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Mechanical ventilation system monitoring: automatic detection of dynamic hyperinflation and asynchrony

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***Abstract*— Automatic monitoring of mechanical ventilation system becomes more and more important with respect to the number of patients per clinician. In this paper, the automatic detections of dynamic hyperinflation (PEEPi) and asynchrony in a monitoring framework are considered. The proposed detection methods are based on a robust non-parametric hypothesis testing, namely Random Distortion Testing (RDT), that requires no prior information on the signal distribution. The experiment results have shown that the proposed algorithms provide relevant detection of abnormalities during mechanical ventilation.**

***Index Terms*— Patient-ventilator interaction monitoring, dynamic hyperinflation, PEEPi, asynchrony, Random Distortion Testing**

I. INTRODUCTION

Mechanical (or artificial) 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 for patients who suffer from chronic respiratory insufficience. It has been shown that patient-ventilator mismatching is frequently exhibited in both intubated patients receiving pressure support ventilation [1] and patients undergoing non-invasive ventilation [2]. Among these abnormalities, dynamic hyperinflation — hereafter called PEEPi (for *intrinsic positive end-expiratory pressure*) — and patient-ventilator asynchronies are very frequent, but are not yet detected in routine. Such imperfect interaction may generate incomplete ventilatory assistance, or even increased respiratory effort, thus generating various deleterious adverse events. The detections — possibly followed by appropriate corrections — of these abnormalities are therefore necessary.

It has been demonstrated that the graphical curves (flow, airway pressure and air volume) available on most recent mechanical ventilators provide much information to analyze the patient-ventilator interface (see [3] amongst others). If the detection of ventilatory abnormality by visually monitoring these curves is simple, it however requires the presence of a well-trained clinician at the patient's bedside. Therefore, automatic detection algorithms have been 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 abnormalities, including PEEPi, have not been adequately considered.

In this paper, the detections of PEEPi and asynchrony during mechanical ventilation are both proposed in the same automatic monitoring framework. The detections are carried out by Random Distortion Testing (RDT) on the flow signal captured from the patient-ventilator interface. RDT involves testing the distortion of a random signal with unknown distribution via its observation in noise. The paper is organized as follows. Section II will briefly summarize the RDT. The platform for automatic detection of PEEPi is then introduced in Section III with extension to the detection of asynchrony in Section IV. Before bringing the overall conclusion and perspectives in Section VI, a virtual ventilatory support simulator is presented in Section V.

II. RANDOM DISTORTION TESTING (RDT)

To begin with, let us consider the observation vector $\mathbf{Y}$ captured by a sensor: $\mathbf{Y} = \mathbf{\Theta} + \mathbf{X}$, where the d-dimensional vector $\mathbf{\Theta}$ is the signal of interest and $\mathbf{X}$ is the additive noise. Very often, $\mathbf{\Theta}$ is random with unknown distribution. Given some nominal deterministic model $\boldsymbol{\theta}_0$, it is then of interest to verify whether or not a realization of $\mathbf{\Theta}$ is a corrupted version of $\boldsymbol{\theta}_0$, i.e. testing [h_0: $\mathbf{\Theta} = \boldsymbol{\theta}_0$] against [$h_1$: $\mathbf{\Theta} \neq \boldsymbol{\theta}_0$]. As announced in [5], [6], no Uniformly Most Powerful (UMP) test exists for this problem. In the deterministic case where $\mathbf{\Theta}$ is not a random vector but an unknown deterministic vector $\boldsymbol{\theta}$, the so-called *holy trinity* — i.e. the generalized likelihood ratio test (GLRT) [7], the Rao score test [8] and the Wald test [9] — could provide powerful tests as long as a sufficient number of independent observations can be collected to benefit from the asymptotic properties of the maximum likelihood estimates and Fisher's information matrix. In [6], the RDT has been proposed to investigate the general case with random signal $\mathbf{\Theta}$ by considering the invariance of noise, particularly Gaussian noise.

It should be noted that, in real-world applications, due to unavoidable unknown random fluctuations of environment regardless of noise, small signal distortion is practically of little interest. Therefore, testing [$\mathbf{\Theta} = \boldsymbol{\theta}_0$] might be too strict — and even impossible — because of physics. It is then more reasonable to introduce some value τ, specified by user based on experience of the domain, to tolerate possibly small distortions around $\boldsymbol{\theta}_0$. The problem resorts to testing [h_0:

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$\|\boldsymbol{\Theta}-\boldsymbol{\theta}_0\| \leqslant \tau]$ against $[h_1: \|\boldsymbol{\Theta}-\boldsymbol{\theta}_0\| > \tau]$, where the Mahalanobis norm is adopted to compensate any variation introduced by the noise covariance matrix. Such a problem is named RDT. In practice, it is expected to maximize the power of the test while restricting the false-alarm rate to some level γ. Although no UMP test exists (cf. [6]), it could, however, be mentioned that the problem is invariant with respect to ellipsoids $\Upsilon_\rho = \{\mathbf{y} \in \mathbb{R}^d : \|\mathbf{y}-\boldsymbol{\theta}_0\| = \rho\}$. Therefore, it is natural to find the most powerful test among those having the same invariance. Such an optimal test is given in [6] by:

$$\mathcal{T}_{\lambda_\gamma(\tau)}(\mathbf{y}) = \begin{cases} 1 & (h_1 \text{ accepted}) \quad \text{if} \quad \|\mathbf{y}-\boldsymbol{\theta}_0\| > \lambda_\gamma(\tau) \\ 0 & (h_0 \text{ accepted}) \quad \text{if} \quad \|\mathbf{y}-\boldsymbol{\theta}_0\| \leqslant \lambda_\gamma(\tau) \end{cases} \tag{1}$$

where $\mathbf{y}$ is an instance of $\mathbf{Y}$. The optimal threshold $\lambda_\gamma(\tau)$ is the unique solution in η to the equation: $1-F_{\chi^2_d(\tau^2)}(\eta^2) = \gamma$, where $F_{\chi^2_d(\rho^2)}(.)$ is the non-central Chi-squared cumulative distribution function with d degrees of freedom and non-centrality parameter ρ^2. The test has MCCP (*maximal constant conditional power*) over Υ_ρ (cf. [6] for more details). It is also unbiased and UMP within the class of tests invariant with respect to ellipsoids. It is also worth mentioning that the proposed test is robust against any signal variation and any model imperfection. No information on the observation distribution is need. No training database is required. The test relies exclusively on knowledge of the observation noise, which is possibly estimated in practice.

III. THE AUTOMATIC DETECTION OF PEEPI

In this section, we address the automatic detection of PEEPi, a common ventilatory abnormality that usually occurs in patients with acute severe asthma or chronic obstructive pulmonary disease. Although not readily quantifiable via flow signal, PEEPi can easily be recognized by the non-return of expiratory flow to zero before the start of the next cycle (cf. Fig. 1). In this respect, an automatic detection of PEEPi due to either expiratory flow limitation and/or inappropriate ventilatory cycling was developed to help optimize care.

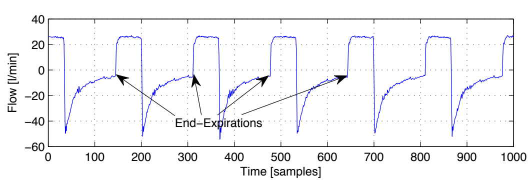


Fig. 1: An example of flow signal with the presence of dynamic hyperinflation (PEEPi).

Let f_t be the clean flow signal and y_t be its observation in additive noise x_t, assumed to be centered gaussian, i.e. $y_t = f_t + x_t$ with $x_t \sim \mathcal{N}(0,\sigma^2)$. PEEPi can be regarded as the event $[f_{t_k} \neq 0]$, where t_k is the end-expiration instant of the considered breath. Given a tolerance τ to take into account possible signal perturbations introduced by various factors, including the mechanical vibration of the air tube, the patient movement, the electro-magnetic interference, etc, the PEEPi detection is then the testing of $|f_{t_k}| \leqslant \tau$ versus $|f_{t_k}| > \tau$ on the basis the flow signal observation in presence of noise. The problem is RDT with dimension $d = 1$.

A. System overview

With respect to the discussion above, a platform for automatic detection of PEEPi based on a noisy observation of the flow signal has been developed as in Fig. 2. For each end-

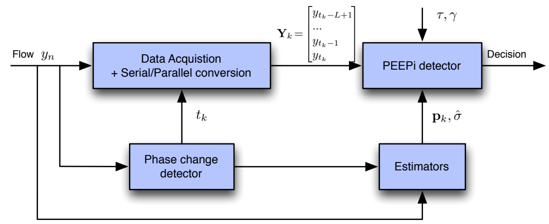


Fig. 2: The automatic PEEPi detection platform.

expiration t_k identified by the phase change detector, L end-expiratory flow samples are logged to form an observation vector $\mathbf{Y}_k$. Based on $\mathbf{Y}_k$ provided by the data acquisition/conversion and parameters given by the estimators, the PEEPi detector performs an optimal testing with respect to the given tolerance τ and level γ to decide whether or not a PEEPi is present. The values τ and γ are specified by clinician. For instance, a typical value of $\gamma = 0.01$ corresponds to a maximum of one false-alarm per 5 minutes with the usual rate of 20 [breaths/min]. Tolerance τ is usually derived from the clinician's expertise of the domain. Other technical factors could also be taken into account, such as: the flow sensor precision, the dynamic range of the signal, etc. Multiple values of τ could also be employed to provide a semi-quantitative evaluation of persisted PEEPi on patient.

B. PEEPi detector

By definition, the presence of PEEPi could be tested exclusively on the final expiratory flow sample y_{t_k} of each breath. However, it is expected that taking multiple samples into account would improve the detection performance. Let $\mathbf{Y}_k$ be the observation vector containing the last L samples of the expiratory phase of the considered k-th breath. We have: $\mathbf{Y}_k = \boldsymbol{\Theta}_k + \mathbf{X}_k$, where $\boldsymbol{\Theta}_k = \begin{bmatrix} f_{t_k-L+1} & \ldots & f_{t_k-1} & f_{t_k} \end{bmatrix}^T$ is the flow signal vector and $\mathbf{X}_k \sim \mathcal{N}(0, \sigma^2 \mathbf{I}_L)$ is gaussian noise. Vector $\boldsymbol{\Theta}_k$ can be factorized as: $\boldsymbol{\Theta}_k = \mathbf{p}_k f_{t_k}$ with $\mathbf{p}_k = \begin{bmatrix} p_1 & p_2 & \ldots & p_L \end{bmatrix}^T$ being 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 samples into a unique decision for the considered breath, $\mathbf{Y}_k$ is projected onto the direction generated by $\mathbf{p}_k$. We thus have: $z = f_{t_k} + u$, where $z = \mathbf{p}_k^T \mathbf{Y}_k / \|\mathbf{p}_k\|_2^2$, $u = \mathbf{p}_k^T \mathbf{X} / \|\mathbf{p}_k\|_2^2$ and $\|.\|_2$ is the Euclidean norm. Noise u is gaussian with smaller variance $\sigma_u^2 = \sigma^2/\|\mathbf{p}_k\|_2^2 \leqslant \sigma^2$. The decision is given by RDT as follows:

$$\hat{h}_{\text{PEEPi}} = \begin{cases} 1 & (\text{PEEPi}) \quad \text{if} \quad |z| > \sigma_u \lambda_\gamma(\frac{\tau}{\sigma_u}) \\ 0 & (\text{Not PEEPi}) \quad \text{if} \quad |z| \leq \sigma_u \lambda_\gamma(\frac{\tau}{\sigma_u}) \end{cases} \tag{2}$$

in which $\lambda_\gamma(\rho)$ is the unique solution in η to equation $1 - [\Phi(\eta-\rho) - \Phi(-\eta-\rho)] = \gamma$, where $\Phi(.)$ is the standard normal cumulative distribution function. It could be noticed that, by reducing the noise standard deviation (i.e. $\sigma_u \leqslant \sigma$), the detection performance is improved.

C. Parameters estimation

For the k-th breath, the waveform vector $\mathbf{p}_k$ can be estimated from the regression of the expiratory flow signal. Due to the resistance of the air ways and the elasticity of the lung, the expiratory flow signal can then be modeled by $g_t = C - \phi e^{-\mu t}$ with $\phi > 0, \mu > 0$. This model is used to estimate $\mathbf{p}_k$ using nonlinear robust regression method. Given the regression $\hat{g}_t$ at the end of expiratory phase, the last L values are used to calculate $\hat{\mathbf{p}}_k$ for the considered breath:

$$\hat{\mathbf{p}}_k = [\hat{g}_{t_k - L+1}, \hat{g}_{t_k - L+2}, ..., \hat{g}_{t_k}]^T / \hat{g}_{t_k} \tag{3}$$

Since g_t is strictly increasing and the flow signal is negative in the expiratory phase, $\|\hat{\mathbf{p}}_k\|_2^2 > L$. Therefore, σ_u decreases when L increases.

As long as noise standard deviation σ is required, it can be estimated from observation. Robust estimators, such as the the MAD (median absolute deviation) [10] and the DATE (d-dimensional adaptive trimming estimator) [11] can be used.

D. Results on clinical data

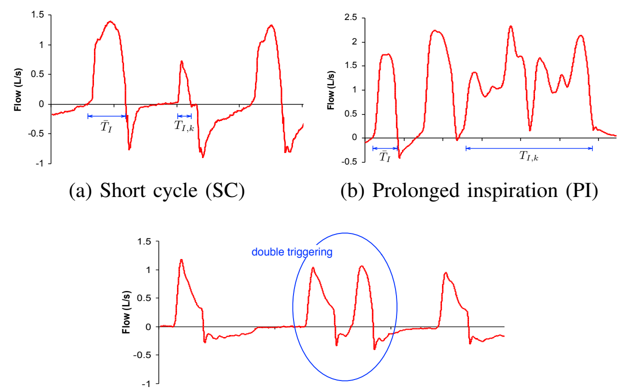
The detection performance of the proposed platform was assessed on clinical data captured from patients at the Medical Intensive Care Unit of Brest University Hospital, France and the Institut Universitaire de Cardiologie et de Pneumologie de Québec, Canada. In total, the final dataset contains 1998 breaths from 15 patients with different health conditions and following different specific treatments. The ground-truth was issued from an independent and double-blinded analysis performed by a set of experts. By this analysis, the dataset includes 1383 breaths with PEEPi and 615 breaths without PEEPi. The tolerance and the level were set to $\tau = 2$ [l/min] and $\gamma = 0.01$, respectively. The detection results have shown that the proposed detector worked very well on patient data with an accuracy higher than 93%, a precision higher than 99%, a recall (sensitivity) higher than 90% and a specificity higher than 98%. Only 7 false positives and 131 false negatives were found among 1998 breaths.

IV. Extension to the Detection of Asynchrony

Given the available functional blocks, the platform proposed above has been extended to the detection of asynchrony during mechanical ventilation. On the basis of how they can be observed and analyzed, asynchronies are classified into two categories: those caused by imperfect triggering (such as short cycles, prolonged inspirations, double triggering) and those related waveform distortion of the respiratory signal (such as ineffective efforts during expiration).

A. Triggering related asynchrony

By nature, the detection of asynchronies of this category resorts to determining the respiratory phase changes, including: inspiratory start/end and expiratory start/end, based exclusively on the available flow signal. In the proposed platform, these instants are given by the phase change detector. Basically, short cycle and prolonged inspiration concern the amount of time given to the inspiratory phase of a breath. When this is too short — more precisely, $T_{I,k} < \frac{1}{2}\ \bar{T}_I$, where $T_{I,k}$ is inspiratory time of the k-th breath and $\bar{T}_I$ is the reference value —, a short cycle (SC) is said to have occurred (cf. Fig. 3a). Similarly, an inspiration is said prolonged (PI) when the inspiratory time is too long, such that $T_{I,k} > 2\ \bar{T}_I$ (cf. Fig. 3b). The reference inspiratory time $\bar{T}_I$ is defined by averaging over previous breaths without timing asynchrony. Empirically, a number of 5 normal breaths are enough to compute this value in practice. On the other hand, double triggerings (DT), referring to cases where two ventilatory cycles are triggered by the mechanical ventilator within a single patient effort, can be revealed by the absence or nearly absence — i.e. presence with a very short duration — of an expiratory phase (cf. Fig. 3c).



(a) Short cycle (SC)

(b) Prolonged inspiration (PI)

(c) Double triggering (DT)

Fig. 3: Triggering related asynchronies

B. Waveform related asynchrony

In this category, an asynchrony can be regarded as the deformation of the waveform — or in other words, the distortion of the signal — from some reference curve. As a typical example, the detection of ineffective effort during expiration (IEE) (cf. Fig. 4), a frequent patient-ventilator asynchrony during mechanical ventilation, is hereafter investigated. Using the same notations as in Section III, let $\mathbf{Y}_k$ be the vector of L_E expiratory samples of the considered breath and $\boldsymbol{\theta}_0$ be the referenced expiration. Noise $\mathbf{X}_k$ is additive and gaussian as before. Given tolerance τ specified by clinician, the IEE detection then amounts to carrying out the event testing with $[h_0 : \|\boldsymbol{\Theta}_k - \boldsymbol{\theta}_0\| \leqslant \tau]$ (i.e. there is not IEE) and $[h_1 : \|\boldsymbol{\Theta}_k - \boldsymbol{\theta}_0\| > \tau]$ (i.e. there is IEE). The problem is RDT with $d = L_E$. With regard to Section II, for a specified level γ, the decision is given by the optimal test (1) as follows:

$$\hat{h}_{\text{IEE}} = \begin{cases} 1 \quad \text{(IEE)} \quad \text{if} \quad \|\mathbf{Y}_k - \mathbf{f}_0\| > \lambda_\gamma(\tau) \\ 0 \quad \text{(Not IEE)} \quad \text{if} \quad \|\mathbf{Y}_k - \mathbf{f}_0\| \leqslant \lambda_\gamma(\tau \end{cases} \tag{4}$$

In practice, either $\boldsymbol{\theta}_0$ is known or it can be estimated from normal cycles, which present no distortion.

As a preliminary detection performance assessment, simulations were carried out. The flow signal was synthesized with a rate of 20 breaths per minute, an inspiratory-to-expiratory time ratio $I{:}E = 1{:}2$ and the sampling time $T_s = 0.02$ [s]. The dimension of the problem was then $L_E = 100$.

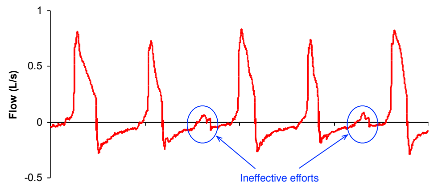


Fig. 4: Waveform related asynchrony: IEE

The presence and absence of IEE in a breath were randomly generated with equal probabilities. The duration of simulated patient effort was set to $T_{\text{es}} = 0.4$ [s]. Its position (when present) was uniformly distributed along the expiratory phase and its amplitude was rather small (the maximum value is 0.5 [cmH_2O]). For the detection, the tolerance was set to $\tau = \frac{T_{\text{es}}}{T_s}\tau_0 = 20\tau_0$ with $\tau_0 = 0.1$ [l/min]. As a result, $\tau = 2$ [l/min]. Indeed, $\frac{T_{\text{es}}}{T_s} = 20$ is merely the expected number of distorted samples in the observation vector. The detection performance is reported in Fig. 5. The results show that, even being masked by rather strong observation noise, IEE can successfully be revealed with high precision. The false-alarm rate is always guaranteed to be lower than the specified level γ.

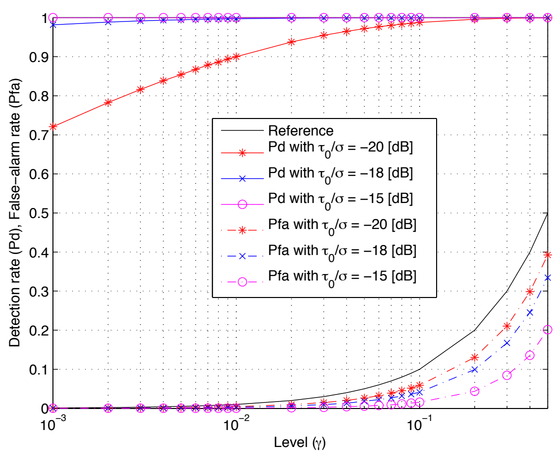


Fig. 5: IEE detection performancel

V. Virtual ventilatory support simulator

As a means of validation, a virtual ventilatory support simulator with integrated abnormality detectors (cf. Fig. 6) has been developed. On the patient's side, different mechanical characteristics of the respiratory system can be parametrized, making it possible to mimic various categories of patients in practice. On the ventilator's side, the control parameters are similar to those in standard ventilators currently used in practice. Other environment parameters are also adjustable, including noise. This simulator makes it possible to study pathologic cases that are rarely found in practice. It also allows us to carried out closed-loop test that are strictly regulated for safety sake. Other aspects of the detection platform, such as the sensitivity of the detection performance to noise, could also investigated by this mean. The software will be available on our site upon acceptance of the paper.

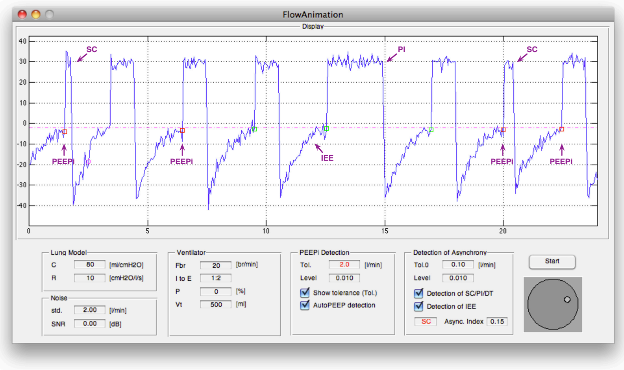


Fig. 6: A snapshot of the simulator with the presence of PEEPi, SC, PI and IEE.

VI. Conclusions

In this paper, the automatic detections of dynamic hyperinflation (PEEPi) and asynchony for a continuous ventilation system monitoring have been introduced. The experiment results have shown that the proposed algorithm is capable of precisely identifying PEEPi based exclusively on the flow signal, which is available in most of the currently used ventilators. Although not fully assessed, the detection of asynchrony has been shown to yield good results. Further validations, including assessment on clinical data and in a real-time closed-loop situation, should be carried in a future work. The approach is very general and could be used in many other applications, including analysis of other physiological signals such as ECG, EEG, etc.

References

[1] A. Thille *et al.*, "Patient-ventilator asynchrony during assisted mechanical ventilation," *Intensive Care Med.*, vol. 32, p. 1515–1522, 2006.

[2] L. Vignaux *et al.*, "Patient-ventilator asynchrony during non-invasive ventilation for acute respiratory failure: a multicenter study," *Intensive Care Medicine*, vol. 35, pp. 840–846, 2009.

[3] J. Roeseler, J.-B. Michotte, and T. Sottiaux, "Patient-ventilator asynchrony during pressure support: Usefulness of the curves displayed by the ventilator," *Réanimation*, vol. 19, pp. 62–65, 2010.

[4] Q. Mulqueeny *et al.*, "Automatic detection of ineffective triggering and double triggering during mechanical ventilation," *Intensive Care Med.*, vol. 33, pp. 2014–2018, 2007.

[5] E. Lehmann and J. Romano, *Testing Statistical Hypotheses*, 3rd ed. Springer, 2005.

[6] D. Pastor and Q.-T. Nguyen, "Random distortion testing in additive independent gaussian noise," *IEEE Transactions on Signal Processing*, 2013 [Accepted]

[7] J. Neyman and E. Pearson, "On the use and interpretation of certain test criteria for purpose of statistical inference," *Biometrika*, vol. 20, pp. 175 – 240, 1928.

[8] C. Rao, "Large sample tests of statistical hypotheses concerning several parameters with applications to problems of estimation," *Proceedings of the Cambridge Philosophical Soc.*, vol. 2, pp. 50–57, 1948.

[9] A. Wald, "Tests of statistical hypotheses concerning several parameters when the number of observations is large," *Transactions of the American Society*, vol. 54, no. 3, pp. 426–482, 1943.

[10] P. J. Rousseeuw and C. Croux, "Alternatives to the median absolute deviation," *Journal of the American Statistical Association*, vol. 88, no. 424, pp. pp. 1273–1283, 1993.

[11] D. Pastor and F. Socheleau, "Robust estimation of noise standard deviation in presence of signals with unknown distributions and occurrences," *IEEE Transactions on Signal Processing*, vol. 60, no. 4, pp. 1545–1555, 2012.