PATIENT-VENTILATOR ASYNCHRONY: AUTOMATIC DETECTION OF AUTOPEEP

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ABSTRACT

This paper introduces a method to automatically detect AutoPEEP (pulmonary distension), a frequent asynchrony in the patient-ventilator interface. The detection algorithm is developed based on a robust non-parametric hypothesis testing that requires no prior information on the distribution of the signal. The experiment results have shown that the proposed algorithm provide relevant AutoPEEP detection on both simulated and real data.

***Index Terms*—** Patient-ventilator interaction, AutoPEEP detection, Signal Norm Testing

1. INTRODUCTION

The objective of mechanical (or artificial) ventilation is to assist or to replace the spontaneous breathing of the patient by a ventilator when the patient breathing becomes inefficient or, in some cases, absent. Mechanical ventilation is routinely used in emergency ward, operating room, or intensive care unit. It can also be used at home or in nursing/rehabilitation institutions, paricularly for patients who suffer from chronic illness and whose spontaneous breathing is insufficient. Unfortunately, imperfect patient-ventilator interaction is very common. It has been shown that patient-ventilator mismatching is very frequently exhibited in both intubated patients receiving pressure support ventilation [1] and patients undergoing non-invasive ventilation [2]. Among these anomalies, pulmonary distension — i.e. AutoPEEP for *intrinsic positive end-expiratory pressure* — and patient-ventilator asynchrony are very frequent, but are not yet detected on currently used ventilators. Such imperfect interaction may generate incomplete ventilatory assistance, or even increased respiratory effort, thus generating deleterious adverse events and decreased prognosis. Therefore, the detection — possibly followed by an appropriate correction — of anomalies in the patient-ventilator interface is necessary.

Study in [3] has shown that the curves (flow, airway pressure and air volume) available on most of the recent mechanical ventilators provide much information to analyze the patient-ventilator interface. By visually monitoring these curves, patient-ventilator mismatching can be observed and detected during the assisted ventilation. Using the same inputs, automatic anomaly detection could also be investigated. In [4], a detection algorithm has been embedded in a ventilator system and has been reported to be successful in detecting ineffective triggering and double triggering, two major types of patient-ventilator asynchrony. Unfortunately, to the best of our knowledge, other types of asynchrony and anomaly, including AutoPEEP, have not been adequately considered.

In this paper, the AutoPEEP detection is considered. The detection is performed by Signal Norm Testing (SNT) on the flow signal captured from the patient-ventilator interface. SNT involves testing the norm of a signal observed in noisy conditions with respect to a certain tolerance fixed by users based on their know-how and/or experience of the domain. The paper is organized as follows. Section 2 will present the AutoPEEP detection based on SNT. The performance assessment will be carried out in Section 3 with the experiment results reported in the same Section. Finally, Section 4 will bring the overall conclusion and perspectives.

2. AUTOPEEP DETECTION USING SNT

2.1. Principle

AutoPEEP can be visually observed and detected through flow signal. Figure 1 shows an example of the flow signal with AutoPEEP captured during mechanical ventilation on real patient. Let $\theta(t)$ be the clean flow signal. AutoPEEP can be regarded as the non-return of the flow signal at the end of each expiratory phase to the null value — i.e. the hypothesis $\theta(t_e) \neq 0$, where t_e is the end-expiration instant of the considered breath. By defining some tolerance $\tau > 0$, the AutoPEEP can be considered as the event $|\theta(t_e)| > \tau$. In practice, τ is specified by the clinician. Its value is usually derived from his/her expertise of the domain. Other technical factors should also be taken into account, including: the flow sensor precision, the noise level, etc. Multiple values of τ could also be employed to provide a semi-quantitative evaluation of the persisted AutoPEEP on patient.

Given observation y in additive gaussian noise x — i.e.

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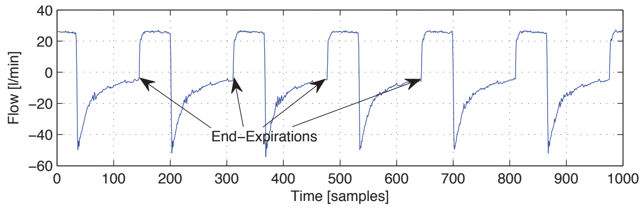


Fig. 1: Flow signal from real patient

$y = \theta + x$, where $\theta \equiv \theta(t_e)$ and $x \sim \mathcal{N}(0, \sigma^2)$ — the AutoPEEP detection resorts to testing the hypothesis $h_0 : |\theta| > \tau$ against the alternative one $h_1 : |\theta| \leq \tau$. This is a SNT problem in the sense given by [5]. In the sequel, a *test* $\mathcal{T}$ is any measurable map of $\mathbb{R}$ into $\{0, 1\}$. The value returned by $\mathcal{T}$ indicates the index of the accepted hypothesis. As in [6], the *power function* of test $\mathcal{T}$ is defined as the probability that $\mathcal{T}$ rejects the null hypothesis h_0, regardless of which hypothesis holds, i.e.

$$\beta_\theta(\mathcal{T}) = \mathrm{P}[\mathcal{T}(y) = 1]. \tag{1}$$

The *size* of $\mathcal{T}$ for testing $h_0 : |\theta| \leq \tau$ is defined as the least upper bound for the probability of false-alarm, i.e.

$$\alpha(\mathcal{T}) = \sup_{|\theta| \leq \tau} \beta_\theta(\mathcal{T}) \tag{2}$$

and its *power* is the value of $\beta_\theta(\mathcal{T})$ for θ such that $|\theta| > \tau$ — in other words, the detection probability. In practice, it is expected to maximize the power of $\mathcal{T}$ while restricting the false-alarm rate below some level γ ($0 < \gamma < 1$). This value γ is specified by the clinician with respect to the acceptable number of false-alarms during a period of time. For instance, a typical value of $\gamma = 0.01$ corresponds to a maximum of one false-alarm per 5 minutes with the usual frequency of 20 [breaths/min]. The UMP (Uniformly Most Powerful) test for the problem does not exist (cf. [6]). Moreover, the problem is invariant to any sign change in θ. Therefore, it is natural that the test itself should also be invariant to sign changes — that is, $\mathcal{T}$ should be an even function. It follows from [5] that, the UMP test among those even tests with size γ is:

$$\mathcal{T}_{\sigma\lambda_\gamma(\frac{\tau}{\sigma})}(y) = \begin{cases} 1 & \text{if} \quad |y| \geq \sigma\lambda_\gamma(\frac{\tau}{\sigma}) \\ 0 & \text{if} \quad |y| < \sigma\lambda_\gamma(\frac{\tau}{\sigma}) \end{cases} \tag{3}$$

in which $\lambda_\gamma(\rho)$ is the unique solution in η to the equation $1 - [\Phi(\eta - \rho) - \Phi(-\eta - \rho)] = \gamma$, where $\Phi(.)$ is the cumulative distribution of any standard normal distributed random variable. Additionally, it is UMPU (UMP unbiased) [5]. This thresholding test is used for the detection of AutoPEEP, one of the most frequent anomalies exhibited during assisted mechanical ventilation.

2.2. Automatic detection of AutoPEEP

Although the definition of AutoPEEP is based solely on the final sample of the expiratory phase of each breath, it is expected that taking multiple samples into account would improve the detection performance. Let $\mathbf{Y}$ be the observation vector containing the last L samples of the expiratory phase of the considered breath. $\mathbf{Y}$ is modeled as: $\mathbf{Y} = \mathbf{\Theta} + \mathbf{X}$, where $\mathbf{\Theta} = \begin{bmatrix}\theta(t_e - L + 1) & \ldots & \theta(t_e - 1) & \theta(t_e)\end{bmatrix}^T$ is the flow signal vector and $\mathbf{X} \sim \mathcal{N}(0, \sigma^2 \mathbf{I}_L)$ is additive gaussian noise. Vector $\mathbf{\Theta}$ can be factorized as: $\mathbf{\Theta} = \mathbf{p}\theta$ with $\theta \equiv \theta(t_e)$ as above and $\mathbf{p} = \begin{bmatrix}p_1 & p_2 & \ldots & p_L\end{bmatrix}^T$ is the waveform vector that corresponds to the form of the flow signal at the end of the expiratory phase. It should be noted that $p_L = 1$.

To aggregate L observed samples into a unique decision for the considered breath, $\mathbf{Y}$ is projected onto the direction generated by $\mathbf{p}$. We thus have: $z = \theta + u$ where $z = \mathbf{p}^T\mathbf{Y}/\|\mathbf{p}\|^2$, $u = \mathbf{p}^T\mathbf{X}/\|\mathbf{p}\|^2$ and $\|\mathbf{p}\|^2 = \mathbf{p}^T\mathbf{p}$ is the L_2 norm of waveform vector $\mathbf{p}$. Noise u follows normal distribution with zero mean and variance $\sigma_u^2 = \sigma^2/\|\mathbf{p}\|^2$. The problem is the same as before except that the noise level is reduced. The detection is thus:

$$\hat{d} = \begin{cases} 1 & \text{(AutoPEEP)} & \text{if} \quad |z| > \sigma_u\lambda_\gamma(\frac{\tau}{\sigma_u}) \\ 0 & \text{(NON-AutoPEEP)} & \text{if} \quad |z| \leq \sigma_u\lambda_\gamma(\frac{\tau}{\sigma_u}) \end{cases} \tag{4}$$

where $\lambda_\gamma(.)$ is calculated by the same way as before. By reducing the noise standard deviation, the detection probability is improved while the false-alarm rate is still limited to the specified level γ.

2.3. Parameter estimation

As long as it is concerned, the waveform vector $\mathbf{p}$ can be calculated based on the first N_{ref} breaths right after a verification/tuning session of clinician. These N_{ref} breaths are considered as the reference for the estimation. For breath k, the estimated waveform vector $\hat{\mathbf{p}}_k$ can be computed from the regression of the flow signal at the end of the expiratory phase. Indeed, during an expiratory phase, the flow signal form is determined by the passive action of the patient lung. Due to the resistance of the air ways and the elasticity of the lung, the flow signal in the expiratory phase can then be modeled by $f(t) = C - \phi e^{-\mu t}$ with $\phi > 0, \mu > 0$. This model is used to estimate $\mathbf{p}$ using nonlinear robust regression method. Given a set of n data points $\{(t_i, y_i), i = 1..n\}$ where $y_i = y(t_i)$ is the observation at instant t_i, the non-linear robust regression aims at solving the least squares problem:

$$(C, \phi, \mu)^* = \underset{C,\phi,\mu}{\arg\min} \sum_{i=1}^{n} w_i \left[y_i - (C - \phi e^{-\mu t_i})\right]^2 \tag{5}$$

where the introduction of weight vector $[w_1, w_2, .., w_n]$ makes it possible to reduce the influence of outliers onto the final result. Given the regression at the end of the expiratory phase, the last L values are used to calculate for the considered breath:

$$\hat{\mathbf{p}}_k = [\hat{y}(t_e - L + 1), \hat{y}(t_e - L + 2), ..., \hat{y}(t_e)]^T / \hat{y}(t_e) \tag{6}$$

The estimate for $\mathbf{p}$ can then be computed from the N_{ref} referenced breaths as: $\hat{\mathbf{p}} = \frac{1}{N_{\text{ref}}} \sum_{k=1}^{N_{\text{ref}}} \hat{\mathbf{p}}_k$. Since $f(t)$ is strictly increasing and the flow signal is negative in the expiratory phase, $\|\hat{\mathbf{p}}\|^2 > L$ and $\|\hat{\mathbf{p}}\|^2 \approx L$ if and only if the flow signal is almost constant at the end of the expiratory phase, i.e. $\hat{\mathbf{p}} \approx [1, 1, ..., 1]^T$.

In practice, noise is unknown. To make it complete, an estimation of noise standard deviation σ is required. Studies on non-parametric estimation based on Wavelet Shrinkage has shown that most of the wavelet coefficients obtained from the first level wavelet decomposition of a regular signal have very small amplitude. Only a small number of these wavelet coefficients, which pertain to the signal, are of higher amplitude [7]. This fact allows the use of robust estimators on the wavelet coefficients to provide a noise estimation. As in [7], we consider the MAD (median absolute deviation) [8, 9] estimator. Let $c_1, c_2, ...c_N$ be the wavelet coefficients obtained from the first level discrete wavelet decomposition of an N-sample segment of the flow signal y_n, the estimate $\hat{\sigma}_{\text{MAD}}$ of σ is provided by: $\hat{\sigma}_{\text{MAD}} = b \times \text{med}_i |c_i - \text{med}_j c_j|$ where $b \approx 1.4826$.

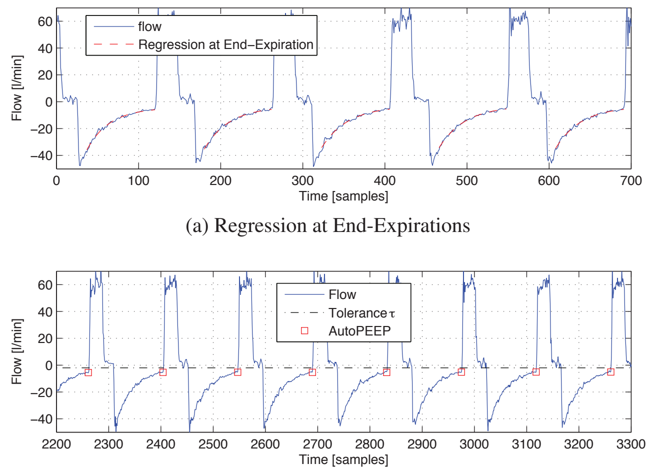
3. RESULTS

3.1. Simulations

To assess the detection performance of the proposed algorithm, the flow signal was synthesized on computer. For each breath, L end-expiration samples were generated. Vector $\mathbf{p}$ was supposed to be known and set to $\mathbf{p} = [1, 1, ..., 1]^T$, which corresponds to the worst case where $\|\mathbf{p}\|^2 = L$ with regard to noise level σ_u. The tolerance was set to $\tau = 2$[l/min] and the values of θ were randomly and uniformly generated between 0 and $-\frac{\tau}{1-\pi}$, where π is the proportion of positive cases (AutoPEEP). Since the false-alarm rate P_{FA} is always restricted to the specified value γ, it is more meaningful to plot the detection rate P_{D} versus different values of π, namely the *detection curve*, than to present the usual ROC (Receiver Operating Curve). Figure 2 shows detection curves for different noise levels and different values of L. The detection rate is significantly improved when more samples are aggregated. Of course, the lower the noise level, the better the detection.

3.2. Experiment results

The proposed AutoPEEP detection was also tested in a more realistic setting in which the interface between a ventilator and a model lung was established. In these experiments, the IngMar Medical model lung ASL5000 was used. Thirteen set of parameters (cf. Table 1) for both the lung emulator and the ventilator, which correspond to various practical situations, were carried out. The tolerance $\tau = 2$ [l/min] was employed again. With respect to this tolerance, among the 13 settings, 7 cases were reported as AutoPEEP and the other 6 cases were labeled as NON-AutoPEEP thanks to an independent clinical



(a) Regression at End-Expirations

(b) AutoPEEP Detection

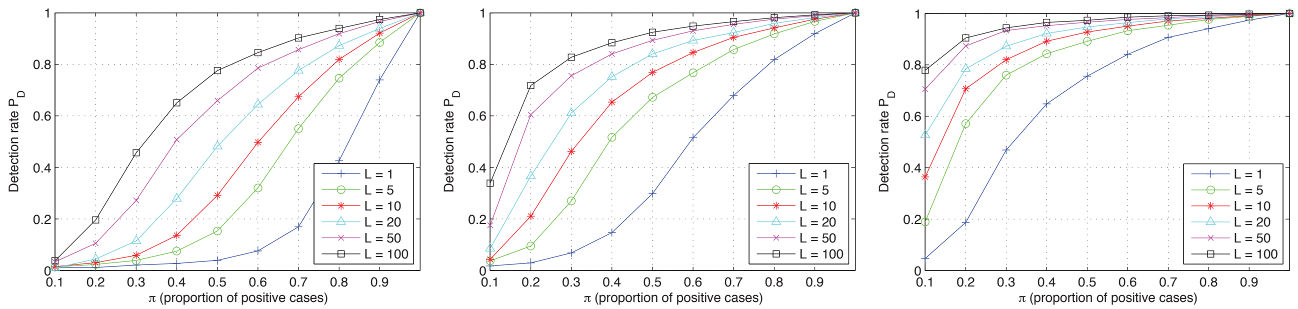
Fig. 3: Detection results on real patient data

analysis from hospital Cavale Blanche, Brest, France. The detection was performed on the basis of the flow signal captured by the sensor integrated in the ASL5000 model lung. For each case, about 1.5 minute of the signal flow was recorded. The corresponding number of breaths varied from 13 to 34, depending on the setting. Level γ was set to 0.01. The detection results are reported in Table 1. All the 13 cases were successfully detected by the proposed method. Moreover, in each case, all the breaths were precisely classified. No detection error has been found among the 323 breaths analyzed.

For further evaluation, experiments on real patient were carried out at hospital Cavale Blanche, Brest, France. For each patient assisted by mechanical ventilation, the signal was recorded during several hours. Figure 3 presents a typical case with the regression at end-expiration and the corresponding detection. It can be seen that the detection algorithm can precisely reveal the true label for all the breaths. Due to the huge amount of data to be clinically analyzed, a more detailed quantitative evaluation on real patients is in progress.

4. CONCLUSION

In this paper, the automatic AutoPEEP detection has been introduced. The experiment results have shown that the proposed algorithm is capable of precisely detecting AutoPEEP based solely on the flow signal, which is available in most of the currently used ventilators. Although the algorithm is developed for AutoPEEP, it can possibly be extended to the detection of other types of asynchrony, which can be regarded as deviations of the observed signal with respect to some reference. The approach is very general and could be used in many applications, including fault detection and structural health monitoring. It is also worth mentioning that, in this work, each breath is considered independently. Since AutoPEEP, once present, usually remains for a certain number of breaths,



(a) $\tau/\sigma = 0$ dB (b) $\tau/\sigma = 10$ dB (c) $\tau/\sigma = 20$ dB

Fig. 2: Simulations with $N = 10000$ breaths, tolerance $\tau = 2$[l/min] and level $\gamma = 0.01$

Table 1: Detection results on emulated flow data

Id	Parameters		True Label	Number of breaths	Detection by SNT [c]		
	Ventilator [a]	Model lung [b]			AutoPEEP	Non	Overall Label
1	PEP=0, V=500, f=15, P=0, I:E=1:2	C=80, R=5	Non	21	0	21	Non
2	PEP=0, V=500, f=15, P=0, I:E=1:2	C=30, R=5	Non	20	0	20	Non
3	PEP=0, V=500, f=25, P=0, I:E=1:2	C=80, R=5	AutoPEEP	33	33	0	AutoPEEP
4	PEP=0, V=500, f=25, P=0, I:E=1:1	C=80, R=5	AutoPEEP	34	34	0	AutoPEEP
5	PEP=0, V=300, f=20, P=0, I:E=1:2	C=80, R=5	Non	27	0	27	Non
6	PEP=0, V=500, f=12, P=0, I:E=1:2	C=80, R=5	Non	16	0	16	Non
7	PEP=0, V=500, f=20, P=15, I:E=1:3	C=80, R=5	Non	27	0	27	Non
8	PEP=5, V=500, f=20, P=0, I:E=1:3	C=80, R=5	Non	27	0	27	Non
9	PEP=5, V=500, f=20, P=0, I:E=1:2	C=120, R=10	AutoPEEP	27	27	0	AutoPEEP
10	PEP=0, V=700, f=20, P=0, I:E=1:2	C=120, R=10	AutoPEEP	27	27	0	AutoPEEP
11	PEP=0, V=700, f=20, P=0, I:E=1:6	C=120, R=10	AutoPEEP	24	24	0	AutoPEEP
12	PEP=0, V=700, f=20, P=0, I:E=1:1	C=120, R=10	AutoPEEP	27	27	0	AutoPEEP
13	PEP=0, V=700, f=20, P=0, I:E=1:2	C=140, R=25	AutoPEEP	13	13	0	AutoPEEP

[a] Ventilator parameters include: Positive Expiratory Pressure PEP [cmH_2O], air volume Vt [ml], frequency f [breaths/min], pause time P [%], Inspiratory to expiratory time ratio I:E.
[b] Model lung parameters include: compliance C [ml/cmH_2O] and resistance R [cmH_2O/l/s].
[c] For each of the experiments, the SNT-based AutoPEEP detection provides: the number of breaths detected as AutoPEEP, the number of breaths detected as NON-AutoPEEP (denoted as Non) and the overall label for the considered setting.

it can be expected that taking multiple consecutive breaths into account should yield better detection performance. In this respect, it could be profitable to extend SNT in a sequential decision framework to deal with such a problem. A complete study of this type will be addressed in future work.

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