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Surface EMG-based Estimation of Breathing Effort for Neurally Adjusted Ventilation Control ⋆

Eike Petersen * Jan Graßhoff * Marcus Eger ** Philipp Rostalski *

* *Institute for Electrical Engineering in Medicine, University of Lübeck, Germany. E-mail: {eike.petersen, j.grasshoff, philipp.rostalski}@uni-luebeck.de.*
** *Drägerwerk AG & Co. KGaA, Lübeck, Germany.*

Abstract. In assisted mechanical ventilation, it is of critical importance to monitor the patient's own effort to breathe. Methods currently available are either invasive (esophageal electromyography and esophageal pressure) or rely heavily on intermittent occlusion maneuvers to identify the properties of the respiratory muscles. In this article, we propose a novel, non-invasive method to identify the patient's respiratory mechanics and estimate the pressure generated by the patient, based on surface electromyographic (sEMG) measurements of the respiratory muscles. Our method is computationally efficient, real-time capable, and can be run continuously during normal ventilation. A numerical comparison with esophageal pressure measurements using three clinical data sets demonstrates the estimation procedure's good performance. Clinically, monitoring a patient's respiratory effort is of high intrinsic, diagnostic value, while also enabling a whole range of new, adaptive control algorithms for assisted mechanical ventilation.

Keywords: Biomedical systems, Biomedical control, System identification, Sensor fusion, Medical applications, Physiological models, Real-time systems, Signal processing algorithms, Recursive least squares

1. INTRODUCTION

Monitoring a mechanically ventilated patient's breathing activity is of critical importance for patient outcomes. Diaphragm fatigue, diaphragm atrophy, resulting from diaphragm disuse for extended periods, as well as self-inflicted lung injury, resulting from excessive driving pressures, are to be avoided by proper choice of ventilator parameters (de Vries et al. (2018); Heunks and Ottenheijm (2018)). More generally, without any knowledge of the patient's breathing activity, it is very challenging to choose the right mode and level of breathing assistance to be provided by the ventilator. As an essential step towards providing optimal, individualized support, it is critical to monitor the amount of pressure generated by the patient continuously.

Figure 1 shows a simplified model of the respiratory control system, comprised of the patient and the mechanical ventilator interacting with each other, indicating the difficulty of supporting the patient adaptively in an optimal fashion. The respiratory control center of the patient is located in the brain stem and primarily driven by central and peripheral chemoreceptors, sensing CO2 as well as O2 levels in the body, and stretch receptors in the lungs. The control center sends a neural control signal to the respiratory muscles, which convert this *neural drive* into a pressure P_{mus}. This conversion's efficiency depends on the length and shape of the muscle fibers, both of which are determined mainly by the lung volume (Braun et al. (1982); Wilson and Troyer (2010)). Depending on the properties of the patient's respiratory system, the pressure P_{mus} generated by the patient, as well as the airway pressure P_{aw} provided by the mechanical ventilator, an airflow $\dot{V}$ emerges. In traditional ventilatory support modes, this airflow is the primary source of information for controlling the level of pressure support P_{aw} provided by the mechanical ventilator. We propose to add a new source of information by using surface EMG (sEMG) measurements of the respiratory muscles, which measure the electrical fields generated by these muscles during contraction, for estimating the pressure P_{mus} generated by the patient.

Many authors have proposed methods to identify the properties of the respiratory system, and, thereby, breathing activity by performing various ventilatory maneuvers (Younes et al. (2001); Sanborn et al. (2006)). These methods have three main drawbacks: Firstly, they necessarily interrupt the normal breathing pattern, potentially (in some cases definitely) disturbing the patient. Secondly, they rely on particular assumptions about the behavior of the patient, which may or may not be fulfilled for any given patient. Finally and thirdly, they estimate the parameters of the respiratory system only during said respiratory maneuvers, which may lead to biased estimates by only considering measurements obtained during a particular, irregular state of the respiratory system. For these reasons, it currently appears preferable to base estimates of the pressure generated by the patient on actual measurements of said activity.

The current gold standard for the quantification of breathing activity is the measurement of the esophageal pressure P_{es}, which requires the insertion of an esophageal catheter, a procedure which is both error-prone as well as invasive and uncomfortable for the patient (Doorduin et al. (2013)). Recently, measurements of the electrical activity of the

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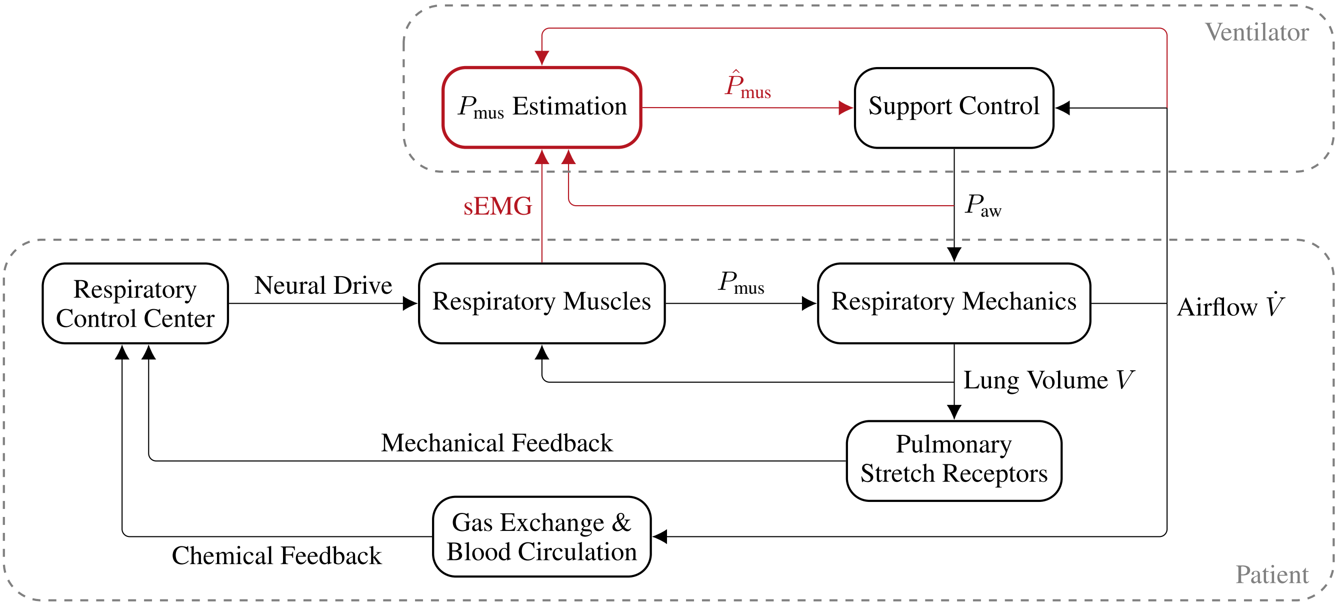

Figure 1. A control systems view of a mechanically ventilated patient interacting with the mechanical ventilator. We propose to use real-time, noninvasive, sEMG-based estimation of the pressure P_{mus} generated by the patient for improved control of ventilatory support.

diaphragm (EAdi) have received significant attention. The only EAdi solution that is currently available commercially uses an esophageal catheter (Sinderby et al. (1999)) and hence shares the drawback of invasiveness with the esophageal pressure measurement. Surface electromyography (sEMG), while more challenging from a signal processing perspective due to an increased noise level, represents a noninvasive alternative. Moreover, it allows for measuring the activity of accessory respiratory muscles in addition to the diaphragm, for which there are currently no other methods available (Doorduin et al. (2013)).

Electromyographic measurements (both EAdi and surface EMG) do not measure force directly but rather represent a measure of muscle activation. Several researchers have therefore attempted to identify the electromechanical ratio of electrical activity and generated pressure, thereby allowing them to derive an estimate of the pressure P_{mus} generated by the patient from the electrical measurement. Both Bellani et al. (2018) and Jansen et al. (2018) have performed occlusion maneuvers during assisted ventilation and calculated the aforementioned electromechanical ratio during these maneuvers. Bellani et al. (2018) calculated P_{mus} from both surface EMG and EAdi in this way and found the result to be well correlated with P_{mus} as measured by esophageal pressure. Jansen et al. (2018) performed a very similar study but considered only EAdi and found the electromechanical ratio to vary strongly between individual maneuvers. Both studies have in common that they estimated the electromechanical ratio only during occlusion maneuvers, an approach which has several drawbacks. Firstly, occlusion maneuvers are uncomfortable and potentially dangerous for the patient, which is why their use should be minimized. Secondly, and maybe even more importantly, the relationship between EMG measurements of a muscle and the generated muscle force is dependent on a large number of time-varying factors, such as the current muscle length and velocity (Farina et al. (2004); Braun et al. (1982); Wilson and Troyer (2010)), the relative position and orientation of the muscle with respect to the recording electrode, the geometry of the surrounding tissue layers, and others (Petersen and Rostalski (2019)). The electromechanical ratio measured during an occlusion therefore differs from the ratio during normal breathing, an effect also observed by Bellani et al. (2013) and Bellani et al. (2018). For these reasons, we propose a different, model-based path.

The method we propose does not require performing occlusion maneuvers. Instead, we use all available data for identifying a complete model of respiratory mechanics, including the electromechanical ratio, in real-time during normal breathing. Our sEMG-based procedure is entirely noninvasive and yields accurate estimates of the pressure signal $P_{\mathrm{mus}}(t)$ generated by the patient. We validate the estimates by comparison with P_{mus} derived from the esophageal pressure signal $P_{\mathrm{es}}(t)$ in three exemplary clinical data sets and discuss opportunities for further improvement.

2. MATERIALS AND METHODS

2.1 *Clinical data sets*

We applied our algorithm to three clinical data sets recorded and kindly provided by Bellani et al. (2018). Subjects were intubated, on pressure support ventilation, and on mechanical ventilation for $T > 48\,\mathrm{h}$. Each data set lasts about $10\,\mathrm{min}$ and once per minute, end-expiratory occlusion maneuvers were performed, where a single inspiratory effort was occluded. Measurements relevant to the present analysis include the airway pressure $P_{\mathrm{aw}}(t)$, airflow $\dot{V}(t)$, esophageal pressure $P_{\mathrm{es}}(t)$, and three channels of surface EMG measurements. Only two EMG channels were used in the present study, because we found them to provide sufficient information about respiratory muscle activity. These channels were obtained through two pairs of surface EMG electrodes, which were located at the following positions:

(1) Lower costal margin, bilaterally on the midclavicular line, for costal diaphragm.
(2) Second intercostal space, bilaterally on the parasternal line, for parasternal external intercostal muscles.

For more details regarding the exact study protocol and measurement setup and hardware, refer to Bellani et al. (2018).

2.2 *Signal processing*

Surface EMG measurements were obtained at a sampling rate of $500\,\mathrm{Hz}$. Firstly, the measurements were digitally high-pass filtered to remove baseline wander and movement artifacts and to obtain an activity signal with a mean close to zero. Cardiac artifacts, which are very prominent in thoracic surface EMG measurements, have been removed using a wavelet denoising approach first proposed by Graßhoff et al. (2018). In this method, the signal is decomposed into several wavelet bands using the stationary wavelet transform (SWT), and a simple threshold is applied in the wavelet domain to detect and remove ECG interference. For details regarding this wavelet-based cardiac artifact removal procedure, refer to Graßhoff et al. (2018) and Petersen et al. (2020). Finally, to obtain a smooth envelope signal for the following regression procedure, the moving median of the absolute values of the signal was calculated over a window length of $250\,\mathrm{ms}$. The right edge of the window was aligned to the current sample, i.e., to calculate the envelope value at time t_k, only measurements up until this point were considered in order to obtain a real-time capable algorithm.

Our sEMG-based estimation procedure, described in detail in the following section, also requires an estimate of the current lung volume. To this end, an estimate of the current lung volume was calculated by continuous, as opposed to breath-wise, integration of the flow measurement. In order to prevent volume estimation drift due to measurement error or gas leakage, a flow measurement offset correction was determined for each breath. To estimate the offset, we considered a moving window of 15 complete breaths with the current breath at its center, and the flow measurement offset was determined such that the integral of the offset-corrected flow signal over this window was equal to zero. This drift correction procedure amounts to the assumption that, throughout these 15 breaths, as much air was inspired by the patient as was exhaled, while still allowing non-zero end-expiratory volumes and thereby obtaining a more realistic, continuous volume signal.

2.3 *Real-time estimation procedure*

The basis of our estimation algorithm is given by the classical first-order model of respiratory mechanics,

$$P_{\text{aw}}(t) = R_1\cdot\dot{V}(t)+R_2\cdot\dot{V}(t)\cdot|\dot{V}(t)|+E_{\mathrm{L}}\cdot V(t)+P_{\text{mus}}(t)+P_0, \tag{1}$$

which corresponds to the assumption of a linear, single-compartment model of the lung, and a linear-quadratic airway resistance, and has been found to approximate the behavior observed in intensive cared patients well (Peslin et al. (1992); Bates (2009)). Furthermore, we assume that $P_{\text{mus}}(t)$ can be reproduced from the linear combination

$$P_{\text{mus}}(t) \approx P_{\text{mus-EMG}}(t) := \sum_{i=1}^{2} \alpha_i \cdot \overline{\mathrm{EMG}}_i(t) + P_{\text{0-EMG}} \tag{2}$$

of the EMG envelope signals $\overline{\mathrm{EMG}}_i(t)$, where $i \in \{1,2\}$ denotes one of the two EMG channels described in the previous section, and the coefficients α_i represent the ratio of pressure generated by the muscle to electromyographic activity. There are several arguments which justify this linearity assumption. Firstly, in many muscles, the relationship between the envelope of a surface EMG measurement and the generated force signal is roughly linear, especially at lower activation levels (Farina et al. (2004)). Moreover, during a normal breath, most subjects will stay within a rather narrow activation range, not displaying extremely high levels of muscle activation, which further supports the linearity assumption. Empirically, we also tested various nonlinearly extended versions of equation (2), with only marginally improved regression performance (results not shown here). Finally, note that we neglected the dependence of the generated pressure on the current lung volume (cf. figure 1) in this model for simplicity. This omission represents a potential avenue for future improvement, as we will discuss later.

Combining equations (1) and (2), we obtain the linear-in-variables model

$$\begin{aligned} P_{\text{aw}}(t) = R_1 \cdot \dot{V}(t) + R_2 \cdot \dot{V}(t) \cdot |\dot{V}(t)| + E_{\mathrm{L}} \cdot V(t) \\ + \alpha_1 \cdot \overline{\mathrm{EMG}}_1(t) + \alpha_2 \cdot \overline{\mathrm{EMG}}_2(t) + P_0^c, \end{aligned} \tag{3}$$

for which parameter estimates can be obtained by means of any static regression method. Note, however, that in our application, all of the coefficients in equation (3) must be assumed to be (at least slowly) time-varying. Lung elastance and airway resistance are known to change gradually over time as a function of the patient's general condition, as well as more suddenly due to events such as changes in patient position (Bates (2009)). The coefficients α_i, on the other hand, depend on many factors, including electrode type and placement, skin conductivity, fat layer thickness, and muscle geometry and fatigue, many of which may be varying over time (Farina et al. (2004)). For this reason, and to facilitate efficient real-time implementation of the estimation procedure, we decided to implement a recursive least squares (RLS) solution to equation (3), using the classical RLS algorithm with exponential decay described in (Ljung, 1999, p. 356). We set the forgetting factor to

$$\lambda = \mathrm{e}^{-1/(T\cdot f_s)}, \quad T = 200\,\mathrm{s}, \tag{4}$$

resulting in a time constant of $T = 200\,\mathrm{s}$, i.e., at time t the measurement from time $t - 200\,\mathrm{s}$ is weighted by $1/\,\mathrm{e}$ for the regression.

The described regression method yields time-varying estimates for the parameters R_1, R_2, and E_{L} of the respiratory system, the coefficients α_i describing the neuromuscular efficiency of the corresponding muscles, as well as the pressure contribution $P_{\text{mus}}(t)$ generated by the patient, all in real-time.

2.4 *Validation*

The estimation procedure described in the previous section was implemented in Python3 and used the NumPy (van der Walt et al. (2011)) and Pandas (McKinney et al. (2010)) packages. For validation purposes, the obtained estimation results were compared to an estimation of $P_{\text{mus}}(t)$ obtained from the esophageal pressure signal $P_{\text{es}}(t)$, which is currently considered the gold standard for this purpose (Bellani et al. (2018); de Vries et al. (2018)). We used the method described in Graßhoff et al. (2019) for estimating $P_{\text{mus}}(t)$ from $P_{\text{es}}(t)$. Briefly, cardiac artifacts were removed from the measurement signal using a template subtraction technique (Graßhoff et al. (2017)) and the chest wall elastance E_{CW} was estimated by fitting a regression line into the expiratory part of the Campbell diagram. Using this estimate for E_{CW}, the volume-related component was then subtracted from the cleaned esophageal pressure measurement $P^c_{\text{es}}(t)$ to obtain the estimate

$$P_{\text{mus-Pes}}(t) = P^c_{\text{es}}(t) - E_{\text{CW}} \cdot V(t) \tag{5}$$

of the pressure generated by the patient. For more details on this method, please refer to Graßhoff et al. (2019).

In the following section, we present regression results for the given clinical data sets, and the estimate $P_{\text{mus-EMG}}(t)$ is compared to the reference $P_{\text{mus-Pes}}(t)$. While a comprehensive performance evaluation is beyond the scope of this initial study and will be the subject of future research, we consider two measures of estimation success: firstly, the mean absolute deviation (MAD) between our EMG-based P_{mus} estimate and $P_{\text{mus-Pes}}$ is calculated. Secondly, since the amplitude of the P_{mus} waveform is of particular clinical importance, we also compare the time-varying amplitudes of the two P_{mus} estimates. To this end, we calculate the interdecile range, i.e., the difference between the 0.1 and 0.9 quantiles, over a moving 5 s window on both signals. We then calculate the mean absolute deviation (MADamp) of these two moving P_{mus} amplitude estimates for each data set. Both measures (MAD and MADamp) are calculated over each whole data set, and not only over the short excerpts shown in figure 2.

3. RESULTS

Figure 2 shows excerpts from the three data sets, including the estimated $P_{\text{mus-EMG}}$ signal and, for comparison, $P_{\text{mus-Pes}}$. Excerpts start at least 100 s after the beginning of each recording, to give the RLS procedure time to initialize. For patients A and B, the two signals are in good accordance (MAD $= 0.59$ mbar, MADamp $= 1.24$ mbar and MAD $= 1.44$ mbar, MADamp $= 1.57$ mbar), while for patient C, the EMG-based estimate is close to zero everywhere, despite the significant respiratory effort visible in $P_{\text{mus-Pes}}$. We hypothesized that the reason for the estimation failure on this data set might be the high prevalence of uninformative samples during normal supported breathing, where many very similar breaths occur that contain little information about the behavior of the physical system. To test this hypothesis, we performed a second regression for patient C, which only uses 5 s of data around an occlusion maneuver and 15 s of data including irregular and atypical respiratory activity (double triggers). The results of this estimator, which we call $P^*_{\text{mus-EMG}}$, are also shown in figure 2 (light green line), and they follow the $P_{\text{mus-Pes}}$ signal very well (MAD $= 1.51$ mbar, MADamp $= 1.79$ mbar) Finally, we also performed regression for this patient using the occlusion maneuver only and not including the selected phase of irregular breathing. Results for this estimator are also shown in figure 2 (red line), and they are clearly inferior to the previous estimator – in particular, they overestimate neuromuscular efficiency and, hence P_{mus} (MAD $= 1.94$ mbar, MADamp $= 2.98$ mbar).

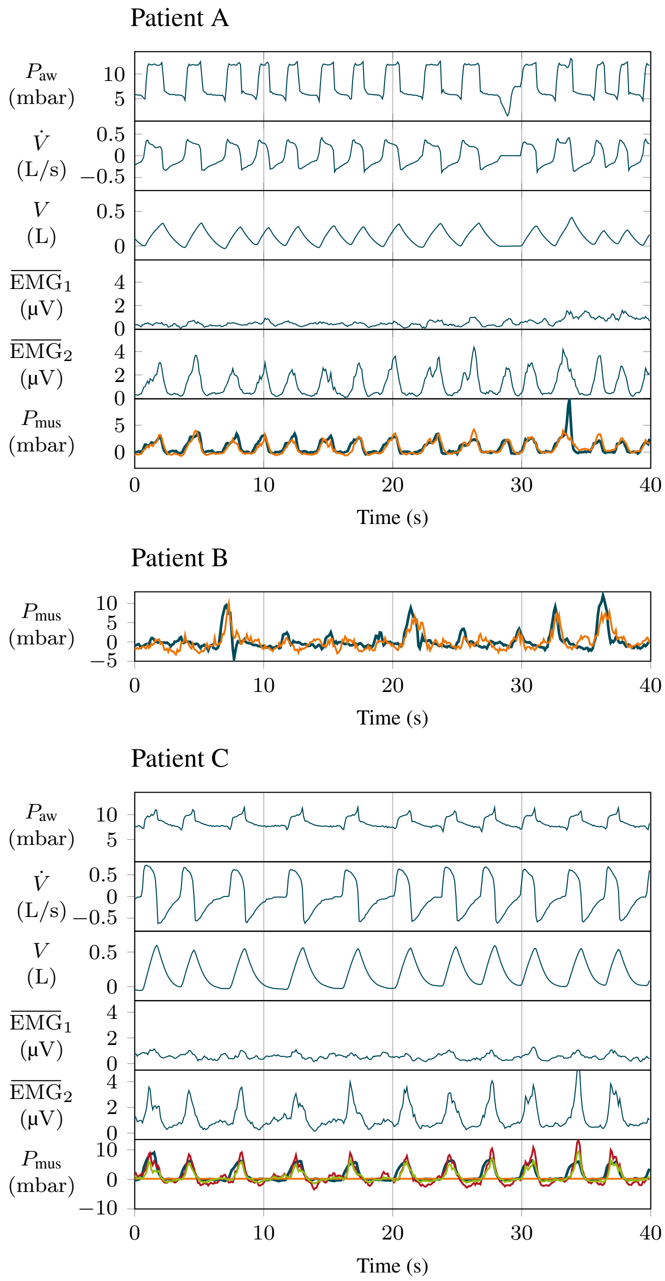

Figure 2. Measurements and resulting P_{mus} estimates for 40 s excerpts from three clinical patient data sets. For patients A and C, all relevant ventilatory measurements are shown, while for patient B only the estimated P_{mus} is displayed. In the P_{mus} panel, the dark line represents the reference signal $P_{\text{mus-Pes}}$, and the orange line represents the newly proposed estimate $P_{\text{mus-EMG}}$. For patient C, two more lines are shown. The first (light green) represents $P^*_{\text{mus-EMG}}$, estimated using only a 20 s subset of the data used for estimating $P_{\text{mus-EMG}}$, including an occlusion maneuver and irregular breathing. The second line (red) is the result of performing estimation *only* on the 5 s subset of the data which contains the occlusion maneuver. For easier visual comparison, the EMG-based estimates of P_{mus} have been aligned to $P_{\text{mus-Pes}}$ by adding a constant offset such that $\text{Median}(P_{\text{mus-EMG}}) = \text{Median}(P_{\text{mus-Pes}})$ over the displayed sample. (Note that it is not possible to recover the baseline $P_{0\text{-EMG}}$ from the identified P^c_0 anyway.)

4. DISCUSSION

Our proposed method for estimating the P_{mus} waveform from the surface EMG is completely noninvasive, computationally efficient and real-time capable. In contrast to the method proposed by Bellani et al. (2018), it takes all available data into account and does not depend on performing any particular type of maneuvers but can instead be used to continuously estimate P_{mus} and mechanical parameters of the respiratory system (E_{L}, R) during normal breathing as well as during any kind of special maneuver. Another significant benefit of the proposed method is that it enables the activity of accessory respiratory muscles to be taken into account, and not only the activity of the diaphragm: from equation (2), the pressure contribution of the different muscles can be obtained easily. This diagnostic information is of high clinical value, and there are currently no known methods to measure it (Doorduin et al. (2013)). Providing a reliable method for identifying the contributions made by the different respiratory muscles may have a significant practical impact in respiratory care. Note that, while demonstrated using surface EMG measurements here, the same estimation procedure could also be employed using invasive EAdi measurements, which would then be restricted to the activity of the diaphragm

The ratio α of electromyographic activity and generated force, which our method estimates, has been called *neuromuscular efficiency (NME)* and has been estimated by many authors, both in respiratory (Bellani et al. (2013, 2018); Jansen et al. (2018)) as well as other settings (Falla et al. (2004)). This ratio depends on many factors, both physiological and technical, and its exact physiological meaning is difficult to interpret (Arabadzhiev et al. (2010)). Hence, we refrain from calling the estimated α_i NMEs, but we remark that they denote the same quantity that has been estimated by other researchers (in other settings). In all of the cited articles, these parameters have been estimated during specialized maneuvers (occlusions in the respiratory studies) and not during normal free movement (ventilation). In addition to the fact that these maneuvers are uncomfortable for the patient, the validity of estimates of physiological parameters obtained during these abnormal conditions for normal ventilation conditions is currently unclear. Our results for patient C indicate that NME may be overestimated if identified mainly during occlusion maneuvers, an observation also made by Bellani et al. (2013). This also makes sense from a physiological point of view: muscles generate more power during isometric contractions (such as occlusions) than during shortening contractions (normal breathing), and more power when they are long (corresponding to a low lung volume, such as during end-expiratory occlusions) than when they are short (normal breathing), cf., e.g., Yamaguchi (2001). Moreover, parameter estimates obtained during regularly repeated occlusions have been found to vary strongly from one occlusion to the next, indicating limited interpretability of these estimates (Jansen et al. (2018)).

Providing a noninvasive, real-time capable method for estimating the pressure P_{mus} generated by mechanically ventilated patients opens up opportunities for improved assisted ventilation modes. Once an estimate $\hat{P}_{\text{mus}}$ is available, various control strategies are conceivable for implementing the support control block in figure 1. Sinderby et al. (1999) proposed neurally adjusted ventilatory assist (NAVA), which uses the invasive EAdi measurement and simply chooses the ventilator output as

$$P_{\text{aw}} = k \cdot \text{EMG}_i + \text{PEEP}, \tag{6}$$

where the proportionality factor k is chosen manually. Even this very simplistic, proportional "control strategy" has already been shown to improve patient outcomes in clinical studies (Schmidt et al. (2015)). In a similar vein, Younes (1992) proposed to control ventilatory support based on an estimate $\hat{P}_{\text{mus}}$ of the pressure generated by the patient, i.e., using

$$P_{\text{aw}} = k \cdot \hat{P}_{\text{mus}} + \text{PEEP} \tag{7}$$

as the control law. This method is typically called Proportional Assist Ventilation (PAV) or Proportional Pressure Support (PPS), and it is implemented in commercially available ventilators (combined with the method of Younes et al. (2001) for estimating P_{mus}, which has the drawbacks mentioned in the introduction). This method, however, still requires choosing the relative level k of support manually. Various algorithms have been proposed for automatically setting the support level (Eger (2007); Lellouche and Brochard (2009)), but much work remains to be done in designing patient-adaptive control schemes. We hope that the new estimation procedure described in this article will help to advance this important field. Finally, note that in using the control law (7) in combination with our EMG-based estimate of P_{mus}, we are in line with a huge body of research on EMG-based proportional upper-limb prosthesis control (see, e.g., Oskoei and Hu (2007); Fougner et al. (2012)).

The results on patient C indicate that the type of data used for the regression has a strong impact on the estimation quality. Thus, an interesting question for future research arises: how can particularly informative samples be automatically detected, and their impact on the regression result be increased, to improve estimation quality? Another avenue for improvement arises from our omission of the dependence of force generation on muscle length and contraction velocity. Classical Hill-type muscle models may prove useful for further improving estimation quality (Yamaguchi (2001)). Finally, as only exemplary results were shown here, a much more comprehensive evaluation of the estimation performance is currently in progress.

5. CONCLUSION

In this article, we have presented a novel algorithm for estimating the amount of pressure generated by a patient on assisted ventilation, based on surface EMG measurements of the respiratory muscles. The algorithm is very efficient, real-time capable, and does not require performing any respiratory maneuvers. A numerical comparison with a state-of-the-art reference signal based on esophageal pressure measurements indicates a high estimation quality. Our method allows for continuously monitoring the patient's breathing activity. This, in turn, enables controlling ventilatory support in a way that may prevent the occurrence of patient-ventilator asynchrony, diaphragm atrophy or self-inflicted lung injury. Further improvements of the algorithm and an extensive validation will be the subject of future publications.

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