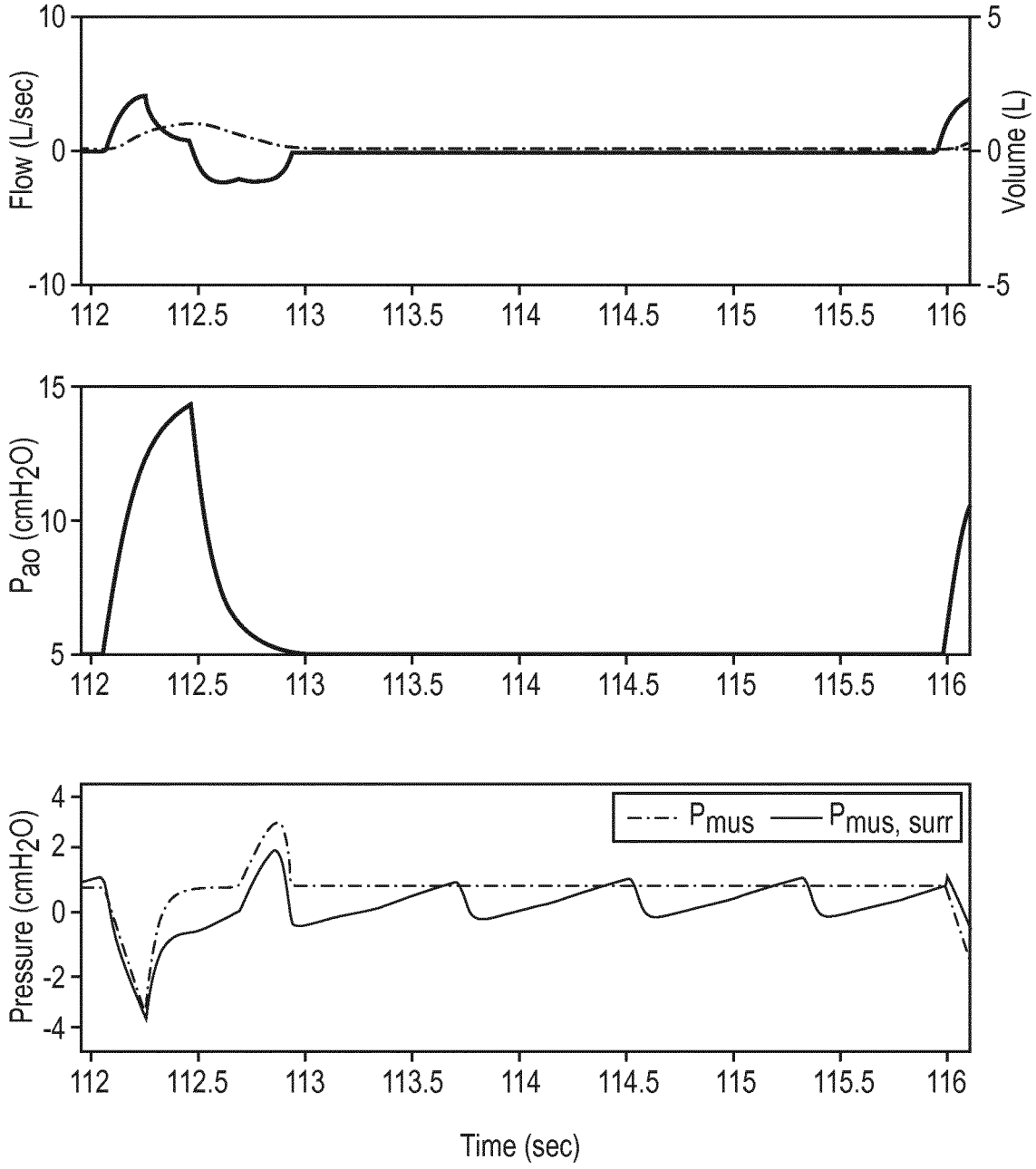
10
0
-10
Flow (L/sec)
5
0
-5
Volume (L)
112
112.5
113
113.5
114
114.5
115
115.5
116
15
10
5
P_{ao} (cmH_2O)
4
2
0
-2
-4
Pressure (cmH_2O)
P_{mus}
$P_{mus, surr}$
Time (sec)

FIG. 9

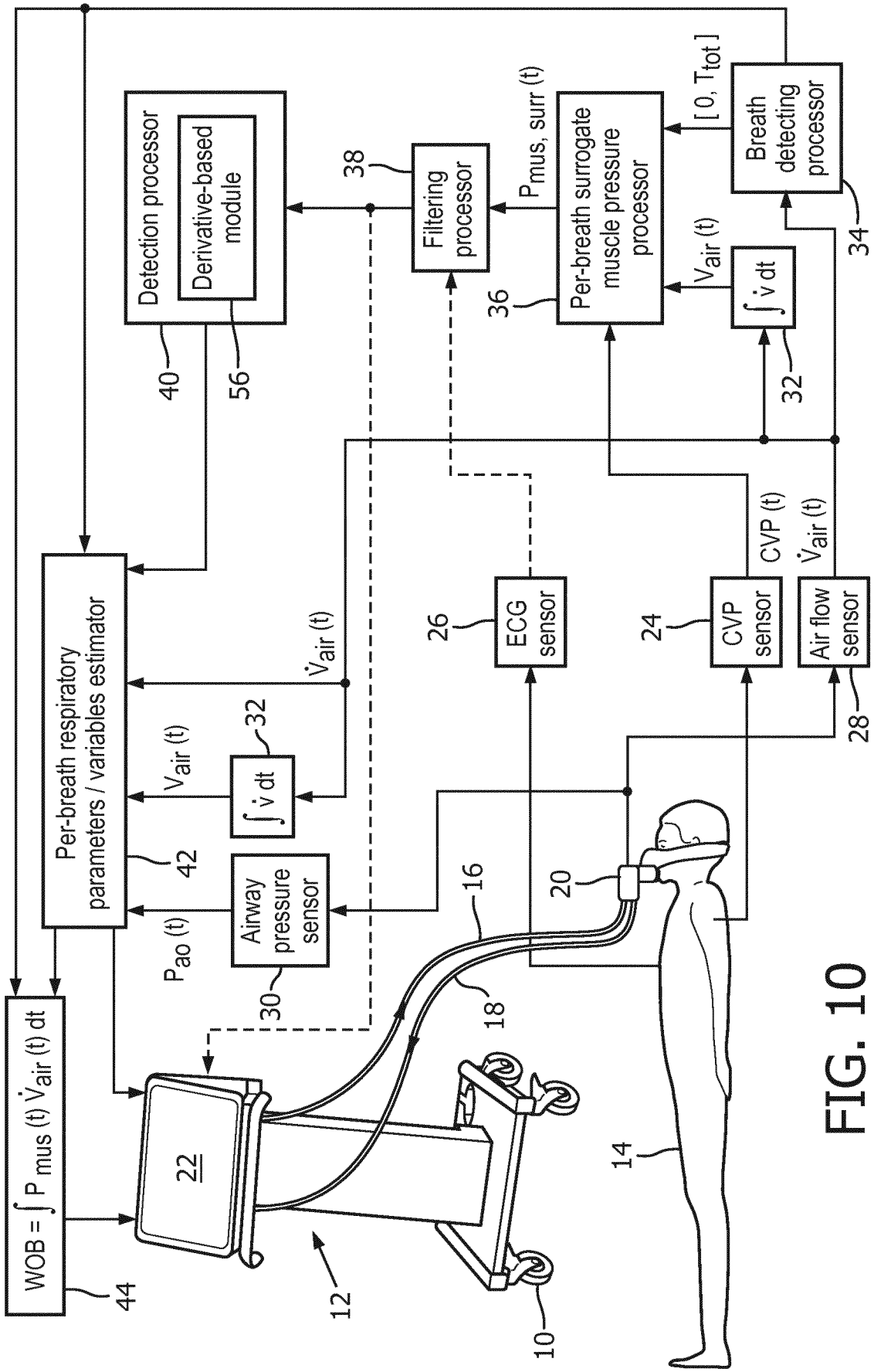
Detection processor
Derivative-based module
40
56
38
Filtering processor
$P_{mus, surr}$ (t)
Per-breath surrogate muscle pressure processor
36
[0, T_{tot}]
Breath detecting processor
34
V_{air} (t)
$\int \dot{v}\, dt$
32
Per-breath respiratory parameters / variables estimator
42
$\dot{V}_{air}$ (t)
V_{air} (t)
$\int \dot{v}\, dt$
32
ECG sensor
26
CVP sensor
24
CVP (t)
Air flow sensor
$\dot{V}_{air}$ (t)
28
Airway pressure sensor
P_{ao} (t)
30
16
20
18
22
12
10
14
WOB = $\int P_{mus}$ (t) $\dot{V}_{air}$ (t) dt
44

FIG. 10

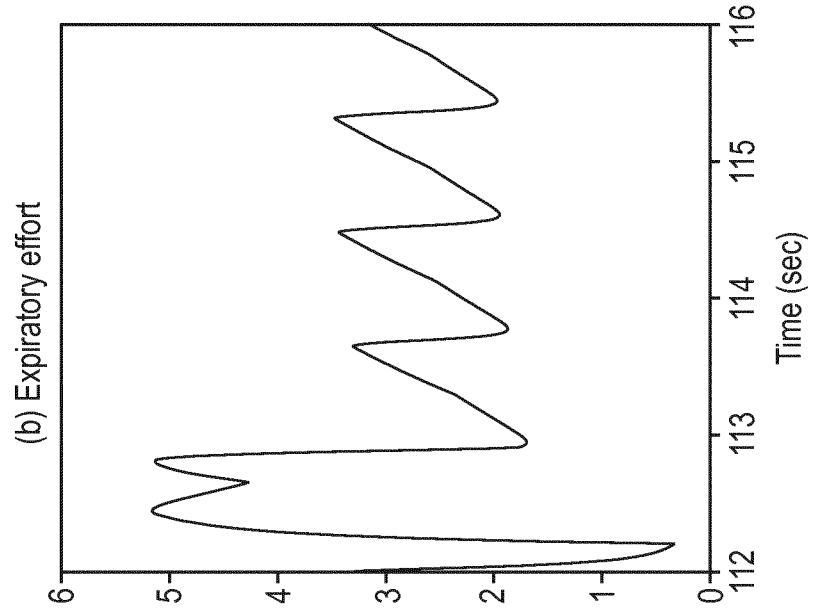

FIG. 11B

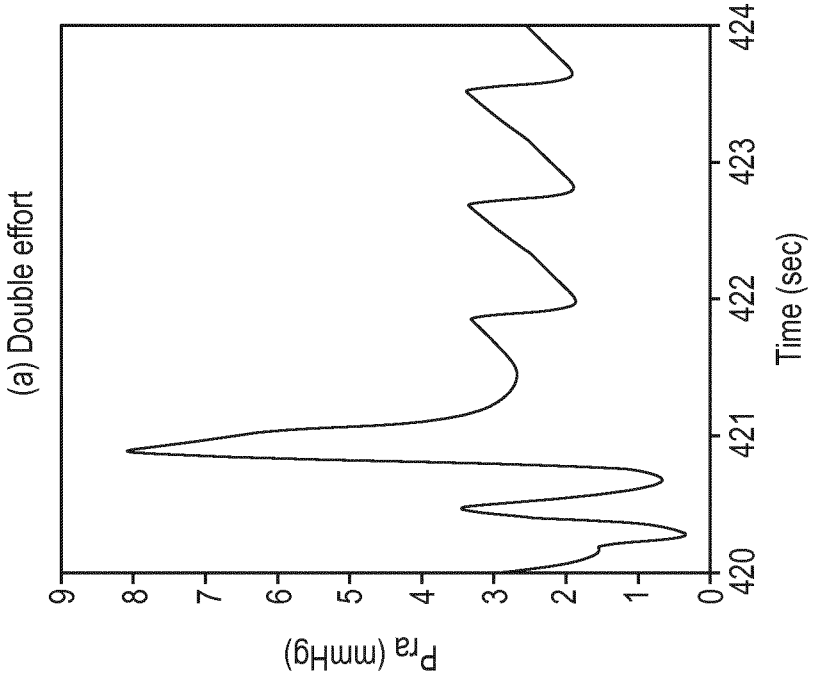

FIG. 11A

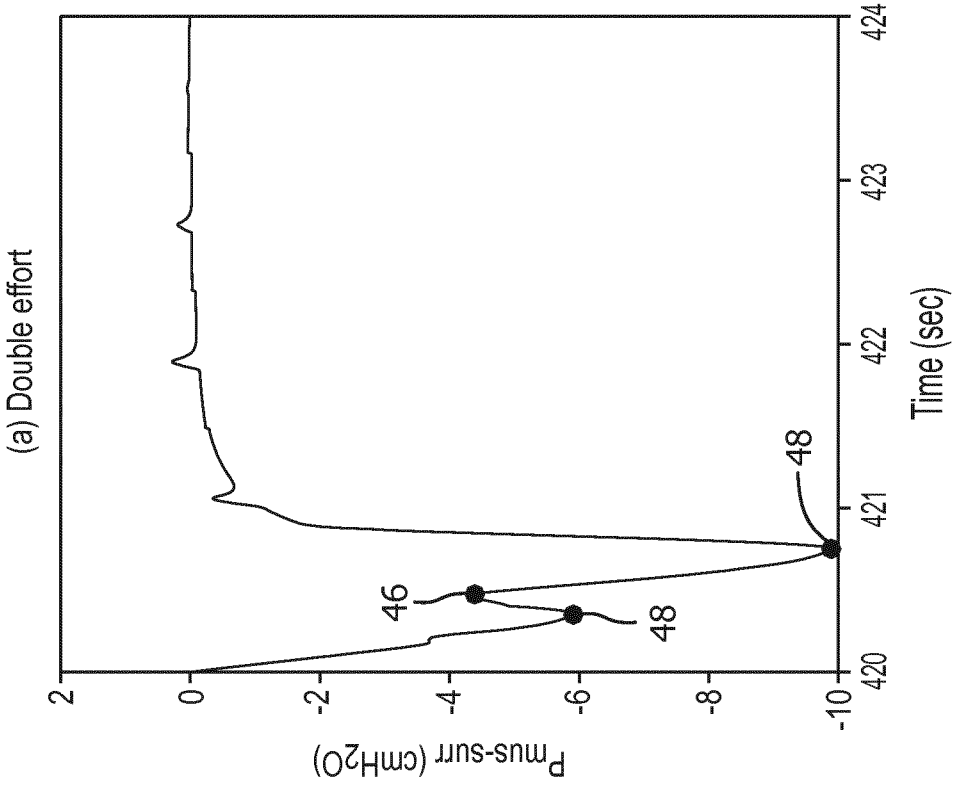

FIG. 12A

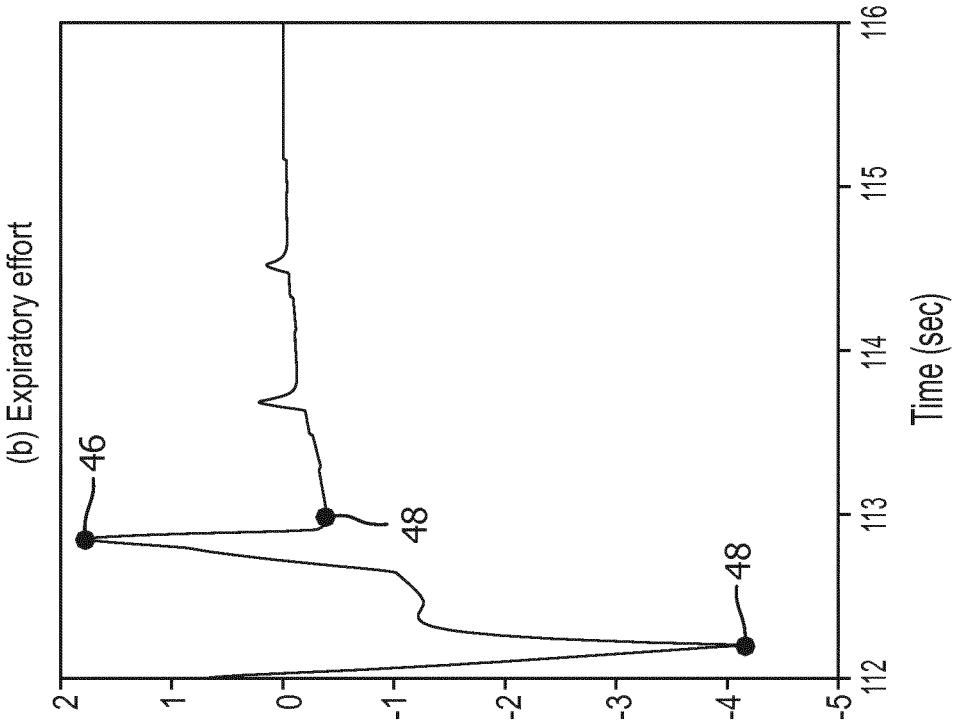

FIG. 12B

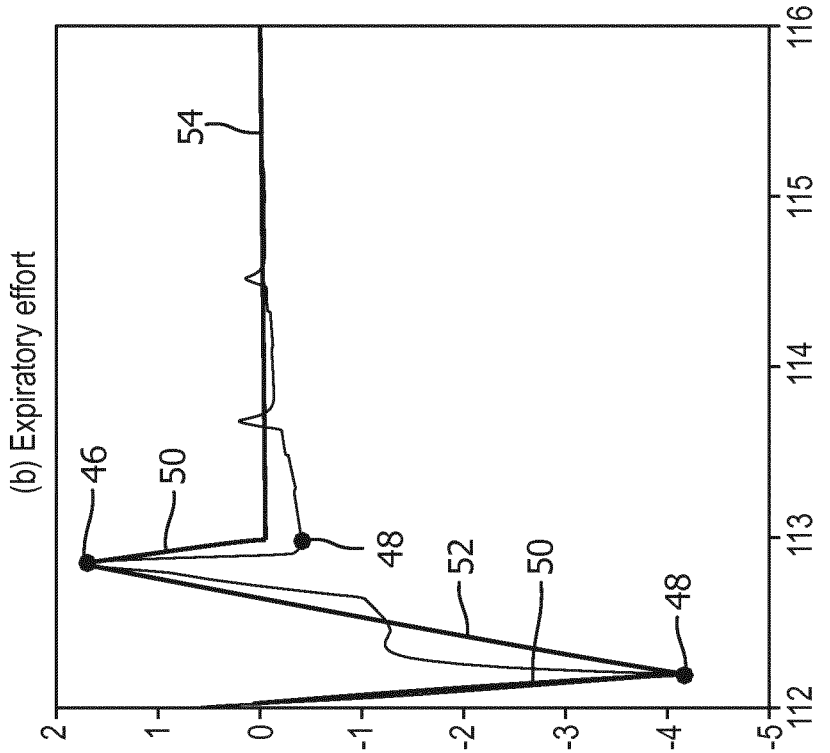

FIG. 13B

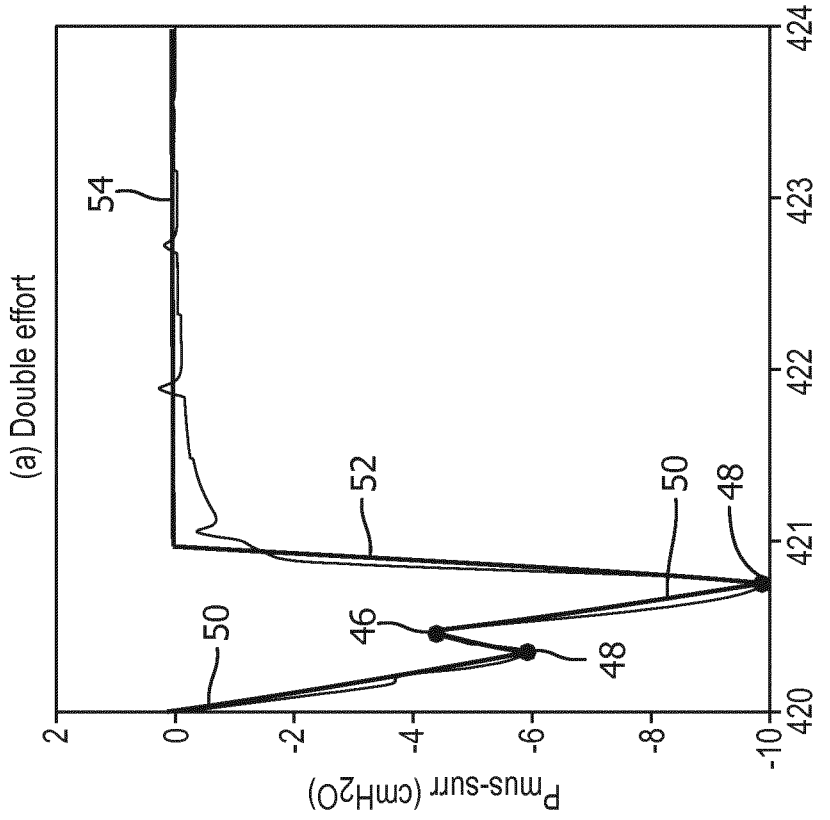

FIG. 13A

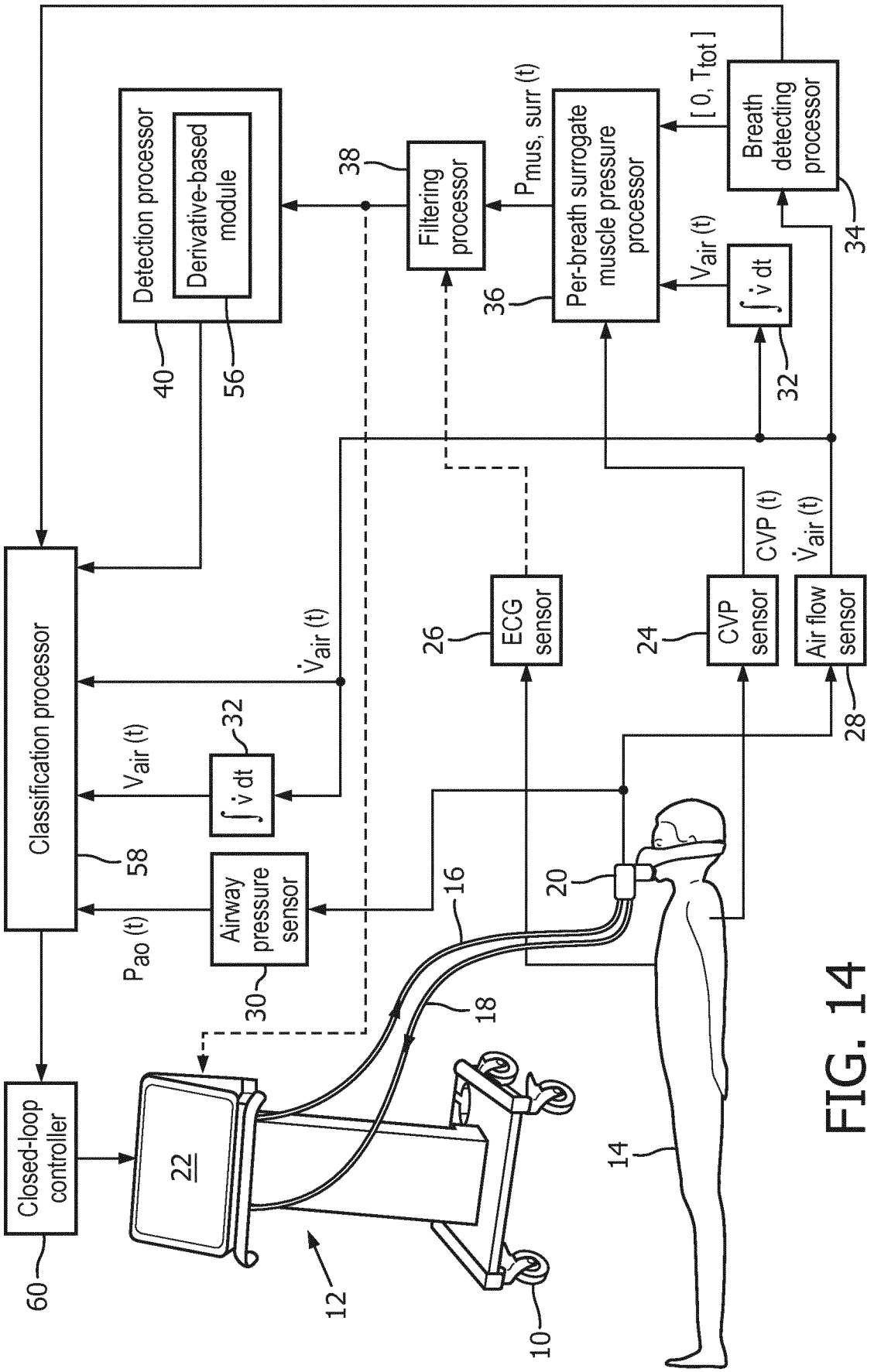
Detection processor
Derivative-based module
40
56
38
Filtering processor
$P_{mus, surr}$ (t)
Per-breath surrogate muscle pressure processor
36
[0, T_{tot}]
Breath detecting processor
34
V_{air} (t)
$\int \dot{v}\, dt$
32
Classification processor
58
V_{air} (t)
$\int \dot{v}\, dt$
32
$\dot{V}_{air}$ (t)
26
ECG sensor
24
CVP sensor
CVP (t)
$\dot{V}_{air}$ (t)
Air flow sensor
28
P_{ao} (t)
Airway pressure sensor
30
16
20
18
Closed-loop controller
60
22
12
10
14

FIG. 14

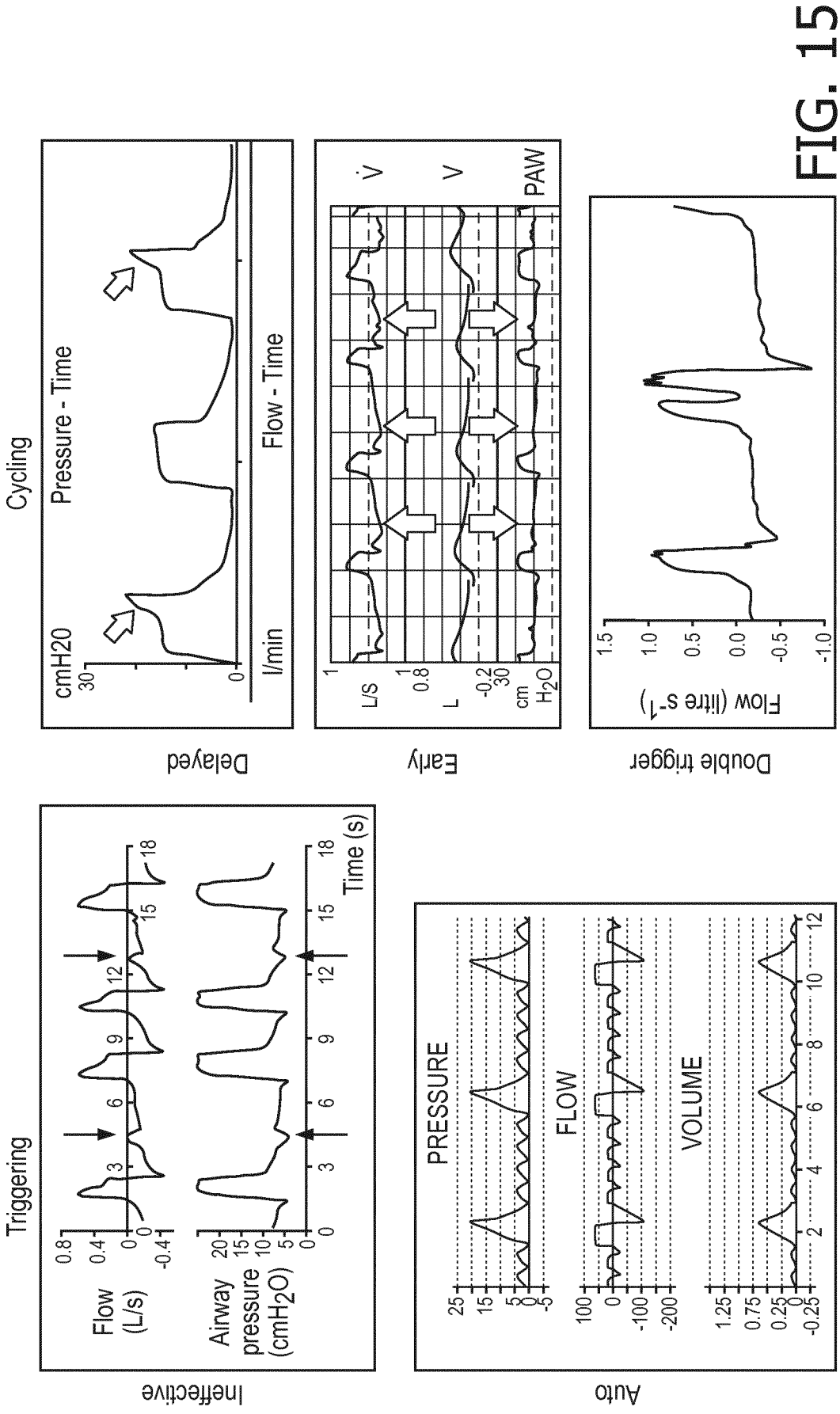
Triggering
Ineffective
Flow (L/s)
Airway pressure (cmH2O)
Time (s)
Auto
PRESSURE
FLOW
VOLUME
Cycling
Delayed
cmH20
Pressure - Time
l/min
Flow - Time
Early
L/S
L
cm H2O
PAW
Double trigger
Flow (litre s-1)

FIG. 15

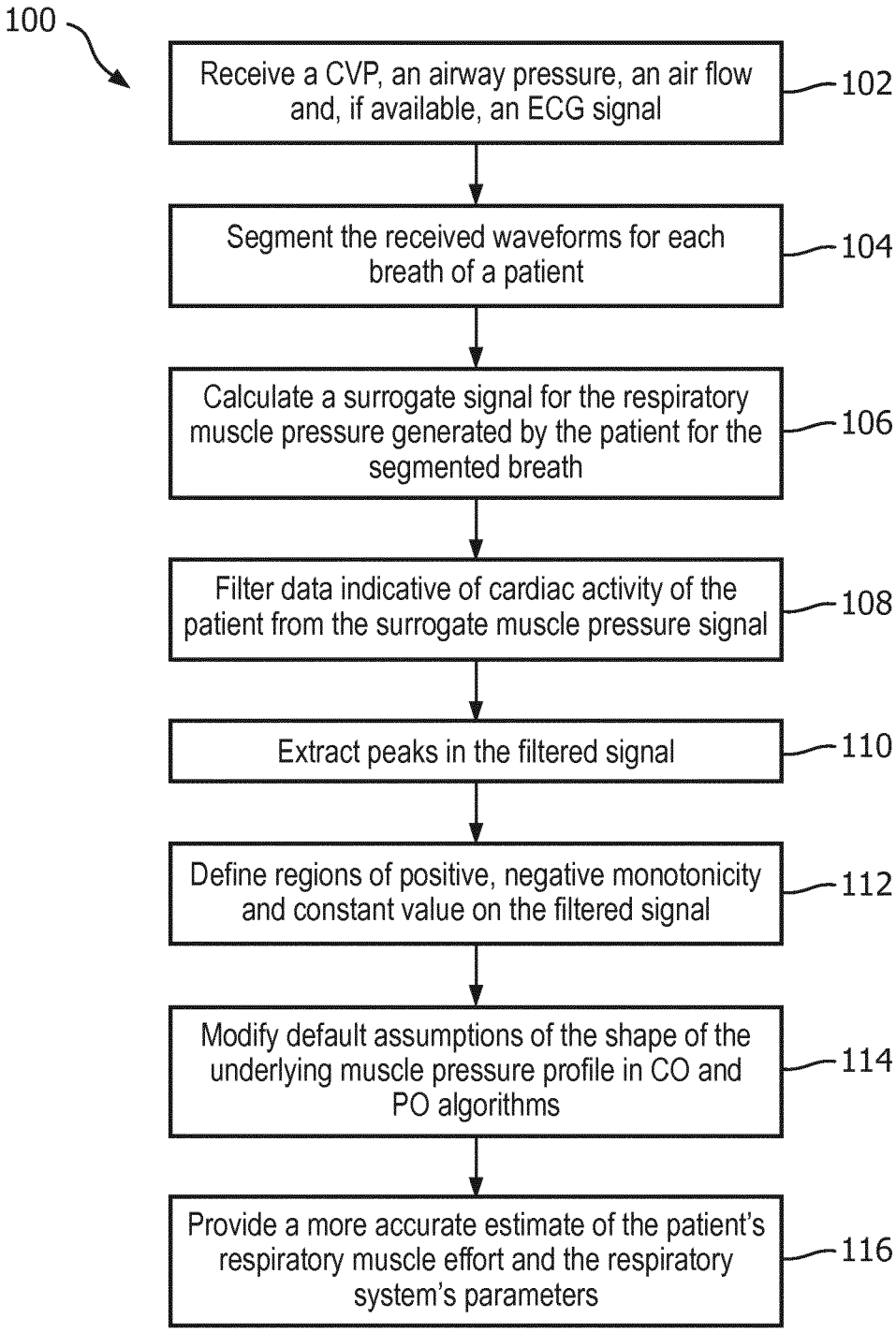
100
Receive a CVP, an airway pressure, an air flow and, if available, an ECG signal
102
Segment the received waveforms for each breath of a patient
104
Calculate a surrogate signal for the respiratory muscle pressure generated by the patient for the segmented breath
106
Filter data indicative of cardiac activity of the patient from the surrogate muscle pressure signal
108
Extract peaks in the filtered signal
110
Define regions of positive, negative monotonicity and constant value on the filtered signal
112
Modify default assumptions of the shape of the underlying muscle pressure profile in CO and PO algorithms
114
Provide a more accurate estimate of the patient's respiratory muscle effort and the respiratory system's parameters
116

FIG. 16

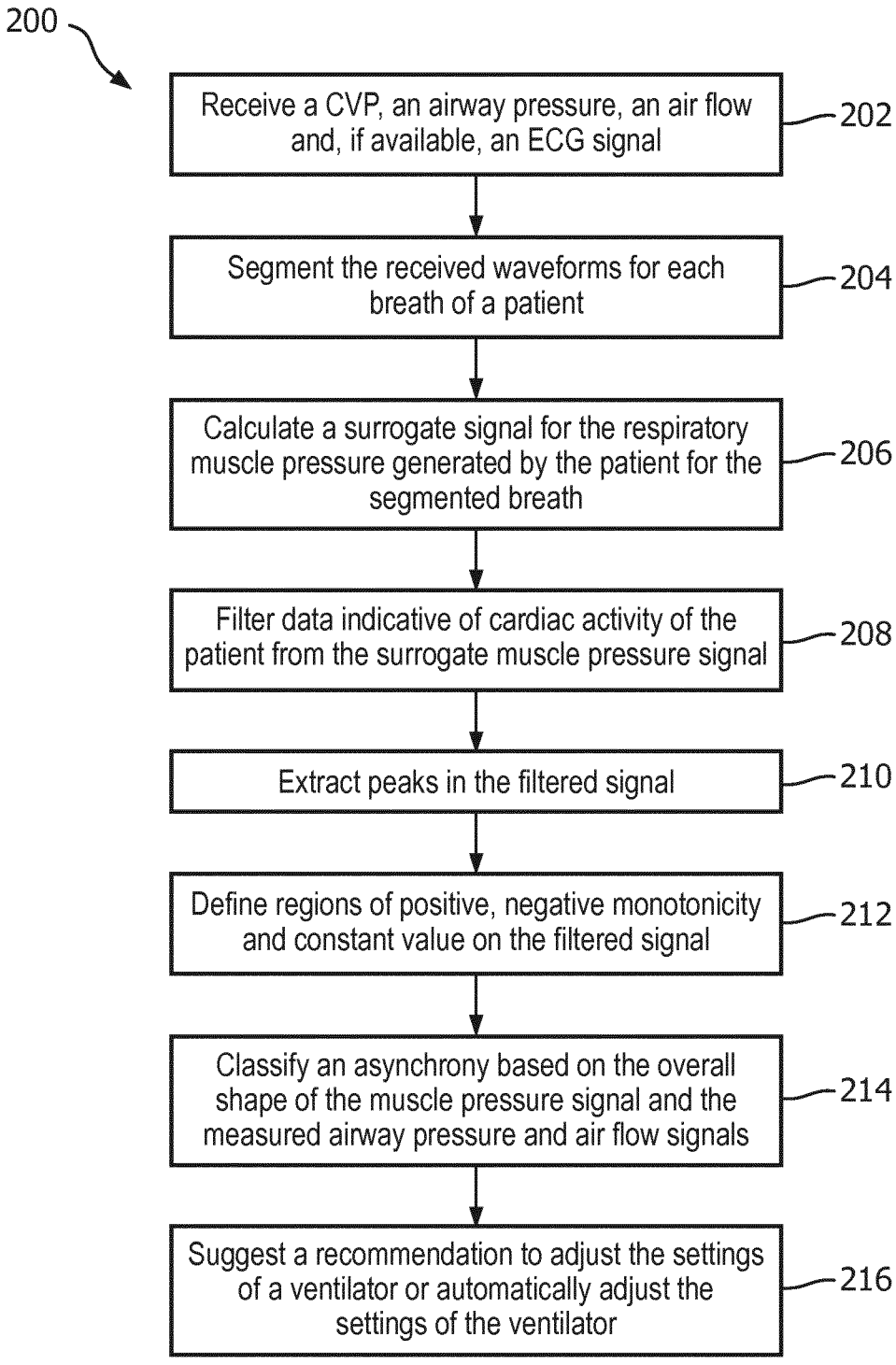
200
Receive a CVP, an airway pressure, an air flow and, if available, an ECG signal
202
Segment the received waveforms for each breath of a patient
204
Calculate a surrogate signal for the respiratory muscle pressure generated by the patient for the segmented breath
206
Filter data indicative of cardiac activity of the patient from the surrogate muscle pressure signal
208
Extract peaks in the filtered signal
210
Define regions of positive, negative monotonicity and constant value on the filtered signal
212
Classify an asynchrony based on the overall shape of the muscle pressure signal and the measured airway pressure and air flow signals
214
Suggest a recommendation to adjust the settings of a ventilator or automatically adjust the settings of the ventilator
216

FIG. 17

INTERNATIONAL SEARCH REPORT

International application No
PCT/EP2017/052140

A. CLASSIFICATION OF SUBJECT MATTER
INV. A61B5/0205 A61B5/0215 A61B5/087 A61B5/00
ADD. A61B5/0402 A61M16/00

According to International Patent Classification (IPC) or to both national classification and IPC

B. FIELDS SEARCHED

Minimum documentation searched (classification system followed by classification symbols)
A61B A61M

Documentation searched other than minimum documentation to the extent that such documents are included in the fields searched

Electronic data base consulted during the international search (name of data base and, where practicable, search terms used)
EPO-Internal, WPI Data

C. DOCUMENTS CONSIDERED TO BE RELEVANT

Category*	Citation of document, with indication, where appropriate, of the relevant passages	Relevant to claim No.
Y	US 2014/116442 A1 (MARTIN DION CHARLES CHEWE [AU] ET AL) 1 May 2014 (2014-05-01)	1-5, 7-13, 15-19,21
A	paragraph [0008] paragraph [0010] paragraph [0022] - paragraph [0023] paragraph [0027] - paragraph [0029] paragraph [0030] paragraph [0036] paragraph [0053] paragraph [0054] paragraph [0074] paragraph [0083] paragraph [0088] paragraph [0164] paragraph [0169] figures 3, 3A	6,14,20

-/--

[X] Further documents are listed in the continuation of Box C.

[X] See patent family annex.

* Special categories of cited documents :

"A" document defining the general state of the art which is not considered to be of particular relevance

"E" earlier application or patent but published on or after the international filing date

"L" document which may throw doubts on priority claim(s) or which is cited to establish the publication date of another citation or other special reason (as specified)

"O" document referring to an oral disclosure, use, exhibition or other means

"P" document published prior to the international filing date but later than the priority date claimed

"T" later document published after the international filing date or priority date and not in conflict with the application but cited to understand the principle or theory underlying the invention

"X" document of particular relevance; the claimed invention cannot be considered novel or cannot be considered to involve an inventive step when the document is taken alone

"Y" document of particular relevance; the claimed invention cannot be considered to involve an inventive step when the document is combined with one or more other such documents, such combination being obvious to a person skilled in the art

"&" document member of the same patent family

Date of the actual completion of the international search	Date of mailing of the international search report
20 April 2017	28/04/2017

Name and mailing address of the ISA/	Authorized officer
European Patent Office, P.B. 5818 Patentlaan 2 NL - 2280 HV Rijswijk Tel. (+31-70) 340-2040, Fax: (+31-70) 340-3016	Weiss-Schaber, C

1

Form PCT/ISA/210 (second sheet) (April 2005)

C(Continuation). DOCUMENTS CONSIDERED TO BE RELEVANT

Category*	Citation of document, with indication, where appropriate, of the relevant passages	Relevant to claim No.
Y	Francesco Vicario ET AL: "Simultaneous Parameter and Input Estimation of a Respiratory Mechanics Model", 6th International Conference on High Performance Scientific Computing, 19 March 2015 (2015-03-19), pages 1-10, XP055354424, DOI: 10.7916/D88K78T3 Retrieved from the Internet: URL:https://academiccommons.columbia.edu/download/fedora_content/download/ac:192809/CONTENT/HPSC2015_EstimationRespMechModel.pdf [retrieved on 2017-03-14]	1-5, 7-13, 15-19,21
A	2.1 Mathematical Model of Respiratory Mechanics 3.1 Constrained Optimization (CO) -----	6,14,20

INTERNATIONAL SEARCH REPORT

Information on patent family members

International application No
PCT/EP2017/052140

Patent document cited in search report	Publication date	Patent family member(s)	Publication date
US 2014116442 A1	01-05-2014	US 2010016694 A1	21-01-2010
		US 2014116442 A1	01-05-2014
		WO 2008058328 A1	22-05-2008

专利名称(译)	通过使用中心静脉压力测压法增强呼吸参数估计和异步检测算法		
公开(公告)号	EP3416543A1	公开(公告)日	2018-12-26
申请号	EP2017704182	申请日	2017-02-01
[标]申请(专利权)人(译)	皇家飞利浦电子股份有限公司		
申请(专利权)人(译)	皇家飞利浦N.V.		
当前申请(专利权)人(译)	皇家飞利浦N.V.		
[标]发明人	VICARIO FRANCESCO KARAMOLEGKOS NIKOLAOS ALBANESE ANTONIO CHBAT NICOLAS WADIH		
发明人	VICARIO, FRANCESCO KARAMOLEGKOS, NIKOLAOS ALBANESE, ANTONIO CHBAT, NICOLAS, WADIH		
IPC分类号	A61B5/0205 A61B5/0215 A61B5/087 A61B5/00 A61B5/0402 A61M16/00		
CPC分类号	A61B5/0205 A61B5/0402 A61B5/087 A61B5/4836 A61M16/024 A61M2016/0027 A61M2016/003 A61M2230/04 A61M2230/30 A61M2230/60 A61M2230/005		
代理机构(译)	德哈恩波尔ERIK		
优先权	62/296666 2016-02-18 US		
外部链接	Espacenet		

摘要(译)

呼吸监测设备（10）包括中心静脉压力传感器（24），其配置成测量患者的中心静脉压（CVP）信号。至少一个处理器（32,34,36,38,40,42,44,58）被编程为处理CVP信号以通过包括以下操作的患者产生呼吸信息：基于检测到的呼吸间隔分割CVP信号;从分段的CVP信号计算替代肌肉压力信号;并且过滤替代肌肉压力信号以去除代孕呼吸肌压力信号的心脏活动成分的心脏活动成分。