Prediction of the extubation outcome through Electrical Impedance Tomography measurements

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***Abstract*—Extubation failure can occur in 10 to 25% of patients who were successfully separated from their ventilator. In which case, patients need to be re-intubated. To reduce the extubation failure rate, we monitor patients during 48h after extubation using Electrical Impedance Tomography (EIT). In total, we recruited 34 patients from which 8 failed their extubation in the ICU ward. Prediction of extubation success or failure using only non-invasive EIT data show a sensitivity of 0.80 and a specificity of 0.73. The prediction for the 8 extubation failures was accurate for most right after the extubation and achieved 100% accuracy for the measurement set preceding the failure.**

***Index Terms*—Electrical impedance tomography, Mechanical ventilation, Weaning, Failure prediction.**

I. Introduction

In the Intensive Care Unit (ICU), a patient can be extubated from the mechanical ventilation once he succeeds the spontaneous breathing trial (SBT) [1]. Until that moment, clinicians use the information provided by the ventilator to monitor the respiratory mechanics of the patient. Once the patient is extubated, the decision relies on clinical examination or arterial blood gases, if available. This method relies greatly on the clinicians experience to detect a potential worsening that should alert and prompt for preventive therapeutic of extubation failure.

Electrical Impedance Tomography (EIT) [2] is a non-invasive and non-ionizing imaging technique that allows observations of conductivity variation in real-time. Applied to the thorax, variation seen in the EIT images have been attributed to conductivity variation induced by the air in the lungs [3] [4]. Different applications have arisen from this technique, particularly in the ICU. The principal use by the clinicians are for positive end expiratory pressure titration [5] [6], monitor ventilation distribution [7] [8] or the perfusion [9] [10].

The EIT could monitor the evolution of the patient's ventilation during the weaning phase to predict the extubation failure. Attempts have already been made to predict the outcome from EIT measurement [11]. To evaluate the prediction capacity of usual EIT features, they tested different thresholds to separate the success from the failed extubation. Measurements were realized before and after the SBT as well as right after the extubation and 30 minutes later. The study founds that the Global inhomogeneity index (GI) [12], yields the best prediction performance. With the failure defined as 1 and success as 0, they found an average between the different measurement to be equal to 0.82 for the sensibility and 0.53 for the specificity.

Our goal is to build an EIT prediction model, by using more than one EIT feature. This involves including the usual EIT features already described in the literature, as well as new ones proposed by our-self. We wants the prediction model to be consistent with medical practice and thus constructing model that can be understood by clinicians. The first contribution of this paper is the integration of new EIT features. The second focus is on improving the prediction results.

This paper is structured as follow: Section II describes the clinical study with the patients, the weaning observation and data acquisition, Section III explains our EIT framework to reconstruct the EIT images and the feature's extraction, Section IV shows the different prediction models, Sections V and VI show the results with related discussion.

II. Materials and methods

A. Clinical study

A clinical study took place between February 2020 to March 2022 in the intensive care unit of the hospital La Pitié Salpêtrière in Paris (NCT04180410). On the 14th of February 2020, a national ethics committee approved the protocol.

B. Patients

After a successful SBT, patients are examined to see whether they can be included in the study. In purpose, we

TABLE I
COUNT OF PATIENTS PER CLASS FOR ALL DATASET.

	H0	H2	H6	H12	H24	H36	H48
Success	26	25	24	14	18	6	13
Failure	8	6	5	2	3	0	0

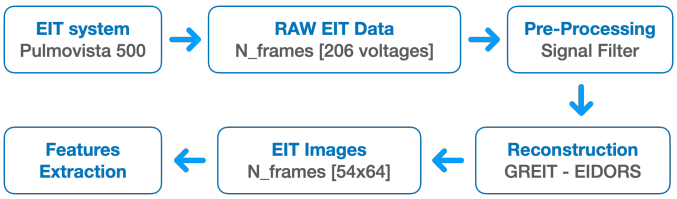

Fig. 1. EIT framework: from the EIT system to the EIT images.

selected high risk patients (i.e. patients with a likelihood to fail extubation based on intrinsic characteristics), to increase the basic 10 to 25% [13]. The inclusion criteria are: (1) age greater than 65 years (2) invasive mechanical ventilation duration superior to 48h (3) known or suspected COPD [1] (4) known or suspected heart failure.

C. Weaning observation

Patients were included once the physician in charge prescribed extubation. The first visit, H0, occurs moments before the extubation while the patient is still ventilated. At this time, the patient is ventilated with the pressure support ventilation mode. EIT measurements are realized as well as other measures such as lung and heart ultrasound or blood analysis. After that first visit, the patient is extubated and observed during 48 hours. The next visits occurs 2, 6, 12, 24, 36 and 48 hours after the extubation (later referred as H2, H6 and so on). The count of patients for all dataset is shown in Table I.

Extubation failure is defined as a post-extubation acute respiratory failure, which can include the following: (1) respiratory rate (RR) $>$ 35 breaths/min (2) SpO2 $<$ 90% with O2 $>$ 5L/min (3) activation of the accessory respiratory muscles (4) if blood gas available, pH $<$ 7.35 with PaCO2 $>$ 45 mmHg.

Patients that failed the extubation for reasons other than ventilation failure are excluded of the study at it falls outside the monitoring scope of the EIT.

D. Data acquisition

At each visit, EIT measurement is realized with the Drager Pulmovista 500 [14] set to 30 frames/s. The 16 electrodes belt is positioned between the 4th and 6th intercostal space. A temporary mark is placed on the thorax to make sure the belt does not move significantly between takes. Each EIT measures last for 5 minutes.

III. EIT FRAMEWORK

A. EIT acquisition

Some of the patients were agitated after the extubation, as they adapted to their new conditions. This created noise in the EIT signal. Spikes in the signal occur due to cough or rapid movement from the patient. Drift of conductivity signal occurs due to sudation or small belt movement during the measure. To remove the spikes and drift, a bandpass filter is applied with cutoff frequencies equal to 0.05Hz and 0.7Hz.

For the reconstruction, we use the algorithm GREIT [15], from the open library EIDORS [16] in Matlab. Different GREIT parameters were tested to find the one that optimize the reconstruction [17]. They were optimized as to minimize the difference between the volume measured by the ventilator and the volume estimated through the EIT [18]. The reconstruction matrix is then exported in our EIT framework which is implemented using Python programming language. Two sorts of images are reconstructed: the dynamic images, which correspond to the images from each recorded frames; the tidal images, which are the difference from inspiratory and expiratory frames. All images have a size of 54x64 pixels. The whole process is sum up in the Figure 1.

[1]COPD: Chronic Obstructive Pulmonary Disease

TABLE II
MACRO LIST OF THE DIFFERENT USED EIT FEATURES.

Usual features from the literature	Added features
CoV [19]	Lung shape
GI [12]	Lung area
Regionnal distribution [20]	Flow EIT
ΔZ [21]	RSBI EIT
Respiratory rate	

B. EIT features extraction

To ensure the capture of the full picture of the ventilation from the EIT perspective, we included most EIT features from the literature (cf. Table II). The Center of Ventilation (CoV) was used to calculate the ventral to dorsal distribution, as well as the right to left side distribution. The regional distribution calculates the percentage of ventilation present on 4 quadrants (ventral left and right sides as well as dorsal left and right). This metric and the conductivity variation ΔZ, which corresponds to the sum of each frame, are calculated on the dynamic and the tidal images.

In addition to the usual features, we added 4 new groups of EIT features. Lung shape measures the pixel dimension of both lungs through 6 underlying features. Those 6 features measures the height and width of both lungs as well as calculating the compasity (width/height). Lung area count the pixel surface on the ventral, dorsal left and right side. Two other metrics in relation with the temporal aspect of the ventilation are also added, RSBI_{EIT} and flow_{EIT}. The Rapid Shallow Breathing Index (RSBI) [22] and the ventilation flow are both metrics already used in ICU. It is possible to calculate EIT equivalent by taking advantages of the linearity between the ventilation volume and ΔZ [21].

It was observed from a previous study, that patients who failed the extubation have reduced breathing variability than patients who succeeded [23]. For this reason, we calculate the coefficient of variation for each EIT features. All of this brings us to a total of 61 EIT features.

IV. Prediction models

A. Models training

At H0, the dataset is made of 26 patients who succeeded the extubation and 8 patients who failed the extubation (cf. Table I). Then the number of failures decrease throughout the hours due to re-intubation that can occurs at different moments. The number of successes decrease due to patients leaving the ICU as their condition got better. In addition to that, measurements from H12 and H36 could not always be realized as night shift were not always available. H36 and H48 were excluded from our analysis due to lack of failure cases.

The tree estimators were tested: decision tree [24], random forest [25] and SVM[2] [26]. They were chosen as they are able of handling databases with few examples. We use the implementation from the Python library, sickit-Learn.

Different hypotheses have been tested to sort the data. One stood out significantly by his prediction performance, which we called "incremental H". We made the hypothesis that EIT results from past dataset, still contains important information that can be used for the training of the current dataset. To that end for each dataset Hx (H2, H6, ...), we include past dataset and the current one for the training set. For the testing set, we use only data from the current dataset not present in the training set.

We design our own cross-validation function to ensure that the training set is balanced between success and failure. The failure patients are split with 70% for the training set and 30% for the testing set. The number of failure patients for the training set is then matched with an equal amount of success patients. The rest of the success patients goes to the testing set. So for H0, the training set is composed of 12 patients (6 success and 6 failures) randomly picked. The testing set contain the 23 remaining patients (20 success and 3 failures). Those steps are iterated 1000 times to cover various possible mix. The results of the 1000 iterations are then average to have an overall performance.

To compare the results, the sensitivity and specificity are calculated, with failure defined as 1 and success as 0.

B. Models optimization

To optimize the models, we opt to optimize the detection of patients that are going to fail the extubation. That way we can increase the accuracy of failure prediction so that clinicians could react in time to administer adapted therapeutics like non-invasive ventilation (NIV). Though, doing so diminish the accuracy to predict success patients. Therefore, we aim to improve the sensibility.

Each model is optimized through two different methods: (1) fine-tuning of the hyperparameters through a grid search (see Table III for the list of hyperparameters) (2) rank the features depending on their correlation with the outcome and reduce the number of features to maximize the sensibility. We use the point biserial correlation as it is designed to calculate the correlation between discrete and continuous data.

[2]Support Vector Machine

TABLE III
Hyperparameters tested for each estimators during the fine-tuning optimization

SVM	Kernel	RBF, Polynomial, Sigmoid
	Regularization parameter	[1, 10, 100, 1000]
Decision tree	Criterion	Gini, Entropy
	Max depth	[2, 3, 4, until leaf is pure]
Random forest	Nb of estimators	[5, 25, 50, 75, 100]
	Criterion	Gini, Entropy
	Max depth	[2, 3, 4, until leaf is pure]

The point biserial is used to calculate the correlation between the different features and the extubation outcome. Th as we want the correlation between discrete and continuous data.

V. Results

A. Results with default settings

We first use the default hyperparameters from Sickit-Learn to have a baseline. SVM uses the RBF kernel with the regularization parameter equal to 1. Decision tree uses the Gini criterion, the estimator creates new nodes until all leaf are pure. Random forest generates 100 decision tree estimators with the same settings than previously stated. By averaging the results from the different dataset, the decision tree have a sensibility of 0.55 and a specificity of 0.75; the SVM have 0.44 and 0.92; the random forest have 0.59 and 0.85.

B. Results after optimization

After fine-tuning the different models, the sensitivity is optimized for the SVM, using the sigmoid kernel with the regularization parameter equal to 1. Random forest and decision tree both use the entropy criterion as well as a max depth equal to 2. From our observation, increasing the depths of the trees increased the specificity while decreasing the sensitivity. Random forest was optimized with 75 estimators. The prediction results after the fine-tuning can be seen in Table IV. From those initial results, the SVM is the best estimator with regards to the sensitivity, and has equivalent performance with regards to the specificity.

The features optimization reduces greatly the number of features for decision tree and random forest. They are respectively left with 7 and 9 from the best features depending on their point biserial correlation score. The SVM on the other hand use 42 features. All prediction results for all takes can be seen in the Table V. Decision tree estimators give the best specificity but low specificity. The random forest is the best predictor for the detection of success patients with the highest specificity. While the SVM has good performance on both account, making it the most balance.

To understand the effect of the added EIT features, we computed the prediction models using only the usual EIT features. Those prediction results are displayed in Table VI with all previous results. We can observe that the new 4 EIT features allowed to improve the sensitivity by 12% and the specificity by 21% for the SVM estimator.

TABLE IV
PREDICTION RESULTS FOR THE EXTUBATION OUTCOME WITH THE FINE-TUNING. SENSI REFERS TO THE SENSIBILITY AND SPECI TO THE SPECIFICITY.

	Decision tree		**Random forest**		**SVM**	
	Sensi	Speci	Sensi	Speci	Sensi	Speci
H0	0.48	0.61	0.45	0.69	0.30	0.79
H2	0.59	0.55	0.37	0.85	0.70	0.71
H6	0.61	0.60	0.44	0.98	0.83	0.86
H12	0.98	0.57	0.64	0.98	1.00	0.74
H24	0.77	0.59	0.76	0.87	1.00	0.66
Mean	0.69	0.58	0.53	0.87	0.77	0.75

TABLE V
PREDICTION RESULTS FOR THE EXTUBATION OUTCOME AFTER THE FINE-TUNING AND FEATURES OPTIMIZATION.

	Decision tree		**Random forest**		**SVM**	
	Sensi	Speci	Sensi	Speci	Sensi	Speci
H0	0.56	0.59	0.54	0.65	0.31	0.81
H2	0.96	0.60	0.91	0.82	0.81	0.70
H6	0.75	0.61	0.57	0.91	0.90	0.84
H12	1.00	0.57	1.00	0.78	1.00	0.72
H24	1.00	0.61	0.76	0.83	1.00	0.58
Mean	0.85	0.59	0.75	0.80	0.80	0.73

We turn to the Table VII to have a finer analysis on the prediction of each patient. The percentage of accurate prediction for the SVM estimator shows that the prediction is accurate hours before the failure.

To finish, a comparison is done between our method and the one proposed by Longhini [11]. As stated in the introduction, their best prediction model is achieved with the GI. So, we compare the prediction capability of the GI on our dataset against the SVM results after feature optimization VIII.

VI. DISCUSSION

In this work, models to predict the extubation failure for a patient during weaning period were assessed. The accuracy over the prediction of patients falling their extubation were prioritized for optimization. For the fine-tuning results, the best estimator is the SVM (cf. Table IV).

We observe that optimizing the features significantly improved the results for decision tree and random forest methods, but stayed relatively the same for SVM. In terms of pure sensitivity, the best model is the decision tree. The results with SVM are more balanced between sensitivity and specificity tough. Moreover, the sensitivity increases through the hours demonstrating that the accuracy increases for the failure group, when it approaches the actual failure.

The Table VI shows the prediction results when using only the features from the literature. Regardless of the estimator, the extubation prediction is better when using the additional EIT features (lung area, lung shape, RSBI_{EIT} and flow_{EIT}).

Comparing our method with Longhini et al., we observe that the GI offers better sensibility at the start (H0 and H2). The GI declines throughout the hours, whereas the opposite effect occurs for the SVM as the sensitivity continuously increases. This confirms the findings by Longhini et al. that the GI is adequate to predict the extubation failure at the start of the extubation. Though, we observe that a more complex model is needed afterwards.

One of the limitations of the study is low number failure patients, especially for H12 and H24. Though for such study, it is not possible to reach a balance dataset as the usual failure rate is around 10 to 25%.

To conclude, we were able to construct a reliable prediction model for the extubation failure using EIT measurements. Our model has better performance near the hours before the failure (cf. Table VII), but most patients have already an accurate prediction 2 hours after the extubation, and continue to have consistent prediction afterward. The use of standard machine learning estimators was the most relevant in our cases for two reasons. The first being that they are better fit to handle database with few examples. Second, those estimators allow for an easier medical interpretation of the results. Which could in time be used to make new rules for extubation, using the EIT.

TABLE VI
AVERAGE OF ALL DATASET FOR EACH DIFFERENT MODELS.

		Decision tree		Random forest		SVM	
		Sensi	Speci	Sensi	Speci	Sensi	Speci
Usual EIT features		0.71	0.62	0.60	0.78	0.72	0.60
With the additional features	Default hyperparameter	0.55	0.75	0.44	0.92	0.59	0.85
	Fine-tuning	0.69	0.58	0.53	0.87	0.77	0.75
	Features optimization	0.85	0.59	0.75	0.80	0.80	0.73

TABLE VII
PERCENTAGE OF ACCURATE PREDICTION FOR EACH FAILURE PATIENT. THE X ARE TAKES THAT WERE NOT REALIZED

Failure patient	H0	H2	H6	H12	H24	Re-intubation [hours]
P01	4	58	100			15
P02	4	97	95	100	100	35
P03	89	93	100	X	100	45
P04	16	70	54	100		24
P09	81					0.5
P14	5	64	100			8
P29	100					1.5
P36	21	89	X	X	100	24

TABLE VIII
COMPARISON BETWEEN LONGHINI METHOD ON OUR DATASET AND THE SVM MODEL AFTER FINE-TUNING.

	GI		SVM	
	Sensi	Speci	Sensi	Speci
H0	0.78	0.58	0.31	0.81
H2	0.83	0.64	0.81	0.70
H6	0.80	0.96	0.90	0.84
H12	0.50	1.00	1.00	0.72
H24	0.67	0.94	1.00	0.58
Mean	0.72	0.82	0.80	0.73

ACKNOWLEDGMENT

We want to thanks Dr Vincent Bonny for his help on including patients, and Bioserenity to have funded this study.

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