

# Is the asynchronous phase of thoracoabdominal movement a novel feature of successful extubation? A preliminary result

Po-Hsun, Huang, Wei-Chan Chung, Chau-Chyun Sheu, Jong-Rung Tsai and Tzu-Chien Hsiao

**Abstract**—Mechanical ventilation is necessary to maintain patients' life in intensive care units. However, too early or too late extubation may injure the muscles or lead to respiratory failure. Therefore, the spontaneous breathing trial (SBT) is applied for testing whether the patients can spontaneously breathe or not. However, previous evidence still reported 15%~20% of the rate of extubation fail. The monitor only considers the ventilation variables during SBT. Therefore, this study measures the asynchronization between thoracic and abdomen wall movement (TWM and AWM) by using instantaneous phase difference method (IPD) during SBT for 120 minutes. The respiratory inductive plethysmography were used for TWM and AWM measurement. The preliminary result recruited 31 signals for further analysis. The result showed that in successful extubation group can be classified into two groups, IPD increase group, and IPD decrease group; but in extubation fail group, the IPD value only increase. Therefore, the IPD decrease group can almost perfectly be discriminated with extubation fail group, especially after 70 minutes (Area under curve of operating characteristic curve was 1). These results showed IPD is an important key factor to find whether the patient is suitable for extubation or not. These finding suggest that the asynchronization between TWM and AWM should be considered as a predictor of extubation outcome. In future work, we plan to recruit 150 subjects to validate the result of this preliminary result. In addition, advanced machine learning method is considered to apply for building effective models to discriminate the IPD increase group and extubation fail group.

**Clinical Relevance**— The finding of this study is that the patients whose average IPD of 95 to 100 minutes was smaller than average IPD of first 5 minutes of SBT could be 100% successful extubation. In addition, ability of discrimination of average IPD after 70 minutes presents AUC 1.

## I. INTRODUCTION

To save critically ill patients who cannot breathe by themselves in intensive care units, mechanical ventilation is necessary. For clinical, the timing of extubation is an important issue. The respiratory failure may occur if too early to remove the artificial airway support. However, prolonged mechanical ventilation also results in diaphragmatic or lung function impairment [1–3]. The previous evidence reported that approximately 15% to 20% of patients would occur respiratory failure after extubation and need reintubation. Reintubation would increase the mortality risk in critically ill patients [4]. In

P.-H Huang is with the Institute of Computer Science and Engineering, College of Computer Science (CS), National Yang Ming Chiao Tung University (NYCU), Hsinchu, Taiwan (e-mail: [pohsun.cs05g@nctu.edu.tw](mailto:pohsun.cs05g@nctu.edu.tw)).

W.-C Chung is with the Division of Respiratory Therapy of Kaohsiung Medical University Hospital (KMUS), Kaohsiung, Taiwan (e-mail: [u97009045@gmail.com](mailto:u97009045@gmail.com)).

C.-C Sheu is with Division of Pulmonary and Critical Care Medicine of KMUS, Kaohsiung, Taiwan. He is also with the School of Medicine, College of Medicine, KMU, Kaohsiung, Taiwan (e-mail: [shuucc@gmail.com](mailto:shuucc@gmail.com)).

general, most of extubation timing were judged by the experience of clinicians. Some factors also used for extubation including the rapid shallow breathing index (RSBI) and maximal inspiratory pressure (Pimax) [5–8]. Both of these two factors are widely used as predictors for predicting the extubation outcome. Nevertheless, only depend on the value of these two factors still cannot avoid extubation failure.

In addition, the spontaneous breathing trial (SBT) is widely applied to test whether the continued mechanical ventilation is necessary for intubated patients or not. The variables measured during SBT are possibly related to the extubation outcome [9, 10]. The indication of tidal volume or breathing rate are common to check whether the patients can breathing by themselves or not. However, Most of clinical variables only consider the ventilation parameters. The respiratory muscles were an important part of breathing but less consider in clinical extubation judgments. Therefore, the wall movement of thoracic (TWM) and abdomen (AWM) were measured during SBT in this study.

To analysis the thoracoabdominal movement, asynchronization between TWM and AWM is an important indicator. Lissajous figure analysis is one of method for measure the asynchronization between TWM and AWM [11]. However, the time resolution of Lissajous figure analysis is limited (only one value per breathing). Therefore, Chen proposed a novel method named instantaneous phase difference (IPD) for TWM and AWM asynchronization measurement [12]. IPD combined the main decomposition method of Hilbert-Huang transform (HHT) and normalization direct quadrature (NDQ) method to meet the condition of Bedrosian's theorem and Nuttall's theorem for meaningful instantaneous phase calculation [13]. Therefore, the IPD of the intubated patients during SBT were calculated in this study to compare the successful extubation group with the extubation failure group.

## II. MATERIALS AND METHOD

### A. Experiment and subjects

The experiment were carried out in Kaohsiung Medical University Hospital, Kaohsiung, Taiwan. The project plan to recruit 150 patients. The 35 subjects were recruited to date for preliminary result. However, because of signal distortion, 4 subjects were excluded. There are several methods for SBT.

J.-R Tsai is with the Department of Internal Medicine of Kaohsiung Municipal Cijin Hospital, Kaohsiung, Taiwan. He is also with the Division of Respiratory Therapy, College of Medicine, KMUH, Kaohsiung, Taiwan (e-mail: [jrtsai@kmu.edu.tw](mailto:jrtsai@kmu.edu.tw)).

T.-C Hsiao is with the Department of Computer Science, College of CS and Institute of Biomedical Engineering, NYCU, Hsinchu, Taiwan (corresponding author to provide phone: 03-571-2121#59329; e-mail: [labview@cs.nctu.edu.tw](mailto:labview@cs.nctu.edu.tw)).

Some studies showed that the pressure support method is more effective than T-tube method [14, 15]. Therefore, a pressure support of 6cmH<sub>2</sub>O were applied in this study. The patients were asked to do SBT and extubation when all parameters of “Weaning protocol of Kaohsiung Medical University Hospital intensive care units” (Fig. 1) met the criteria. The duration of SBT in this study was 120 minutes. The respiratory inductive plethysmography (RIP, RIPmate Inductance Belt Abdomen Kit, Adult, Alice 5, Ambu Inc., Denmark) were used for TWM and AWM measurement during whole SBT. A DAQCard (NI Corp., Austin, USA) with a sampling rate of 128 Hz was used to acquire signals. Only first 100 minutes of signal were used for further analysis. Patients who experienced respiratory failure or died within 48 hours after extubation were defined as the extubation failure group, and those who did not were defined as successful extubation group. In addition, the basic information were also acquired from medical record which including sex, age, point of Acute Physiology And Chronic Health Evaluation II (APACHE II), height, body weight (BW), ideal BW (IBW), Glasgow coma scale (GCS) when enter ICU, GCS before doing SBT, endotracheal tube diameter, systolic blood pressure (SBP) before SBT, diastolic blood pressure (DBP) before SBT, heart rate before SBT (HR), oxygen saturation (SpO<sub>2</sub>) before doing SBT, maximal inspiratory pressure (Pimax) and leak of cuff of endotracheal tub, . The experiment was approved by the Institutional Review Board of Kaohsiung Medical University Chung-Ho Memorial Hospital (KUMHIRB-F(1)-20200033).

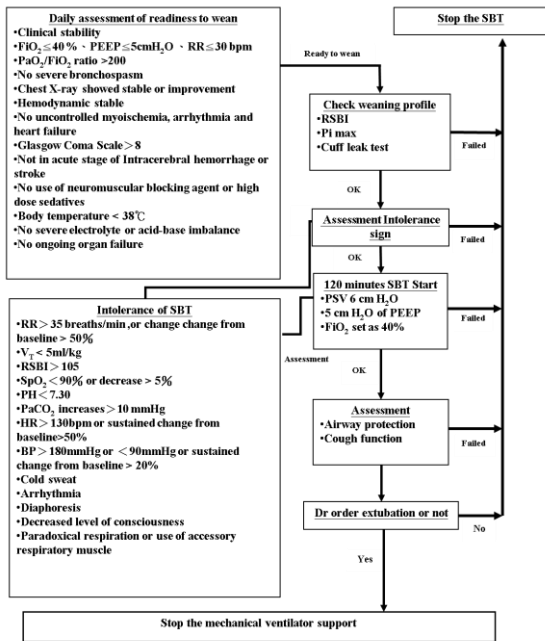


Figure 1. Weaning protocol of Kaohsiung Medical University Hospital intensive care units.

### B. Signal processing

Firstly, the lowpass filter of 0.5 Hz were applied on RIP signal to eliminate the noise. The IPD procedure was described following.

### 1) Empirical mode decomposition (EMD)

The EMD is a main decomposition method of HHT [16]. The main purpose of EMD is to decompose the signal into intrinsic mode functions (IMF), which the average envelope is approximate to 0 at any point and number of local maximum and local minimum must be equal or differ most by 1 to the number of zero-crossing. The main loop procedure called sifting process of EMD was described in following:

- Find the local maximum and minimum of input signal.
- Produce the upper envelope by local maximum and lower envelope by local minimum by using cubic spline interpolation.
- Calculate the mean envelope of upper and lower envelopes.
- Subtract the mean by input signal to get output signal.
- Check the output signal is IMF or not. If output signal is not an IMF, replace the input signal by output signal to redo this loop; otherwise, output the output signal as an IMF.

After output an IMF, subtract this IMF by the first one input signal to get the residual signal. Using the residual signal to be input signal to redo the sifting process until the residual signal is monotone. Therefore, the relationship of original input signal, IMFs, and residual is

$$S(t) = \sum IMF(t) + r(t) \quad (1)$$

where  $S(t)$  is the raw RIP signal and  $r(t)$  is the residual.

However, the mode mixing problem, which means that the different frequency band components are possibly decomposed into one IMF, may occur in EMD. For solving the problem, the complete ensemble EMD (CEEMD) is one of the effectively method [17]. A white noise be added into and be subtracted by the raw signal before doing sifting process.

$$\begin{bmatrix} S_p(t) \\ S_n(t) \end{bmatrix} = \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix} \begin{bmatrix} S(t) \\ N(t) \end{bmatrix} \quad (2)$$

where  $N(t)$  is the Gaussian white noise,  $S_p(t)$  and  $S_n(t)$  denote the  $S(t)$  adding and subtracting  $N(t)$ , respectively.

For reducing the influence of Gaussian white noise, redo many times of CEEMD and average all corresponding IMFs to get ensemble IMFs. In this study, 50 times was set.

### 2) Main component selection

After the CEEMD, many IMFs were extracted. To determine which one is the main component, the energy density method was applied in this study. The energy of each IMF is calculated by

$$E_n = \sum_{t=0} IMF_n^2(t) \quad (3)$$

where  $E_n$  is the energy of  $n^{\text{th}}$  IMF,  $IMF_n(t)$ . The main component was determined by the max energy one of IMF between IMF<sub>4</sub> to IMF<sub>6</sub>.

### 3) Normalized direct quadrature (NDQ)

The NDQ was applied for instantaneous phase calculation. The main component of IMFs can be served as cosine function. Therefore, the sine function and tangent function can be calculated by

$$\sin\theta(t) = \sqrt{1 - \cos^2\theta(t)} \quad (4)$$

$$\tan\theta(t) = \frac{\sin\theta(t)}{\cos\theta(t)} \quad (5)$$

Therefore, the phase can be calculated by arctangent. The unwrapped phase was produced for IPD calculation.

#### 4) Instantaneous phase difference (IPD)

After the instantaneous phase of RIP of TWM ( $\theta_{TWM}(t)$ ) and RIP of AWM ( $\theta_{AWM}(t)$ ) calculated, the IPD can be calculated by

$$IPD(t) = \theta_{TWM}(t) - \theta_{AWM}(t) \quad (6)$$

Because the resolution of IPD time series is too high, calculate the trimmed mean (25%) of IPD in a window without overlapping. The window size was set to 5 minutes. Therefore, total 20 values per subject can be indication (window 0 presents 0 to 5 minutes, window 1 presents 5 to 10 minutes, and so on.).

#### C. Statistical analysis

The basic information result would be showed in mean  $\pm$  standard deviation. The IPD result of mean and standard deviation would be showed by error bar plot per window. Because of small size and unequal sample sizes between two groups, the Mann-Whitney U test was applied in this study for independent variable distribution difference analysis in two-tailed tests. A p-value of  $<.01$  indicated a significant difference. The result would be showed by p-value. The receiver operating characteristic curve (ROC) was applied to test the discriminatory ability of the IPD in each window, with results expressed as the area under curve (AUC) value. In addition, for combining total 20 values of IPD during SBT, the multivariable logistic regression (MLR) was applied to create model. The calibration accuracy, AUC and F-score of model were reported. Moreover, the leave-one-out validation (LOO) was also applied to test the model. The result of LOO was reported as accuracy and Cohen's k. All analyses were conducted and signal processing was coded by using the LabVIEW platform (National Instruments Corporation, Austin, TX, USA).

### III. RESULT AND DISCUSSION

The basic characteristics of 31 subjects were showed in Table I. After extubation, total of 7 subjects were extubation fail. Only GCS before SBT had lower p-value (0.013) between successful extubation group and extubation fail group.

For IPD result, the Fig. 2 showed the error bar plot, p-value and AUC of each window. The minimum p-value and maximum AUC are about 0.1 and 0.7, respectively (window 9 and window 13). However, after our observation, the successful extubation group can be discriminated into IPD increase group and IPD decrease group. If the average IPD in last window (95 to 100 minutes) larger than the one in first window (0 to 5 minutes), defined as IPD increase group; otherwise, defined as IPD decrease group. After this grouping, 15 subjects were classified into IPD increase group, 9 subjects were classified into IPD decrease group. The Fig. 3 showed the result among three groups (extubation fail group, IPD increase group, and IPD decrease group). The IPD trend of all subjects in extubation fail group were increase. There are significant difference between extubation fail group and IPD decrease group in all windows. The AUC of IPD between

these two groups reached 1 after window 13 (65 to 70 minutes), which means that the IPD can discriminate two group perfectly after 65 minutes of SBT. However, no significant difference between IPD increase group and extubation fail group. The minimum p-value and maximum AUC are only 0.3 and 0.6, respectively.

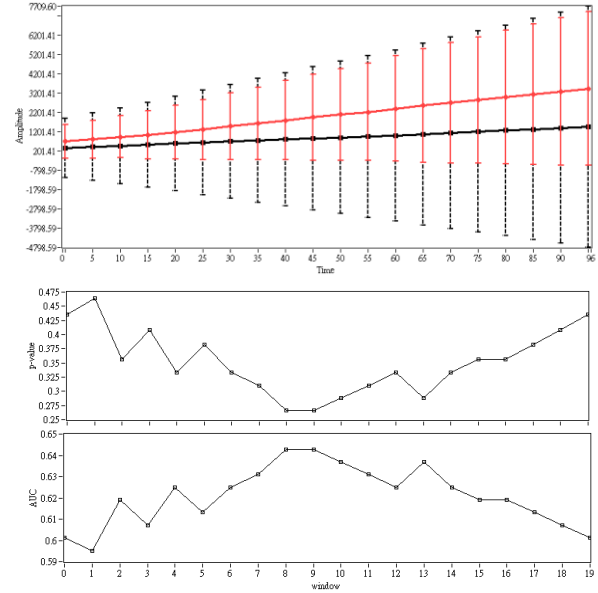


Figure 2. The error bar plot (first row), p-value (second row), and AUC (third row) of successful extubation group (black, square point) and extubation fail group (red, circle point).

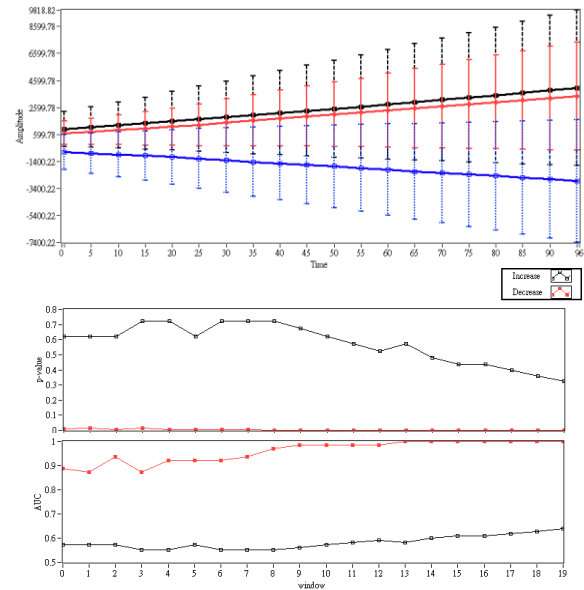


Figure 3. The error bar plot (first row) of three group (extubation fail group: red, circle plot; IPD increase group: black, solid square point; IPD decrease group: blue, hollow square point); p-value (second row) and AUC (third row) compared extubation fail group with IPD increase group (black, hollow square point) and IPD decrease group (red, solid square point).

TABLE I. BASIC INFORMATION OF SUBJECTS

Clinical Characteristics	successful extubation (24)	extubation fail (7)	p-value	AUC
Sex (n, male/female)	18/6	3/4	N/A	N/A
Age (year)	66.57±21.12	63.63±9.48	0.201	0.664
APACHEII (point)	22.57±9.74	20.79±8.63	0.689	0.554
Height (cm)	158.71±7.50	163.875±7.46	0.089	0.717
BW (kg)	63.54±14.36	61.37±18.31	0.542	0.580
IBW (kg)	56.03±5.64	59.18±5.40	0.177	0.673
GCS enter ICU (point)	7±3	3.54±1.25	0.013	0.815
GCS before SBT (point)	10.14±1.21	9.75±1.48	0.603	0.568
Endo_size (mm)	7.29±0.27	7.42±0.19	0.308	0.631
SBP_before_SBT (mmHg)	128.29±31.98	150.67±35.89	0.15	0.685
DBP_before_SBT (mmHg)	71.86±22.44	69.17±13.45	0.757	0.542
HR_before_SBT (bpm)	93.57±11.98	88.25±15.01	0.332	0.625
SpO2_before_SBT (%)	96.29±3.04	97.83±1.93	0.238	0.652
Pimax (cmH <sub>2</sub> O)	32±5.57	32.92±9.07	0.96	0.509
cuff_leak (ml)	245.71±157.15	245.42±113.71	0.726	0.548

For MLR model, the Table II showed the result between two groups (model 1: successful extubation group vs. extubation fail group; model 2: IPD increase group vs. extubation fail group; model 3: IPD decrease group vs. extubation fail group). In model 1, though the calibration accuracy and AUC were 0.77 and 0.59, the F-score and Cohen's k were only 0.4 and 0, which means the model may be affected by unbalance sample size and over fitting. In model 2, the calibration accuracy and AUC were only 0.68 and 0.59, respectively. The F-score and Cohen's k were also poor. The discrimination ability of model 1 and model 2 were weak. However, in model 3, each assessment parameter reported almost best value (calibration accuracy 100%, AUC was 1, F-score was 1, LOO accuracy was 0.94, Cohen's k was 0.88). The Fig. 4 showed the mean, max and min value of each coefficient of model 3 of all LOO models. B0 means the constant, B1 means the IPD value of first window, and so on. It can be found that the window in later SBT was more important than early SBT.

Fewer studies were applied RIP for the research of extubation outcome. To our best knowledge, the present study is the first one to apply IPD technique to measure the asynchronization between TWM and AWM of intubation patients during SBT. Some studies applied IPD for abdominal breathing assessment [12], classify the symptom of pulmonary disease of patients [18]. Some studies also applied RIP for tidal volume estimation [18–20]. A study compared the tidal volume estimated by RIP of postextubation with the one of preextubation [21]. However, their impacts were not related to discriminate the successful extubation and extubation fail. In our finding, the IPD decrease group presented 100% successful extubation. For the IPD value lower than 0 means that the speed of AWM is higher than TWM. For someone whose breathing can be dominated by abdomen may have more powerful ability to do spontaneous breathing after extubation. For IPD increase group, maybe they also had ability to breathing dominated by abdomen, but they did not do it. However, it still need more research to confirm.

TABLE II. THE MLR MODEL

Compared group	Calibration accuracy (range)	Mean AUC of model (range)	Mean F-score of model (range)	LOO accuracy (Cohen's k)
model 1	0.77 (0.77-0.80)	0.59 (0.52-0.67)	0.40 (0.32-0.48)	0.77 (0)
model 2	0.68 (0.52-0.71)	0.59 (0.52-0.68)	0.46 (0.40-0.59)	0.55 (-0.13)
model 3	1.00 (1.00-1.00)	1.00 (1.00-1.00)	1.00 (1.00-1.00)	0.94 (0.88)

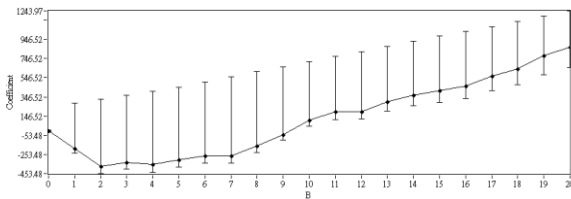


Figure 4. The max-min error bar of the coefficient of model 3 of all LOO model.

Though this research plan to recruit 150 subjects, in this preliminary result still can find the trend of these 3 groups: the IPD must increase in extubation fail group; the IPD decrease present the patient is suitable to extubation. In further work, to discriminate the IPD increase group and extubation fail group is the main purpose. In this study, we had tried to build MLR model by using trimmed mean value of IPD in 20 windows. In addition to trimmed mean, other statistic variables like standard deviation also can be calculated for MLR model. Moreover, some studies applied machine learning method to build model for extubation outcome prediction [22–24]. To test other machine learning method by using IPD is also a further work.

#### IV. CONCLUSION

The preliminary result in this study showed the asynchronous phase of thoracoabdominal movement via IPD method in intubation patients may an important feature for the extubation outcome prediction. A decreased IPD value after SBT presents the suitable condition for extubation. Moreover, the result also showed that the duration of SBT should larger than 70 minutes is better to judge whether a patient is suitable for extubation or not. Test other statistic variables of IPD and applying other machine learning methods to discriminate the IPD increase group and extubation fail group is the main purpose of future work.

#### ACKNOWLEDGMENT

This work was fully support by the project “Medical artificial intelligence joint project of Kaohsiung Medical University/ National Chiao Tung University” (NCTUKMU 108-AI-09).

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