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(54) **NON-INVASIVE METHOD FOR MONITORING PATIENT RESPIRATORY STATUS VIA SUCCESSIVE PARAMETER ESTIMATION**

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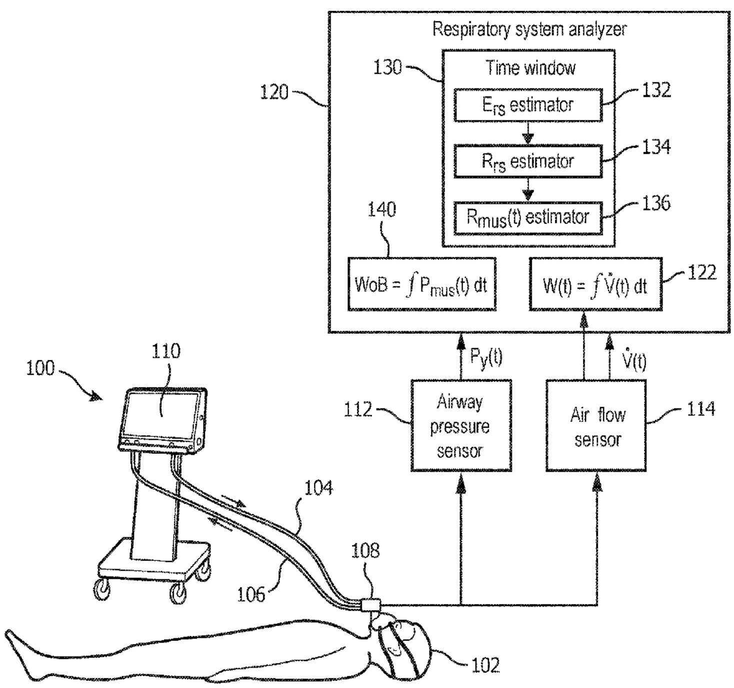
(57) **ABSTRACT**

A Moving Window Least Squares (MWLS) approach is applied to estimate respiratory system parameters from measured air flow and pressure. In each window, elastance E_{rs} (or resistance R_{rs}) is first estimated, and a Kalman filter may be applied to the estimate. This is input to a second estimator that estimates R (or E), to which a second Kalman filter may be applied. Finally, the estimated E_{rs} and R_{rs} are used to calculate muscle pressure $P_{mus}(t)$ in the time window. A system comprises a ventilator (**100**), an airway pressure sensor (**112**), and an air flow sensor (**114**), and a respiratory system analyzer (**120**) that performs the MWLS estimation. Estimated results may be displayed on a display (**110**) of the ventilator or of a patient monitor. The estimated $P_{mus}(t)$ may be used to reduce patient-ventilator dyssynchrony, or integrated to generate a Work of Breathing (WOB) signal for controlling ventilation.



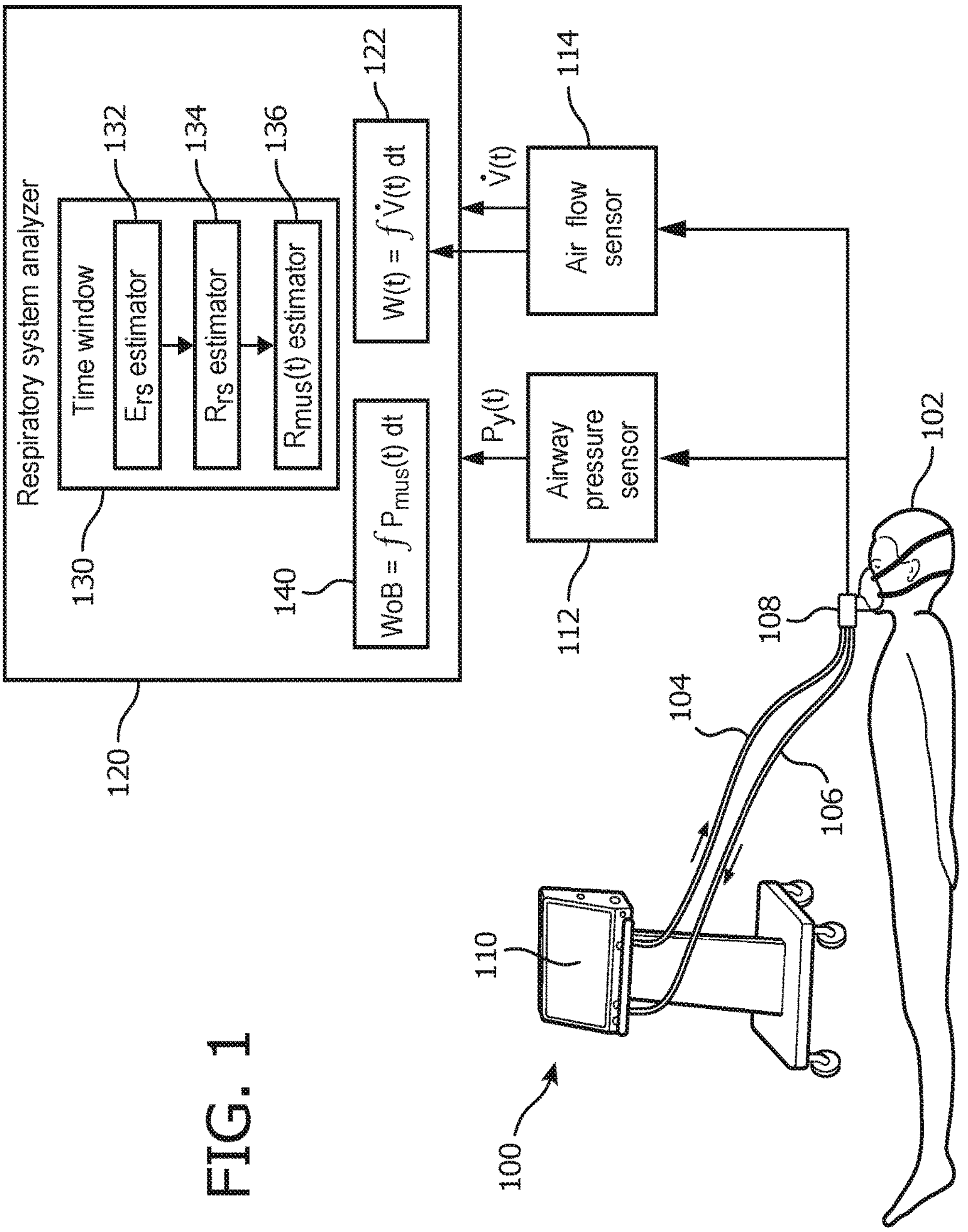
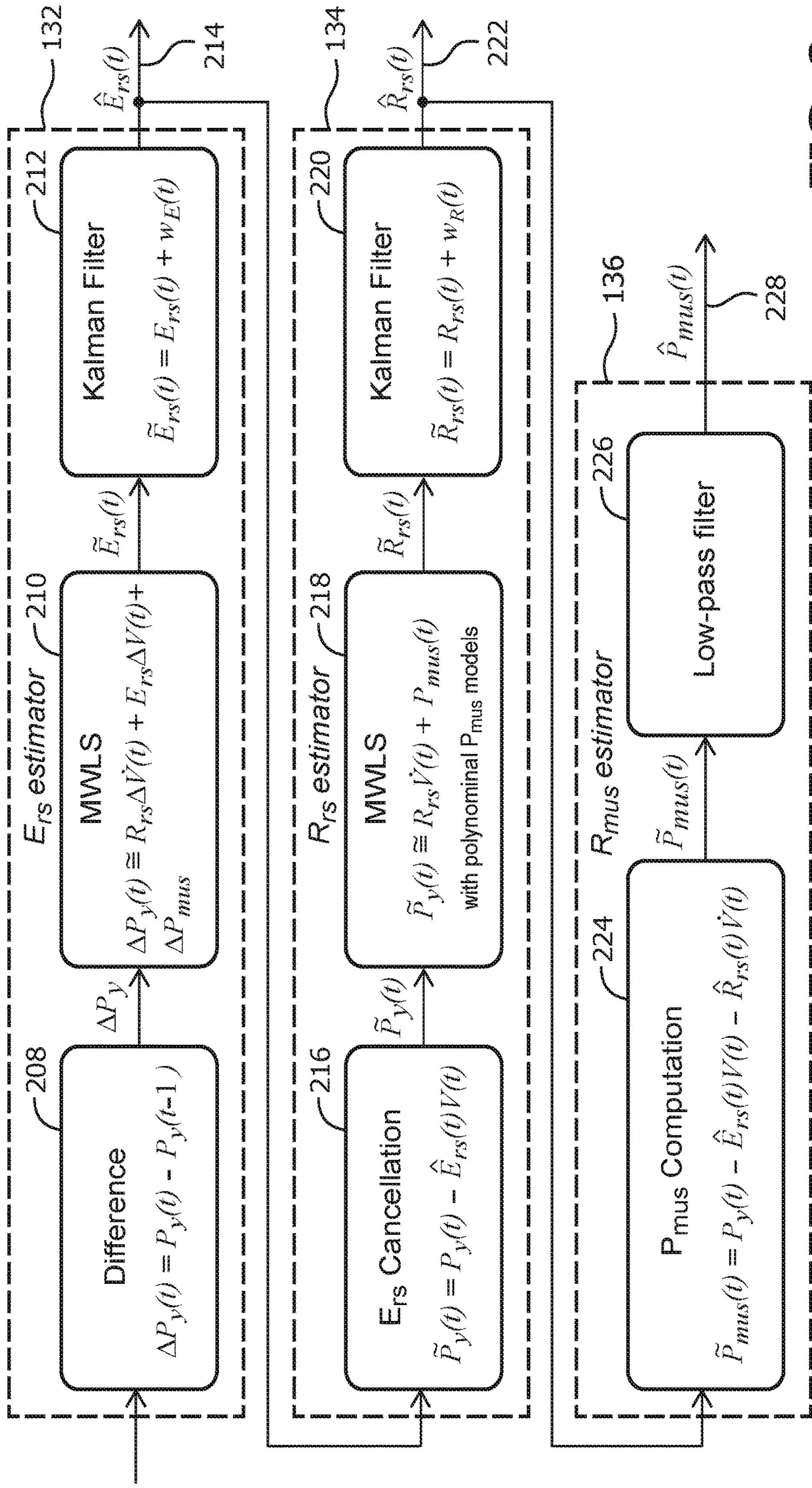
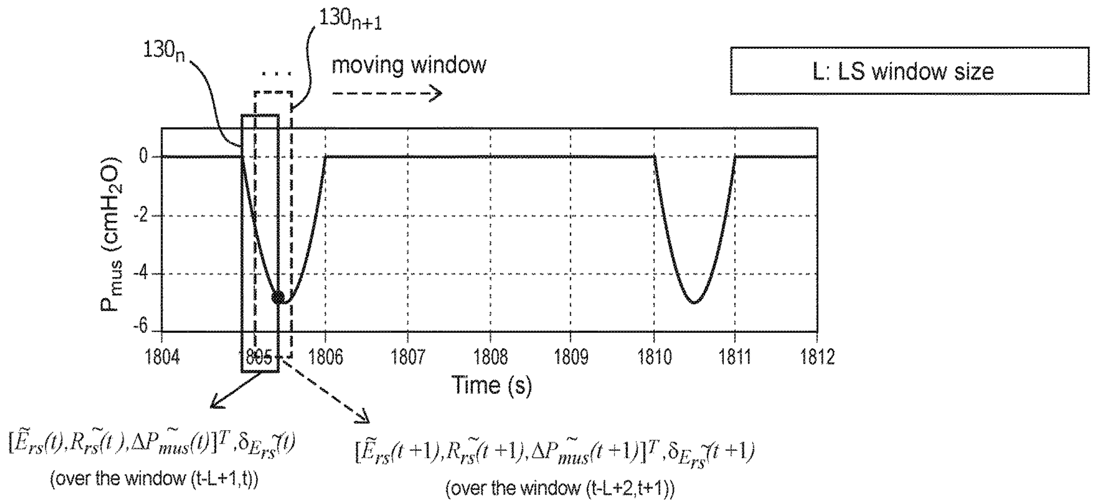

Respiratory system analyzer
Time window
E_{rs} estimator
R_{rs} estimator
$R_{mus}(t)$ estimator
$W(t) = \int \dot{V}(t)\,dt$
$WoB = \int P_{mus}(t)\,dt$
$\dot{V}(t)$
$P_y(t)$
Air flow sensor
Airway pressure sensor
100
102
104
106
108
110
112
114
120
122
130
132
134
136
140

FIG. 1



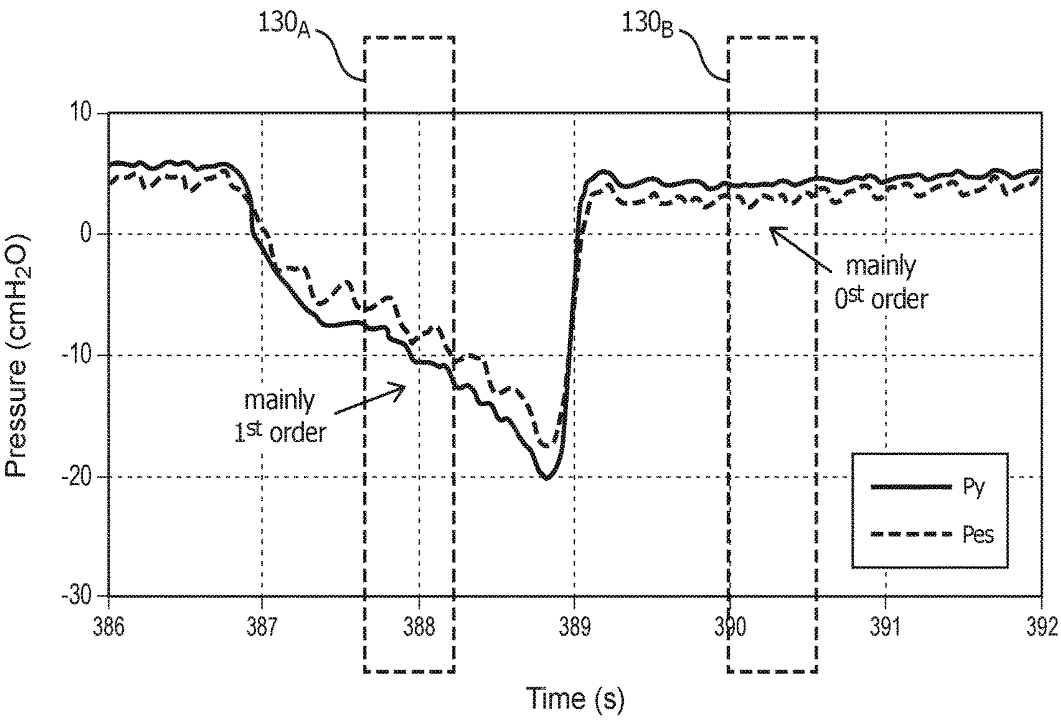
MWLS: Moving Window Least Square, $E_{rs}(t) = 1/C_{rs}(t)$

FIG. 2



130_{n+1}
130_n
moving window
L: LS window size
P_{mus} (cmH$_2$O)
0
-2
-4
-6
1804
1805
1806
1807
1808
1809
1810
1811
1812
Time (s)
$[\tilde{E}_{rs}(t), \tilde{R_{rs}}(t), \Delta \tilde{P_{mus}}(t)]^T, \delta_{E_{rs}}(t)$
(over the window (t-L+1,t))
$[\tilde{E}_{rs}(t+1), \tilde{R_{rs}}(t+1), \Delta \tilde{P_{mus}}(t+1)]^T, \delta_{E_{rs}}(t+1)$
(over the window (t-L+2,t+1))

FIG. 3



130A
130B
10
0
-10
-20
-30
Pressure (cmH2O)
386
387
388
389
390
391
392
Time (s)
mainly
0st order
mainly
1st order
Py
Pes

FIG. 4

$$\tilde{R}_{rs} = \tilde{R}_{rs,0} * w_0 + \tilde{R}_{rs,1} * w_1 + \tilde{R}_{rs,2} * w_2$$

$$w_0 = \frac{\frac{1}{\delta\tilde{R}_{rs},0}}{\frac{1}{\delta\tilde{R}_{rs},0} + \frac{1}{\delta\tilde{R}_{rs},1} + \frac{1}{\delta\tilde{R}_{rs},2}}$$

$$w_1 = \frac{\frac{1}{\delta\tilde{R}_{rs},1}}{\frac{1}{\delta\tilde{R}_{rs},0} + \frac{1}{\delta\tilde{R}_{rs},1} + \frac{1}{\delta\tilde{R}_{rs},2}}$$

$$w_2 = \frac{\frac{1}{\delta\tilde{R}_{rs},2}}{\frac{1}{\delta\tilde{R}_{rs},0} + \frac{1}{\delta\tilde{R}_{rs},1} + \frac{1}{\delta\tilde{R}_{rs},2}}$$

$$\delta\tilde{R}_{rs} = \frac{1}{\frac{1}{\delta\tilde{R}_{rs},0} + \frac{1}{\delta\tilde{R}_{rs},1} + \frac{1}{\delta\tilde{R}_{rs},2}}$$

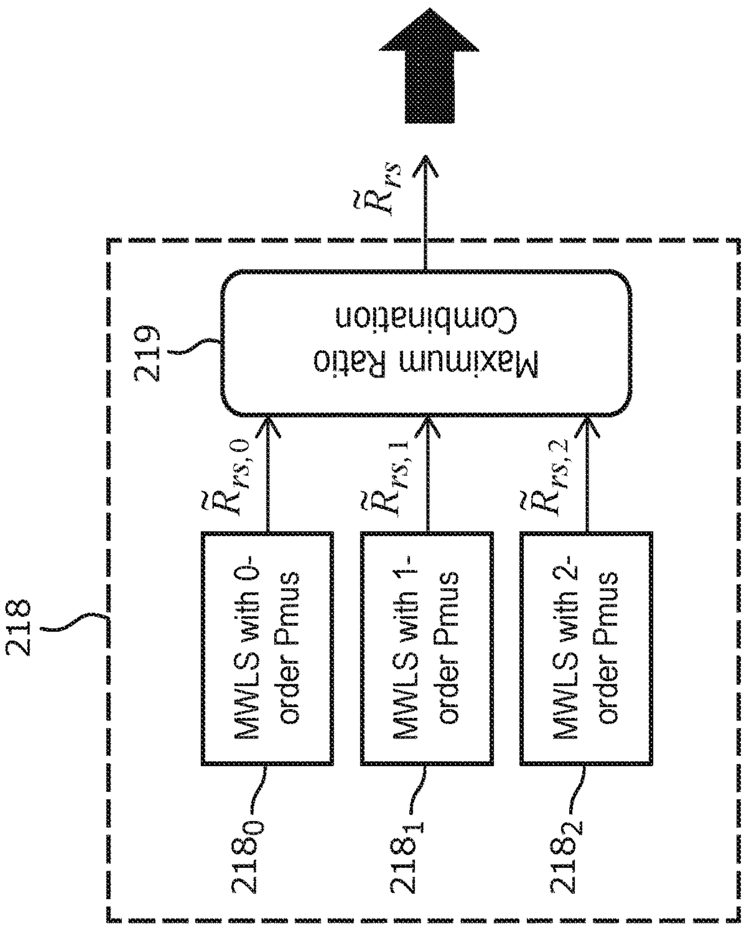


FIG. 5

NON-INVASIVE METHOD FOR MONITORING PATIENT RESPIRATORY STATUS VIA SUCCESSIVE PARAMETER ESTIMATION

FIELD

[0001] The following relates generally to systems and methods for monitoring and characterizing respiratory parameters during patient ventilation. It finds particular application in a system to provide real-time diagnostic information to a clinician to personalize a patient's ventilation strategy and improve patient outcomes and will be described with particular reference thereto. However, it is to be understood that it also finds application in other usage scenarios and is not necessarily limited to the aforementioned application.

BACKGROUND

[0002] Real-time assessment of the respiratory system's parameters (resistance R_{rs} and compliance C_{rs}) and patient's inspiratory effort (respiratory muscle pressure $P_{mus}(t)$) provides invaluable diagnostic information for clinicians to optimize ventilation therapy.

[0003] A good $P_{mus}(t)$ estimation can be used to quantify patient's inspiratory effort and select the appropriate level of ventilation support in order to avoid respiratory muscle atrophy and fatigue. Moreover, the estimated $P_{mus}(t)$ waveform can also be used for triggering and cycling off the ventilator so as to reduce patient-ventilator dyssynchrony. Estimates of R_{rs} and C_{rs} are also important, as they provide quantitative information to clinicians about the mechanical properties of the patient's respiratory system and they can be used to diagnose respiratory diseases and better select the appropriate ventilator settings.

[0004] $P_{mus}(t)$ is traditionally estimated via esophageal pressure measurement. This technique is invasive, in the sense that a balloon needs to be inserted inside the patient's esophagus, and moreover, not reliable when applied during long periods in intensive care conditions.

[0005] Another option to estimate $P_{mus}(t)$ is to calculate it based on the Equation of Motion of the Lungs. Assuming R_{rs} and C_{rs} are known, it is indeed possible to estimate $P_{mus}(t)$ via the following equation, known as the Equation of Motion of the lungs:

$$P_y(t) = R_{rs}\dot{V}(t) + \left(\frac{1}{C_{rs}}\right)V(t) + P_{mus}(t) + P_0 \tag{1}$$

where $P_y(t)$ is the pressure measured at the Y-piece of the ventilator, $\dot{V}(t)$ is the flow of air into and out of the patient's respiratory system (measured again at the Y-piece), $V(t)$ is the net volume of air delivered by the ventilator to the patient (measured by integrating the flow signal $\dot{V}(t)$ over time), P_0 is a constant term to account for the pressure at the end of expiration (needed to balance the equation but not interesting per se) and will be considered as part of $P_{mus}(t)$ in the following discussion. However, R_{rs} and C_{rs} have to be measured or estimated first.

[0006] R_{rs} and C_{rs} may be estimated by applying the flow-interrupter technique (also called End Inspiratory Pause, EIP), which however interferes with the normal operation of the ventilator, or under specific conditions where the term $P_{mus}(t)$ can be "reasonably" assumed to be zero (i.e. totally unload patient's respiratory muscles). These conditions include: periodic paralysis in which the patient is under Continuous Mandatory Ventilation (CMV); periodic high pressure support (PSV) level; specific portions of each PSV breath that extend both during the inhalation and the exhalation phases; and exhalation portions of PSV breaths where the flow signal satisfies specific conditions that are indicative of the absence of patient's inspiratory effort.

[0007] R_{rs} and C_{rs} estimation using the EIP maneuver has certain drawbacks and relies on certain assumptions. The EIP maneuver interrupts the normal ventilation needed by the patient. It also assumes that patient respiratory muscles are fully relaxed during the EIP maneuver in order for the R_{rs} and C_{rs} computation to be valid. Further, the R_{rs} and C_{rs} estimates obtained via the EIP maneuver, which affect the estimate of $P_{mus}(t)$ on the following breath, are assumed to be constant until the next EIP maneuver is executed, so that continuous and real-time estimates of R_{rs} and C_{rs} are not obtained. In practice, changes in patient's conditions can occur in between two consecutive EIP maneuvers, and this would jeopardize the estimate of $P_{mus}(t)$. A further disadvantage is that the static maneuver (EIP) is performed in a specific ventilation mode (Volume Assisted Control, VAC) and the obtained values for R and C might not be representative of the true values that govern the dynamics of the lungs in other ventilation modes, such as Pressure Support Ventilation (PSV). Therefore, the accuracy of $P_{mus}(t)$ computed via equation (1) during PSV operation can be compromised.

[0008] The above mentioned estimation methods operate on the assumption that $P_{mus}(t)$ is negligible. Implementation of this assumption can be problematic in clinical settings. For example, imposing periodic paralysis and CMV on a patient is generally not clinically feasible. Similarly, imposing periodic high PSV interferes with the normal operation of the ventilator and may not be beneficial to the patient. The assumption of negligible $P_{mus}(t)$ during PSV breaths is debatable, especially during the inhalation phase. Approaches which operate on a chosen portion of the respiration cycle also limit the fraction of data points that are used in the fitting procedure, which makes the estimation results more sensitive to noise.

[0009] In the following, non-invasive methods are disclosed for monitoring patient respiratory status via successive parameter estimation, which overcome various foregoing deficiencies and others.

SUMMARY

[0010] In accordance with one aspect, a medical ventilator device is described. The device includes a ventilator configured to deliver ventilation to a ventilated patient, a pressure sensor configured to measure the airway pressure $P_y(t)$ at a Y-piece of the ventilator and an air flow sensor configured to measure the air flow $\dot{V}(t)$ into and out of the ventilated patient at the Y-piece of the ventilator. The device also comprises a respiratory system monitor comprising a microprocessor configured to estimate respiratory parameters of the ventilated patient using moving window least squares (MWLS) estimation including (i) respiratory system elastance or compliance (E_{rs} or C_{rs}), (ii) respiratory system resistance (R_{rs}), and (iii) respiratory muscle pressure ($P_{mus}(t)$).

[0011] In accordance with another aspect, a method comprises: ventilating a patient using a ventilator; during the ventilating, measuring airway pressure $P_y(t)$ and air flow $\dot{V}(t)$ of air into and out of the patient; using a microprocessor, applying moving window least squares (MWLS) estimation to estimate (i) the patient's respiratory system elastance or compliance E_{rs} or C_{rs}, (ii) the patient's respiratory system resistance R_{rs}, and (iii) the patient's respiratory muscle pressure $P_{mus}(t)$; and displaying on a display one or more of the respiratory parameters of the patient estimated by applying MWLS estimation.

[0012] One advantage resides in providing a non-invasive method for monitoring patient respiratory status via successive parameter estimation including resistance, compliance, and respiratory muscle pressure.

[0013] Another advantage resides in providing a ventilator with improved data analysis.

[0014] Still 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 is to be appreciated that none, one, two, or more of these advantages may be achieved by a particular embodiment.

BRIEF DESCRIPTION OF THE DRAWINGS

[0015] The disclosure may take form in various components and arrangements of components, and in various steps and arrangement of steps. The drawings are only for purposes of illustrating the preferred embodiments and are not to be construed as limiting the invention.

[0016] FIG. **1** illustrates a ventilation system for use on a patient with the proposed ventilation estimation scheme.

[0017] FIG. **2** illustrates a block diagram of the described estimation scheme.

[0018] FIG. **3** illustrates a moving window least squares algorithm for the E_{rs} estimation.

[0019] FIG. **4** illustrates a moving window least squares algorithm example of the polynomial order of the local $P_{mus}(t)$ waveform.

[0020] FIG. **5** illustrates the maximum ratio combination for the MWLS R_{rs} estimation results.

DETAILED DESCRIPTION

[0021] The following relates to characterization of respiratory parameters during patient ventilation and in particular to the respiratory muscle pressure $P_{mus}(t)$, respiratory resistance R_{rs}, and respiratory compliance C_{rs} or elastance $E_{rs}=1/C_{rs}$. In principle, these parameters can be estimated using the Equation of Motion of the Lungs (Equation (1)), which relates these parameters to the pressure $P_y(t)$ at the ventilator mouthpiece and the air flow $\dot{V}(t)$, along with the air volume in the lungs $V(t)=\int\dot{V}(t)dt$. In practice, because the respiratory muscle pressure $P_{mus}(t)$ varies over time, estimating $P_{mus}(t)$, R_{rs}, and E_{rs} jointly using the Equation of Motion of the Lungs is generally underdetermined and cannot be analytically solved. Various approaches to dealing with this include measuring additional information using invasive probes, or creating "special case" circumstances by operations such as interrupting normal breathing. Invasive probes have apparent disadvantages, while techniques that rely upon manipulating normal patient breathing cannot provide continuous monitoring of normal respiration and may be detrimental to the patient.

[0022] With reference to FIG. **1**, a medical ventilator system includes a medical ventilator **100** that delivers air flow at a positive pressure to a patient **102** via an inlet air hose **104**. Exhaled air returns to the ventilator **100** via an exhalation air hose **106**. A Y-piece **108** of the ventilator system serves to couple air from the discharge end of the inlet air hose **104** to the patient during inhalation and serves to couple exhaled air from the patient into the exhalation air hose **106** during exhalation. Note the Y-piece **108** is sometimes referred to by other nomenclatures, such as a T-piece. Not shown in FIG. **1** are numerous other ancillary components that may be provided depending upon the respiratory therapy being received by the patient **102**. 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 the Fraction of Inspired Oxygen (FiO_2) ventilator parameter set by the physician or other medical personnel); a humidifier plumbed into the inlet line **104**; a nasogastric tube to provide the patient **102** with nourishment; and so forth. The ventilator **100** includes a user interface including, in the illustrative example, a touch-sensitive display component **110** via which the physician, respiratory specialist, or other medical personnel can configure ventilator operation and monitor measured physiological parameters and operating parameters of the ventilator **100**. 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. It is also noted that the illustrative ventilator **100** is merely an illustrative example.

[0023] The illustrative ventilator **100** is a dual-limb ventilator with proximate sensors. However, the disclosed patient respiratory status monitoring techniques may be employed in conjunction with substantially any type of ventilator, such as with a single-limb or dual-limb ventilator, a ventilator having valves or blower, a ventilator with an invasive coupling to the patient (e.g. via a tracheostomy or endotracheal tube) or a ventilator with a noninvasive coupling to the patient (e.g. using a facial mask), a ventilator with proximal sensors for measuring pressure and flow as illustrated or a ventilator without such proximal sensors that relies upon sensors in the ventilator unit, or so forth.

[0024] With continuing reference to FIG. **1**, the patient **102** is monitored by various physiological parameter sensors. In particular, FIG. **1** illustrates two such sensors: an airway pressure sensor **112** that measures pressure P_y (t) at the coupling to the patient (usually measured at the Y-piece **108**, hence P_y (t)) and an air flow sensor **114** that measures air flow $\dot{V}(t)$ to or from the patient (also usually measured at the Y-piece **108**). The sensors **112**, **114** may be integrated into the Y-piece **108**, interposed on the air lines **104**, **106**, or integrated into the ventilator **100**. During mechanical ventilation, other physiological parameters may be monitored by suitable sensors, such as heart rate, respiratory rate, blood pressure, blood oxygenation (e.g. SpO_2), respiratory gases composition (e.g. a capnograph measuring CO_2 in respiratory gases), and so forth. Other physiological parameters may be derived from directly measured physiological parameters.

[0025] The system further includes a respiratory system analyzer **120** comprising a microprocessor, microcontroller, or other electronic data processing device programmed to process input data including the airway pressure P_y (t) and air flow $\dot{V}(t)$ to generate information about the patient respiratory system parameters: resistance R_{rs}, compliance C_{rs} (or, equivalently, elastance $E_{rs}=1/C_{rs}$), and the patient's inspiratory effort characterized as a function of time by the respiratory muscle pressure $P_{mus}(t)$. These parameters are determined as a function of time, in real-time, by evaluating the Equation of Motion of the Lungs (Equation (1)) using moving window least squares estimation (MWLS) applied to the airway pressure P_y (t) and air flow $\dot{V}(t)$ along with the air volume $V(t)=\int\dot{V}(t)dt$ determined from $\dot{V}(t)$ by an air flow integrator **122**. (Alternatively, a dedicated air volume sensor may be employed). To overcome the underdetermined nature of Equation (1), the MWLS estimation is performed using successive estimation of: (1) the elastance or compliance (E_{rs} or C_{rs}) parameter via an E_{rs} estimator **132**; followed by (2) estimation of the resistance (R_{rs}) parameter via an R_{rs} estimator **134**; followed by (3) estimation of the respiratory muscle pressure ($P_{mus}(t)$) parameter via a $P_{mus}(t)$ estimator **136**.

[0026] These successive estimators **132**, **134**, **136** are applied within the time window **130** which is generally of duration two seconds or less, and more preferably of duration one second or less, and in an illustrative example of duration 0.6 seconds with data sampling at 100 Hz so that the time window contains 60 samples. An upper limit on the duration of the time window is imposed by the respiration rate, which for a normal adult is typically 12 to 20 breaths per minute corresponding to a breathing cycle of duration 3-5 seconds. The duration of the time window **130** is preferably a fraction of the breathing cycle duration so that the parameters E_{rs} and R_{rs} can be reasonably assumed to be constant within each time window **130**, and variation of $P_{mus}(t)$ within each time window **130** can be represented using a relatively simple approximation function (e.g. a low-order polynomial in the illustrative examples disclosed herein).

[0027] The estimators **132**, **134**, **136** are successively applied within each time window **130**, and for each successive (and partially overlapping) time interval **130** (hence the term "moving" time window), to provide estimation of E_{rs}, R_{rs}, and $P_{mus}(t)$ in real time. In the illustrative examples, the values of E_{rs} and R_{rs} are assumed to be constant within each time window **130**, so that the estimation of these parameters is in real-time with a time resolution comparable to the duration of the time window **130**, e.g. two second or less in some embodiments, or more preferably one second or less, and 0.6 seconds in the illustrative examples. If successive time windows partially overlap, this can further improve the effective time resolution. The real-time estimation of $P_{mus}(t)$ can be of higher temporal resolution than E_{rs} and R_{rs}, since variation of $P_{mus}(t)$ with time within the time window **130** is, in the illustrative examples, modeled by a low-order polynomial function of time.

[0028] The approach disclosed herein leverages the recognition that, of the three parameters being estimated, the elastance/compliance (E_{rs} or C_{rs}) generally varies most slowly over time. In the Equation of Motion of the Lungs (Equation (1)), E_{rs} is the coefficient of the air volume V(t) which, as an integral, varies slowly over time. The next most slowly varying parameter is generally the resistance R_{rs}, which is the coefficient of the air flow $\dot{V}(t)$. Finally, the respiratory muscle pressure $P_{mus}(t)$ has the potential to vary most rapidly over time as it changes in response to the patient actively inhaling and exhaling. In view of this, the illustrative examples of the $P_{mus}(t)$ estimator **136** do not assume $P_{mus}(t)$ is a constant within the time window **130**, but instead employ a low-order approximation polynomial function. Instead of a low-order polynomial approximation of $P_{mus}(t)$ within the time window **130**, in other contemplated embodiments some other parameterized function of time is contemplated, such as a spline function.

[0029] With continuing reference to FIG. **1**, the outputs E_{rs} (or C_{rs}), R_{rs}, and $P_{mus}(t)$ can be used for various purposes. In one application, one or more of the estimated parameters may be displayed on the display component **110** of the ventilator **100**, for example as a numeric real-time value and/or as a trend line plotted as a function of time. Typically, the respiratory elastance or compliance (E_{rs} or C_{rs}) and the respiratory resistance (R_{rs}) are of most interest to the clinician and are suitably displayed and/or trended. The respiratory muscle pressure $P_{mus}(t)$ is a waveform acquired as a function of time in real-time during normal clinically operative mechanical ventilation accordingly, $P_{mus}(t)$ can be used by the ventilator **100** for triggering and cycling off the mechanical ventilation so as to reduce patient-ventilator dyssynchrony (that is, to synchronize application of positive pressure by the ventilator **100** with the inhalation portion of the patient's respiratory muscle action).

[0030] In some embodiments, a work of breathing (WoB) estimator **140** integrates the respiratory muscle pressure $P_{mus}(t)$ over volume, i.e. $WoB=\int P_{mus}(t)dV(t)$. The WoB is a metric of how much effort the patient **102** is applying to breathe on his or her own. The WoB may be displayed and/or trended on the display component **110** to provide the clinician with useful information for setting ventilator pressure settings in ventilation modes such as Pressure Support Ventilation (PSV). Moreover, since the WoB estimator **140** provides WoB in real-time (e.g. with a time lag and resolution on the order of a second or less in some embodiments) the ventilator **100** optionally employs the WoB as a feedback control parameter, e.g. adjusting controlled ventilator settings to maintain the WoB at a constant set-point value. For example, if the WoB increases, this implies the patient **102** is struggling to breathe and accordingly the positive pressure applied by the ventilator **100** in PSV mode should be increased to provide the struggling patient with increased respiration assistance.

[0031] With reference to FIG. **2**, some illustrative embodiments of the successive estimators **132**, **134**, **136** are described. successive estimation of the parameters E_{rs}, R_{rs}, and $P_{mus}(t)$ over a time window of a fraction of a second over which the parameters E_{rs} and R_{rs} are assumed to be constant is shown. In the first pass (performed by the E_{rs} estimator **132**), all three parameters E_{rs}, R_{rs}, and $\Delta P_{mus}(t)$ are assumed to be constant over the time window **130** and are computed simultaneously—but only the estimated $\hat{E}_{rs}$ is retained from this first pass. (In notation used herein, the overscript "hat", i.e. $\hat{p}$, is used to indicate the estimated value of parameter p.) In a second pass (performed by the R_{rs} estimator **134**), the contribution of the now known (estimated) $\hat{E}_{rs}$ is removed by subtraction, and the remaining portion of the Equation of Lung Motion is fitted for R_{rs} and $P_{mus}(t)$, the latter being approximated using a low order polynomial (n=0, 1, or 2). In experiments, it was found that the best choice of polynomial order is dependent upon the respiratory phase at which the time window **130** is located due to possible overfitting—as respiratory phase is not known a priori, in illustrative embodiments disclosed herein a weighted combination of polynomials of zeroeth, first, and second order is used. The output of the R_{rs} estimator **134** is the estimated value of the respiratory resistance, i.e. $\hat{R}_{rs}$. Finally, in a third pass (performed by the $P_{mus}(t)$ estimator **136**), the contribution of the now known (estimated) $\hat{R}_{rs}$ is removed by further subtraction, and the remaining portion of the Equation of Lung Motion is directly fitted to obtain the estimated respiratory muscle pressure, i.e. $\hat{P}_{mus}$ (t).

[0032] With continuing reference to FIG. **2**, the illustrative E_{rs} estimator **132** is further described. At **208** a difference operation is performed on the airway pressure $P_y(t)$ and the output $\Delta P_y(t)$ is calculated as $\Delta P_y(t)=P_y(t)-P_y(t-1)$. A Moving Window Least Squares (MWLS) estimator is used to at **210** to continuously estimate $E_{rs}(t)$—which is the respiratory system's elastance, $E_{rs}(t)=1/C_{rs}(t)$—and is based on the following difference equation:

$$\Delta P_y(t) \cong R_{rs}\Delta\dot{V}(t)+E_{rs}\Delta V(t)+\Delta P_{mus}$$

It should be noted that $E_{rs}(t)$ is estimated as a function of time insofar as the estimate $\hat{E}_{rs}$ is generated for each time window **130**, so that the time function $\hat{E}_{rs}(t)$ is generated as the value $\hat{E}_{rs}$ for successive time windows **130** as successive (partially overlapping) time windows are applied over time. However inside each time window **130**, $\Delta P_{mus}(t)$, the difference signal of the $P_{mus}(t)$ waveform, and the parameters $R_{rs}(t)$ and $E_{rs}(t)$ are modeled as constants and jointly estimated by a least squares minimization method. For the E_{rs} estimator **132**, only the estimate of $E_{rs}(t)$, namely $\hat{E}_{rs}$, is used (after filtering by a Kalman filter **212** in the illustrative example of FIG. **2**), while the other estimation outputs are discarded. Moreover, the E_{rs} estimator **132** also calculates the variance of the estimate $\hat{E}_{rs}$, denoted herein as $\delta_{\hat{E}_{rs}}$.

[0033] The input to the MWLS estimator **210** is the difference signal of $P_y(t)$, that is, $\Delta P_y(t)$, which is output by the difference operation **208**. Based on the equation of the motion (Equation (1)), $\Delta P_y(t)$ can be modeled as:

$$\Delta P_y(t) \cong R_{rs}(t)\Delta\dot{V}(t)+E_{rs}(t)\Delta V(t)+\Delta P_{mus}(t)$$

where $\Delta\dot{V}(t)=\dot{V}(t)-\dot{V}(t-1)$ is the flow difference signal, $\Delta V(t)=V(t)-V(t-1)=\dot{V}(t)T$ is the volume difference signal (where T is the sampling time interval, e.g. sampling at 100 Hz corresponds to T=0.01 sec), and $\Delta P_{mus}(t)=P_{mus}(t)-P_{mus}(t-1)$ is the $P_{mus}(t)$ difference signal.

[0034] In the following, the size (or duration) of the sliding time window **130** is denoted as L, which is optionally a system parameter that can be set by the user. The sliding window at a current time t spans the interval [t−L+1, t]. For the MWLS estimator **210**, the $P_{mus}(t)$ difference signal, $\Delta P_{mus}(t)$, in the sliding window is modeled as a constant, ΔP_{mus}. It is further assumed that R_{rs} and E_{rs} are constant in the sliding time window **130**. Therefore, the equation for $\Delta P_y(t)$ becomes:

$$\Delta P_y(t) \cong R_{rs}\Delta\dot{V}(t)+E_{rs}\Delta V(t)+\Delta P_{mus}$$

At time t, the MWLS algorithm **210** uses the input signals in the sliding window **130**, that is to say, the samples $\Delta P_y(n)$ and $\dot{V}(n)$ in the interval $t-L+1 \le n \le t$, to estimate R_{rs}, E_{rs}, and ΔP_{mus} jointly, but only the E_{rs} estimate $\hat{E}_{rs}$ is used in the subsequent operations (i.e. the subsequent estimators **134**, **136**).

[0035] As further shown in FIG. **3**, specifically, at time t, the MWLS formulation solves the least square problem **300** based on the equation described above:

[0036] At time t,

$$\Delta P_y(t) \cong R_{rs}\Delta\dot{V}(t)+E_{rs}\Delta V(t)+\Delta P_{mus}$$

$$[\tilde{E}_{rs},\tilde{R}_{rs},\Delta\tilde{P}_{mus}]^T=(X^TX)^{-1}X^TY$$

$$Y=[\Delta P_y(t),\Delta P_y(t-1),\ \ldots\ ,\Delta P_y(t-L+1)]^T$$

$$X=[x(t),x(t-1),\ \ldots\ ,x(t-L+1)]^T$$

$$x(t)=[\Delta V(t),\Delta\dot{V}(t),1]^T$$

$$\delta_{\tilde{E}_{rs}}=(X^TX)^{-1}(1,1)*\delta_{\Delta P_y}$$

Moreover, the variance of the E_{rs} estimate, $\delta_{\tilde{E}_{rs}}$, is also calculated, where $\delta_{\Delta P_y}$ is the least square residual variance,

$$\delta_{\Delta P_y}=(Y-X[\tilde{E}_{rs},\tilde{R}_{rs},\Delta\tilde{P}_{mus}]^T)^T(Y-X[\tilde{E}_{rs},\tilde{R}_{rs},\Delta\tilde{P}_{mus}]^T)/L$$

[0037] As indicated in FIG. **3**, the MWLS estimation **210** is performed continuously as the moving window moves forward, e.g. window $\mathbf{310}_n$ succeeded by next window $\mathbf{310}_{n+1}$, and so forth. Since the MWLS method is sensitive to the P_y measurement noise and the modelling error, only the estimate of E_{rs}, $\tilde{E}_{rs}$, is retained by the E_{rs} estimator **132** and the other estimate outputs (e.g. $\tilde{R}_{rs}$ and $\Delta\tilde{P}_{mus}$) are discarded.

[0038] To further improve the E_{rs} estimation performance, a Kalman filter **212** is optionally used to reduce the E_{rs} estimation error. As previously mentioned, the respiratory system elastance, E_{rs}, typically does not change rapidly as a function of time. The Kalman filter **212** is used to filter the estimation noise in $\tilde{E}_{rs}(t)$ and improve the $E_{rs}(t)$ estimation results. The inputs to the Kalman filter **212** are $\tilde{E}_{rs}$ (t) and $\delta_{\tilde{E}_{rs}}(t)$. The output of the Kalman filter **214** is the final estimate of $E_{rs}(t)$, notated herein as $\hat{E}_{rs}(t)$, and $\tilde{E}_{rs}(t)=E_{rs}(t)+\omega_E(t)$ where $\omega_E(t)$ is a noise or uncertainty metric. The above model assumes that $\tilde{E}_{rs}$ (t) is an unbiased estimate of $E_{rs}(t)$ that has a noise term $\omega_E(t)\sim N(0, \delta_{\tilde{E}_{rs}}(t))$.

[0039] The Kalman filter can be designed to reduce the MWLS estimation noise based on the following assumptions: (1) a state process equation where E_{rs} changes slowly and can be modelled as a random walk, i.e. $E_{rs}(t)=E_{rs}(t-1)+\omega_E(t)$, $\omega_E(t)\sim N(0, \delta_E)$; and (2) an observation equation where the MWLS estimate $\tilde{E}_{rs}(t)$ can be modelled as $\tilde{E}_{rs}(t)=E_{rs}(t)+\omega_{LE}(t)$, $\omega_{LE}(t)\sim N(0, \delta_{\tilde{E}_{rs}}(t))$. A standard Kalman filter can be implemented with A=1, B=0, $Q=\delta_E$, H=1, and $R=\delta_{\tilde{E}rs}(t)$. The Kalman filter has certain advantages, including computationally efficient implementation in the context of a sliding time window, intuitive operation and output of weighted averages. The parameter δ_E is an algorithm parameter that controls the average window length.

[0040] With continuing reference to FIGS. **1** and **2**, the final output $\hat{E}_{rs}$ (t) **214** of the E_{rs} estimator **132** is utilized by the succeeding R_{rs} estimator **134** in performing the $R_{rs}(t)$ estimation. To estimate $R_{rs}(t)$, the elastic pressure component $E_{rs}V(t)$ is cancelled out of P_y (t) using $\hat{E}_{rs}(t)$. This E_{rs} cancellation operation **216** can be expressed as:

$$\tilde{P}_y(t)=P_y(t)-\hat{E}_{rs}(t)V(t)$$

The E_{rs} cancellation **216** removes one unknown (E_{rs}) from the Equation of Motion of the Lungs, and thus simplifies the R_{rs} estimation. Assuming the estimation $\hat{E}_{rs}(t)$ output by the E_{rs} estimator **132** is correct and the elastic pressure component is perfectly cancelled, the MWLS operation **218** of the R_{rs} estimator **134** optimizes the equation:

$$\tilde{P}_y(t)=\cong R_{rs}\dot{V}(t)+P_{mus}(t)$$

Using the Moving Window Least Squares (MWLS) estimator **218**, the respiratory resistance R_{rs} is estimated.

[0041] In the E_{rs} estimator MWLS operation **210** of the E_{rs} estimator **132**, the respiratory muscle pressure $P_{mus}(t)$ is indirectly estimated as a linear function of t since the difference of $P_{mus}(t)$, namely $\Delta P_{mus}(t)$, is estimated as a constant value ΔP_{mus} for each time window. However, it has been found herein that this estimate is unduly coarse in the case of the MWLS operation **218** of the R_{rs} estimator **134**, and that significantly improved estimation of the respiratory resistance R_{rs} is provided if the time dependence of the respiratory muscle pressure $P_{mus}(t)$ is adaptively modeled in the MWLS operation **218**. In illustrative examples herein, $P_{mus}(t)$ is modeled using a low order polynomial, e.g. of order 0 (constant value), 1 (linear), or 2 (quadratic). The order of the $P_{mus}(t)$ polynomial function, M, can significantly change the estimation performance.

[0042] With brief reference to FIG. **4**, moreover, the optimal order M of the polynomial used to model $P_{mus}(t)$ depends on the position of the moving window **130** within the respiratory cycle. In illustrative FIG. **4**, the first time window $\mathbf{130}_A$ is located at a respiratory phase for which a first order (M=1) polynomial is an effective model of $P_{mus}(t)$; whereas, for the respiratory phase at which the second time window $\mathbf{130}_B$ is located a zeroeth order (M=0) polynomial is effective. However, the respiratory phase at which the current time window **130** resides is generally not an input to the R_{rs} estimator **134**.

[0043] With brief reference to FIG. **5**, for the R_{rs} MWLS **218**, the $P_{mus}(t)$ waveform is modeled as an M^{th}-order polynomial function (M>=0), i.e. $P_{mus}(t)=a_0+a_1t+\ldots+a_Mt^M$, and the $R_{rs}(t)$ parameter is assumed to be constant. (While a polynomial model of $P_{mus}(t)$ is described herein for illustration, other models comprising a parameterized function of time such as a spline model are also contemplated.) To accommodate the differences in optimal polynomial order over the respiratory cycle, the R_{rs} MWLS estimator **218** calculates three R_{rs} estimates: an MWLS estimate $\mathbf{218}_0$ using a 0^{th}-order polynomial (M=0, i.e. $P_{mus}(t)$ is modeled as a constant); an MWLS estimate $\mathbf{218}_1$ using a 1^{st}-order polynomial (M=1, i.e. $P_{mus}(t)$ is modeled as a linear function of t); and an MWLS estimate $\mathbf{218}_2$ using 2^{nd}-order polynomial (M=2, i.e. $P_{mus}(t)$ is modeled as a quadratic function of t). The MWLS formulation for each MWLS estimator $\mathbf{218}_0$, $\mathbf{218}_1$, $\mathbf{218}_2$ is listed in the righthand box of FIG. **5** as well as in Table 1 below.

TABLE 1

R_{rs} estimator formulations for each $P_{mus}(t)$ model

	P_{mus} Model	Moving Window Least Squares Estimator
0^{th} Order	$P_{mus}(t) = a_0$	$\tilde{P}_y(t) \cong R_{rs}\dot{V}(t) + P_{mus}(t)$ $[\tilde{R}_{rs,0}, a_0]^T = (X^T X)^{-1}X^TY$ $Y = [\tilde{P}_y(t), \tilde{P}_y(t-1), \ldots, \tilde{P}_y(t-L+1)]^T$ $X = [x(t), x(t-1), \ldots, x(t-L+1)]^T$ $x(t) = [\dot{V}(t), 1]^T$ $\delta_{\tilde{R}_{rs,0}} = (X^T X)^{-1}(1, 1) * \delta_{Py}$
1^{st} Order	$P_{mus}(t) = a_0 + a_1t$	$\tilde{P}_y(t) \cong R_{rs}\dot{V}(t) + P_{mus}(t)$ $[\tilde{R}_{rs,1}, a, a_0, a_1]^T = (X^T X)^{-1}X^TY$ $Y = [\tilde{P}_y(t), \tilde{P}_y(t-1), \ldots, \tilde{P}_y(t-L+1)]^T$ $X = [x(t), x(t-1), \ldots, x(t-L+1)]^T$ $x(t) = [\dot{V}(t), 1, t]^T$ $\delta_{\tilde{R}_{rs,1}} = (X^T X)^{-1}(1, 1) * \delta_{Py}$

TABLE 1-continued

R_{rs} estimator formulations for each $P_{mus}(t)$ model

	P_{mus} Model	Moving Window Least Squares Estimator
2^{nd} Order	$P_{mus}(t) = a_0 + a_1t + a_2t^2$	$\tilde{P}_y(t) \cong R_{rs}\dot{V}(t) + P_{mus}(t)$ $[\tilde{R}_{rs,2}, a_0, a_1, a_2]^T = (X^T X)^{-1}X^TY$ $Y = [\tilde{P}_y(t), \tilde{P}_y(t-1), \ldots, \tilde{P}_y(t-L+1)]^T$ $X = [x(t), x(t-1), \ldots, x(t-L+1)]^T$ $x(t) = [\dot{V}(t), 1, t, t^2]^T$ $\delta_{\tilde{R}_{rs,2}} = (X^T X)^{-1}(1, 1) * \delta_{Py}$

[0044] With continuing reference to FIG. **5**, the three $R_{rs}(t)$ estimates output by the respective MWLS operations $\mathbf{218}_0$, $\mathbf{218}_1$, $\mathbf{218}_2$ are combined together by a combining operation **219** to produce the final MWLS estimate, $\tilde{R}_{rs}(t)$. The combining operation **219** may use various combinational techniques, such as a maximum ratio combination operation or a minimum variance selection combination. The maximum ratio combination employed by the illustrative combiner **219** assigns the largest weight to the estimate with the least estimation variance (e.g. the one with the best polynomial order) so that the one with the best polynomial order will dominate the R_{rs} estimation output. The MWLS **218** also calculates the variance of $\tilde{R}_{rs}(t)$, $\delta_{\tilde{R}_{rs}}$.

[0045] With returning reference to FIG. **2**, in the case of the R_{rs} estimator **134** only the $R_{rs}(t)$ estimate, $\tilde{R}_{rs}$ (t), output by the MLS operation **218** is retained while the other estimation outputs (e.g. $P_{mus}(t)$ polynomial coefficients) are discarded. In the final stage of the R_{rs} estimator **134**, a Kalman filter **220** is applied to further improve the R_{rs} estimation output by the MWLS **218**. The Kalman filter **220** is suitably similar to the Kalman filter **212** described above with respect to the E_{rs} estimator **132**. The Kalman filter **220** for the R_{rs} estimator **134** can be designed to reduce the MWLS estimation noise based on the following assumptions: (1) a state process equation where R_{rs} changes slowly and can be modelled as a random walk, i.e. $R_{rs}(t)=R_{rs}(t-1)+\omega_R(t)$, $\omega_R(t-1)\sim N(0,\delta_R)$; and (2) an observation equation where the MWLS estimate $\tilde{R}_{rs}(t)$ can be modelled as $\tilde{R}_{rs}(t)=R_{rs}(t)+\omega_{LR}(t)$, where ω_{LR} (t)~N(0, $\delta_{\tilde{R}_{rs}}(t)$). A standard Kalman filter can be implemented with A=1, B=0, Q=δ_R, H=1, and R=$\delta_{\tilde{R}rs}(t)$. Again, the Kalman filter has certain advantages, including computationally efficient implementation in the context of a sliding time window, intuitive operation and output of weighted averages. The parameter δ_R is an algorithm parameter that controls the average window length.

[0046] The output **222** of the $R_{rs}(t)$ Kalman filter **220** is the R_{rs} estimate notated here as $\hat{R}_{rs}(t)=R_{rs}(t)+\omega_r(t)$. This output assumes that $\tilde{R}_{rs}(t)$ is an unbiased estimate of $R_{rs}(t)$, but has a noise term ω_r (t)~N(0, $\delta_{\tilde{R}_{rs}}$).

[0047] With reference back to FIG. **2**, in the final pass, once the E_{rs} and R_{rs} estimates are obtained by the respective estimators **132**, **134**, the $P_{mus}(t)$ estimator **136** is applied to estimate P_{mus} (t). Using the previously estimated $R_{rs}(t)$ and $C_{rs}(t)$, a $P_{mus}(t)$ computation **224** computes the $\tilde{P}_{mus}(t)$ estimate according to:

$$\tilde{P}_{mus}(t)=P_y(t)-\hat{E}_{rs}(t)V(t)-\hat{R}_{rs}(t)\dot{V}(t)$$

evaluated over the samples of P_y (t), $\dot{V}(t)$, and (via integrator **122**) V(t) in the time window **130**. Said another way, $\tilde{P}_{mus}(t)=P_y(t)-\hat{R}_{rs}\dot{V}(t)-\hat{E}_{rs}V(t)$ is evaluated in the time window **130** of the MWLS. To remove high-frequency noise in $\tilde{P}_{mus}(t)$, an optional low-pass filter **226** can be used to further improve the $P_{mus}(t)$ estimate. Additionally or alternatively, physiological knowledge of the $P_{mus}(t)$ waveform can be infused to further improve the $P_{mus}(t)$ estimation.

[0048] In the illustrative embodiments, the respiratory elastance (or compliance) estimator **132** is applied first, followed by the respiratory resistance estimator **134** and finally the respiratory muscle pressure estimator **136**. However, it is contemplated to estimate the respiratory resistance first, followed by estimation of the respiratory elastance or compliance (that is, to reverse the order of the estimators **132**, **134**). In such a variant embodiment, the second (E_{rs}) estimator would suitably include an R_{rs} cancellation operation analogous to the operation **216** of the illustrative embodiment. Regardless of the order of estimation of E_{rs} (or C_{rs}) and R_{rs}, it will be appreciated that the final $P_{mus}(t)$ estimator **136** could optionally be omitted if $P_{mus}(t)$ and WoB (computed therefrom by integrator **140**) are not used.

[0049] If the respiratory elastance (or compliance) and/or resistance are displayed on the display component **110** of the ventilator **100**, these values may optionally also be displayed with their respective uncertainty metrics, for example expressed in terms of the δ or ω statistics described herein or functions thereof. While these or other respiratory parameters are described as being displayed on the display component **110** of the ventilator **100** in the illustrative examples, it will be appreciated that such values may additionally or alternatively be displayed on a bedside patient monitor, at a nurses' station computer, and/or may be stored in an Electronic Health Record (EHR) or other patient data storage system, or so forth. The illustrative respiratory system analyzer **120** is suitably implemented via the microprocessor of the ventilator **100**; however, the respiratory system analyzer **120** could additionally or alternatively be implemented via a microprocessor of a bedside patient monitor or other electronic data processing device. The disclosed respiratory system analyzer functionality may also be embodied by a non-transitory storage medium storing instructions that are readable and executable by such a microprocessor or other electronic data processing device to perform the disclosed functionality. By way of example, the non-transitory storage medium may, for example, include a hard disk or other magnetic storage medium, optical disk or other optical storage medium, flash memory or other electronic storage medium, various combinations thereof, or so forth.

[0050] As previously noted, in addition to displaying one or more of the estimated values (e.g. one or more of the values $\hat{E}_{rs}(t)$, $\hat{C}_{rs}(t)=1/\hat{E}_{rs}$, $\hat{R}_{rs}(t)$, $\hat{P}_{mus}(t)$ optionally with its statistical uncertainty) as a real-time value, trend line or so forth, in another illustrative application the $\hat{P}_{mus}(t)$ waveform may be used to synchronize the positive pressure applied by the ventilator **100** with respiratory effort expended by the patient **102**, so as to reduce patient-ventilator dyssynchrony. In this application, the positive air pressure applied by the ventilator **100** is adjusted, e.g. increased or decreased, in synch with increasing or decreasing magnitude of $\hat{P}_{mus}$ (t). In another control application, the WoB output by the integrator **140** may be used as a feedback signal for control of the ventilator **100**. In general, the positive pressure applied by the ventilator **100** should increase with increasing measured WoB output by integrator **140**, and this increased mechanical ventilation should result in a consequent reduction in patient WoB until the setpoint WoB is reached. As illustration, a proportional and/or derivative and/or integral controller (e.g. PID controller) may be used for this feedback control with the WoB signal from the integrator **140** serving as the feedback signal, a target WoB serving as the setpoint value, and the positive pressure being the controlled variable.

[0051] The respiratory system analyzer **120** has been tested with simulated data and with pig respiratory data, and the results show the analyser **120** can provide comparable results to invasive solutions and is stable under different ventilator settings, including low PSV settings. The analyzer **120** provides various benefits, including (but not limited to): providing real-time data (with a lag of a few seconds or less); sample-by-sample estimation (if successive windows overlap and are spaced by a single sample); tailorable trade-off between computational complexity and temporal resolution (faster computation by larger spacing between possibly overlapping windows traded off against reduced temporal resolution); rapid convergence (within 10 breaths in some tests) providing low initiation time; stability against unexpected disturbances; good computational efficiency employing, for example, efficient pseudo-inverse ($L\times4$) matrix computation (where L is the window size, e.g. 60-90 samples in some suitable embodiments); and low memory requirements (storing the data for the current time window, around 60-90 samples for some embodiments).

[0052] As a further advantage, the respiratory system analyzer **120** suitably estimates the elastance or compliance $E_{rs}(t)$, resistance $R_{rs}(t)$, and respiratory muscle pressure $P_{mus}(t)$ without receiving as input the respiratory phase or respiratory rate, and without making any a priori assumptions about these parameters (other than that E_{rs} and R_{rs} are assumed to be constant within any given time window of the MWLS estimation). The respiratory system analyzer **120** suitably operates only on the measured air pressure $P_y(t)$ and air flow $\dot{V}(t)$ along with $V(t)=\int\dot{V}(t)dt$ which is derived by integrating $\dot{V}(t)$ over time.

[0053] 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 constructed as including all such modifications and alterations insofar as they come within the scope of the appended claims or the equivalents thereof.

1. A medical ventilator device comprising:

a ventilator configured to deliver ventilation to a ventilated patient;

a pressure sensor configured to measure the airway pressure $P_y(t)$ of the ventilated patient;

an air flow sensor configured to measure the air flow $\dot{V}(t)$ into and out of the ventilated patient; and

a respiratory system analyzer comprising a microprocessor configured to estimate respiratory parameters of the ventilated patient using moving time window least squares (MWLS) estimation including (i) respiratory system elastance or compliance (E_{rs} or C_{rs}), (ii) respiratory system resistance (R_{rs}), and (iii) respiratory muscle pressure ($P_{mus}(t)$).

2. The medical ventilator device of claim **1** wherein the MWLS estimation in cludes, for each time window of the MWLS estimation, performing the following operations in order:

(1) estimating one of (i) elastance or compliance and (ii) resistance;

(2) estimating the other of (i) elastance or compliance and (ii) resistance using the estimated value from operation (1); and

(3) estimating respiratory muscle pressure using the values estimated in operations and.

3. The medical ventilator device of claim **2** wherein the operation estimates elastance or compliance and the operation estimates resistance using the estimated value of elastance or compliance from operation.

4. The medical ventilator device of claim **2** wherein the operation optimizes elastance E_{rs}, resistance R_{rs}, and the difference ΔP_{mus} of the respiratory muscle pressure P_{mus} of the equation:

$$\Delta P_y(t)=R_{rs}\Delta\dot{V}(t)+E_{rs}\Delta V(t)+\Delta P_{mus}$$

with respect to the measured values of $P_y(t)$ and $\dot{V}(t)$ in the time window of the MWLS where $V(t)=\int\dot{V}(t)dt$ and $\Delta P_y(t)=P_y(t)-P_y(t-1)$ and $\Delta\dot{V}(t)=\dot{V}(t)-\dot{V}(t-1)$ and $\Delta V(t)=V(t)-V(t-1)$.

5. The medical ventilator device of claim **4** wherein the operation optimizes the respiratory muscle pressure $P_{mus}(t)$ and one of elastance E_{rs} and resistance R_{rs} of the equation:

$$P_y(t)=R_{rs}\dot{V}(t)+E_{rs}V(t)+P_{mus}(t)$$

with respect to the measured values of $P_y(t)$ and $\dot{V}(t)$ in the time window of the MWLS with the estimated value from operation held fixed and $P_{mus}(t)$ modeled by a parameterized function of time.

6. The medical ventilator device of claim **5** wherein $P_{mus}(t)$ is modeled by a polynomial function of time.

7. The medical ventilator device of claim **6** wherein operation is repeated with $P_{mus}(t)$ modeled by zeroeth, first, and second order polynomial functions of time and the optimized elastance E_{rs} or resistance R_{rs} of the three repetitions are combined.

8. The medical ventilator device of claim **5** wherein the operation estimates respiratory muscle pressure as $P_y(t)-\hat{R}_{rs}\dot{V}(t)-\hat{E}_{rs}V(t)$ in the time window of the MWLS where $\hat{R}_{rs}$ and $\hat{E}_{rs}$ are estimated values from operations and.

9. The medical ventilator device of claim **2** wherein one or both of the operations and includes applying a Kalman filter to the estimated value.

10. The medical ventilator device of claim **9** wherein one or both of the operations and further includes generating an uncertainty metric for the estimated value based on a noise variance of the Kalman filter.

11. The medical ventilator device of claim **1** further comprising:

a display configured to display one or more of the respiratory parameters of the ventilated patient estimated by the respiratory system analyzer.

12. The medical ventilator device of claim **1** wherein the ventilator is programmed to adjust positive air pressure output by the ventilator in synch with increasing or decreasing magnitude of the respiratory muscle pressure ($P_{mus}(t)$) in order to reduce patient-ventilator dyssynchrony.

13. The medical ventilator device of claim **1** wherein:

the respiratory system analyzer is configured to estimate a work of breathing (WoB) as $WoB=\int P_{mus}(t)dV(t)$ where $P_{mus}(t)$ is the respiratory muscle pressure as a function of time estimated using the MWLS estimation; and

the ventilator is programmed to control mechanical ventilation provided by the ventilator to maintain the estimated WoB at a setpoint WoB value.

14.-**19**. (canceled)

20. A non-transitory storage medium storing instructions readable and executable by an electronic data processing device to perform a method operating on measurements of airway pressure $P_y(t)$ and air flow $\dot{V}(t)$ of a patient on a ventilator, the method including:

applying moving window least squares (MWLS) estimation to estimate (i) respiratory system elastance E_{rs}, (ii) respiratory system resistance R_{rs}, and (iii) respiratory muscle pressure $P_{mus}(t)$, wherein:

the MWLS estimation (i) comprises fitting:

$$\Delta P_y(t)=R_{rs}\Delta\dot{V}(t)+E_{rs}\Delta V(t)+\Delta P_{mus}$$

to $\Delta P_y(t)$ to obtain values for E_{rs}, R_{rs}, and ΔP_{mus}, where $\Delta P_y(t)$ is a difference signal of the measured airway pressure, $\Delta\dot{V}(t)$ is a difference signal of the measured air flow, $\Delta V(t)$ is a difference signal of respiratory system air volume $V(t)=\int\dot{V}(t)dt$, and ΔP_{mus} is a constant, and

the MWLS estimation (ii) comprises fitting:

$$P_y(t)=R_{rs}\dot{V}(t)+E_{rs}V(t)+P_{mus}(t)$$

to obtain values for R_{rs} and $P_{mus}(t)$, where E_{rs} is set the value determined in the MWLS estimation (i) and with $P_{mus}(t)$ is approximated as a parameterized function, and

the MWLS estimation (iii) comprises evaluating:

$$P_{mus}=P_y(t)-R_{rs}\dot{V}(t)-E_{rs}V(t)$$

where E_{rs} is set the value determined in the MWLS estimation (i) and R_{rs} is set the value determined in the MWLS estimation (ii).

21. The non-transitory storage medium of claim **20** wherein the respiratory system elastance E_{rs} is represented in the MWLS estimation operations as a respiratory system compliance $C_{rs}=1/E_{rs}$.

* * * * *

专利名称(译)	通过连续参数估计监测患者呼吸状态的非侵入性方法		
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[标]申请(专利权)人(译)	皇家飞利浦电子股份有限公司		
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摘要(译)

应用移动窗最小二乘（MWLS）方法从测量的空气流量和压力估计呼吸系统参数。在每个窗口中，首先估计弹性E rs （或电阻R rs ），并且可以将卡尔曼滤波器应用于估计。这被输入到估计R（或E）的第二估计器，可以应用第二卡尔曼滤波器。最后，估计的E rs 和R rs 用于计算时间窗口中的肌肉压力P mus （t）。系统包括呼吸机（ 100 ），气道压力传感器（ 112 ）和气流传感器（ 114 ）和呼吸系统系统分析仪（ 120 ）执行MWLS估算。估计结果可能会显示在呼吸机或患者监护仪的显示屏上（ 110 ）。估计的P mus （t）可以用于减少患者 - 呼吸机不同步，或者集成以产生用于控制通气的呼吸功（WOB）信号。