CMBES/SCGB

2018 ACCES23-CMBEC41

Joint Conference
Charlottetown PEI
May 8-11, 2018

SUPPRESSION OF CARDIOGENIC OSCILLATIONS IN ESOPHAGEAL PRESSURE SIGNALS USING ENSEMBLE EMPIRICAL MODE DECOMPOSITION

Michael Zara[1,3], Irene Telias[2,3], Lu Chen[2,3], Takeshi Yoshida[2,3], Laurent Brochard[2,3], and Sridhar Krishnan[1,3]

[1]*Dept. of Electrical & Computer Engineering, Ryerson University, Toronto, Canada*
[2]*Keenan Research Centre, Li Ka Shing Knowledge Institute, St. Michael's Hospital, Toronto, Canada*
[3]*Institute for Biomedical Engineering, Science and Technology (iBEST), St. Michael's Hospital, Toronto, Canada*

INTRODUCTION

Understanding a patient's respiratory health is an important task, especially in critical care settings like intensive care units (ICUs). Clinical parameters such as chest wall compliance (C_{cw}) and work of breathing (WOB) are important to monitor, because they provide insight into a patient's respiratory mechanics and aid in treatment planning [1], [2]. For many of the aforementioned parameters, the pleural pressure (P_{pl}) must be measured [1]. However, direct measurement of P_{pl} can be risky due to the invasive procedure required to obtain the measurement, and may result in a collapsed lung (i.e. pneumothorax) [3]. Recent research surveys have suggested that using esophageal pressure (P_{eso}) as a surrogate for P_{pl} has significant potential for clinical use [1], [4].

The P_{eso} signal is measured using a pressure transducer via an air-filled balloon connected to the distal end of a catheter [4]. The balloon catheter is inserted through the nostril and placed in the lower third of the esophagus [4]. Pressure changes observed in the measured P_{eso} signal are mostly in part due to respiratory mechanics [2]. However, due to the close proximity of the balloon catheter to the beating heart, small oscillatory pressure fluctuations known as cardiogenic oscillations (CGOs) are also observed in the measured P_{eso} [2].

Interference of CGOs in the P_{eso} poses a problem during respiratory health monitoring, because the amplitude fluctuations may result in inaccurate estimates of clinical parameters [5]. Under normal circumstances, the frequency range for P_{eso} is 0.17 - 0.67 Hz, and 0.8 - 2.5 Hz for CGO [6]. However, it has also been suggested that the frequency spectra for both signals may overlap [5], [6]. Because of the possible overlapping frequency spectra, conventional fixed filtering may not be ideal for CGO removal. Several research groups have already tried to tackle the issue of CGO removal using adaptive filtering schemes [2], [5], [6]. Owing to the periodic nature of CGO and P_{eso} waveforms, an interesting approach to the problem is the use of adaptive signal decomposition algorithms to separate CGO and P_{eso}.

In this paper, we present a filtering method using Ensemble Empirical Mode Decomposition (EEMD) to suppress CGO interference in P_{eso} signals obtained from a clinical setting. The Methods and Materials section of this paper will provide information about the raw clinical data that was used in this project; a detailed description of the Empirical Mode Decomposition (EMD) algorithm, which is the basis for EEMD; and an outline of how EEMD was used to suppress CGO interference. The results of the EEMD-based filtering method will be shown in the Preliminary Results section. Important observations, comments and potential future steps regarding the filtering results will be made in the Conclusions and Future Works section.

METHODS AND MATERIALS

Dataset

The P_{eso} signals used in this project were provided by Dr. Laurent Brochard and his research team at St. Michael's Hospital located in Toronto, Ontario, Canada. The current dataset consists of four signals: flow [L/s], airway pressure [cmH_2O], esophageal pressure [cmH_2O], and gastric pressure [cmH_2O]. The signals were obtained from four spontaneously breathing patients assisted by mechanical ventilation at a sampling rate of 62.5 Hz. The duration of the signals vary in the range of 1 to 2 minutes.

Empirical Mode Decomposition (EMD)

The EMD algorithm is a popular data analysis method proposed by Huang in the late 90s [7]. Over the past two decades, the algorithm has been applied in various research areas to adaptively decompose time series data into a finite set of zero-mean AM-FM components [8]. What makes the algorithm popular among researchers is the fact that EMD performs the decomposition without assuming linearity and stationarity of the data [7], [8]. Furthermore, the algorithm is entirely data driven; unlike tools such as the Fourier and Wavelet transforms that rely on basis functions, EMD decomposes the time series based on intrinsic properties of the data [7].

The extracted AM-FM components described previously are known as intrinsic mode functions (IMFs), which represent the oscillatory modes embedded in the data [7], [8]. While the IMFs allow for the calculation of instantaneous frequency via the Hilbert Transform [7], it has been suggested that the IMFs are also related to specific physical phenomena present in the measured data [9]. Since EMD is capable of decomposing non-linear and non-stationary signals into components that may represent physical phenomena, the algorithm has been used successfully in many applications related to biomedical signal processing [9], [10].

According to [7], the extracted components must satisfy two conditions to be considered an IMF:

1. The number of extrema and the number of zero crossings may only differ by one.
2. The mean value between the envelopes generated by the local maxima and local minima must be zero at all times.

The IMFs are obtained by performing EMD on a given signal, $x(t)$, through the sifting process [7]. The EMD algorithm and the sifting process are described as follows [7], [8]:

1. Identify all local maxima and minima in $x(t)$.
2. Generate the upper envelope, $x_{max}(t)$, and lower envelope, $x_{min}(t)$, using the maxima and minima, respectively.
3. Calculate the point-by-point mean between the upper and lower envelopes:
$$m(t) = [x_{max}(t)+x_{min}(t)]/2$$
4. Subtract $m(t)$ from $x(t)$ to obtain a potential IMF, $h(t)$:
$$h(t) = x(t) - m(t)$$
5. Check the properties of $h(t)$:
   a. If $h(t)$ satisfies the conditions to be considered an IMF, calculate the residual: $r(t) = x(t) - h(t)$
   b. Otherwise, replace $x(t)$ with $h(t)$ and iterate through steps 1 to 5 until $h(t)$ satisfies 5.a.
6. Repeat steps 1 to 6 until the residual, $r(t)$, satisfies a predefined stopping criteria.

The original time series signal, $x(t)$, can then be represented as a sum of the IMFs, $h_i(t)$ *for* $i=1..n$, and the residual, $r(t)$:
$$x(t) = \Sigma\, h_i(t) + r(t)$$

Ensemble EMD (EEMD)

Although EMD has been quite successful in many fields, a major obstacle associated with the algorithm is the concept of mode mixing [11]. Mode mixing occurs when a single IMF contains more than one oscillatory mode, which results in a loss of physical meaning for the IMF [9], [11]. To overcome the mode-mixing problem, Wu and Huang [11] developed a noise-assisted data analysis method known as Ensemble EMD (EEMD). The EEMD method decomposes a signal into its IMFs via EMD over several trials [11], [12]. White noise with finite amplitude is added to the original signal at the start of each trial before proceeding with EMD, which results in an ensemble for each IMF [9],

[11]. The ensemble average for each of the corresponding IMFs are taken, which are then treated as the true IMFs [15]. The addition of white noise during the process ensures that no scales are missing, thereby overcoming the problem of mode mixing [11], [12]. The true IMFs do not contain the injected white noise as they are cancelled out during the ensemble averaging [9], [11].

Suppression of Cardiac Oscillations

As mentioned previously, the main form of interference observed in P_{eso} signals are cardiogenic oscillations (CGOs) caused by the beating heart. While various pressures acting on the esophageal balloon may influence the measured signal, $\mathbf{P_{meas}}$, the work presented here assumes that $\mathbf{P_{meas}}$ contains only two components superimposed on each other: the esophageal pressure ($\mathbf{P_{eso}}$) and the cardiogenic oscillations ($\mathbf{P_{CGO}}$). The assumption can be described by the following equation:

$$\mathbf{P_{meas} = P_{eso} + P_{CGO}}$$

In order to suppress the cardiogenic oscillations from the measured signal, the EEMD algorithm was used to decompose $\mathbf{P_{meas}}$ into its IMFs. The number of ensemble trials used in the decomposition was fixed at 100 to maintain a sufficiently good SNR while reducing computational complexity [12]. The amplitude of white noise injected into each trial was fixed at 0.02.

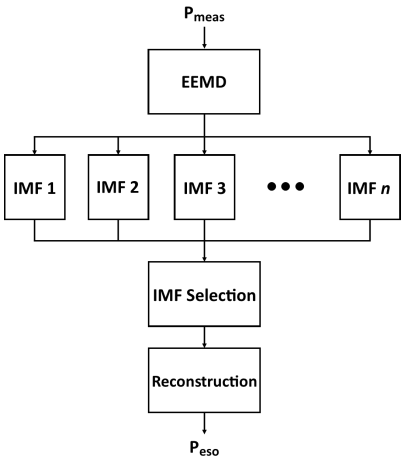

Figure 1: The block diagram of the EEMD-based filtering method.

Based on the frequency characteristics of $\mathbf{P_{eso}}$ and $\mathbf{P_{CGO}}$ as mentioned in the Introduction and summarized in [6], the two components were expected to appear in different IMFs: $\mathbf{P_{eso}}$ in the IMFs representing lower frequency bands, and $\mathbf{P_{CGO}}$ in the IMFs with higher frequency bands. The IMFs containing frequency components related to $\mathbf{P_{CGO}}$ were ignored during reconstruction, which resulted in suppression of the cardiac interference. The block diagram for the proposed method is shown in Figure 1.

PRELIMINARY RESULTS

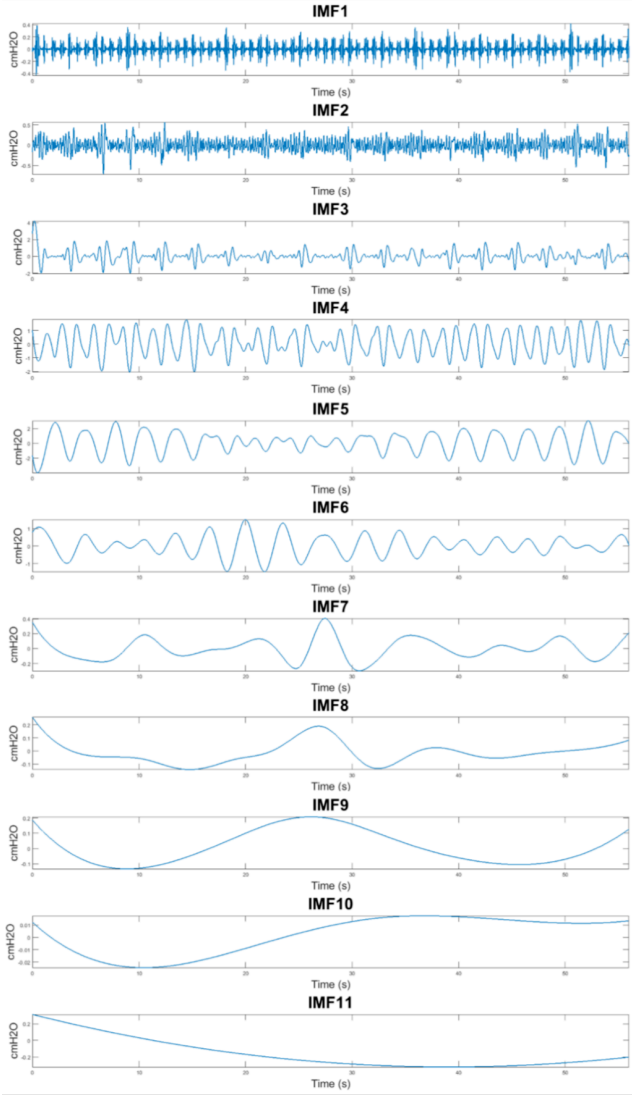

Figure 2: The resulting 11 IMFs obtained from applying EEMD to the P_{eso} signal for patient 12D5

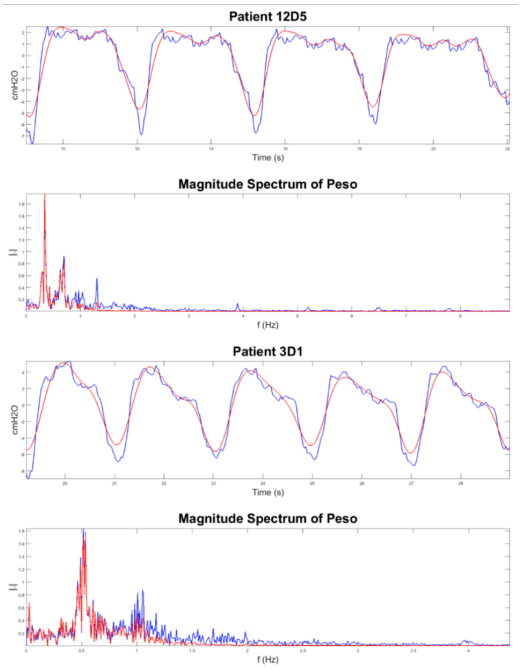

Figure 3: The original signal (blue) and its frequency spectrum compared to the filtered result using proposed method (red) for two patients.

CONCLUSIONS AND FUTURE WORKS

After decomposing the measured P_{eso} signal into its IMFs as shown in Figure 2, our clinical collaborators identified the first three IMFs as noise and CGO interference through visual inspection. The last two IMFs represent the residuals of the signal and correspond to low frequency drifts. The initial observations mentioned previously are consistent among the four patients in the current dataset. Thus, IMFs 4 to 9 were used during the reconstruction process while the remaining IMFs were ignored. The resulting P_{eso} signals in red shown in Figure 3 have very little amplitude fluctuations when compared to the original measured P_{eso} in blue. A comparison between the frequency spectra shows that the higher frequency components associated with CGO are completely removed while maintaining P_{eso} frequency components.

Although the proposed technique shows promising preliminary results, several steps will be taken to further refine the method. To ensure that the proposed method is robust, the dataset must be expanded to include more patients. An automatic IMF selection method must also be developed to identify and select relevant IMFs for reconstruction.

ACKNOWLEDGEMENTS

We would like to acknowledge the funding provided by NSERC and the QEII-GSST.

REFERENCES

[1] T. Mauri, "Esophageal and transpulmonary pressure in the clinical setting: meaning, usefulness and perspectives," *Intensive Care Med*, vol. 42, no. 9, pp. 1360-1373, 2016.

[2] J. Graßhoff, E. Petersen, M. Eger, G. Bellani and P. Rostalski, "A template subtraction method for the removal of cardiogenic oscillations on esophageal pressure signals," *2017 39th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, Seogwipo, 2017, pp. 2235-2238.

[3] C.R. Fernandes, "Importance of pleural pressure for the evaluation of respiratory mechanics," *Rev. Bras. Anestesiol.*, vol. 56, no. 3, pp. 287-303, 2006.

[4] E. Akoumianki, "The application of esophageal pressure measurement in patients with respiratory failure," *Am J Respir Crit Care Med.*, vol. 189, no. 5, pp. 520-531, 2014.

[5] T.F. Schuessler, S.B. Gottfried, P. Goldberg, R.E. Kearney, and J.H.T. Bates, "An adaptive filter to reduce cardiogenic oscillations on esophageal pressure signals," *Annals of Biomedical Engineering*, vol. 26, no. 2, pp. 260-267, 1998.

[6] Y.P. Cheng, H.D. Wu, G.J. Jan, and C.Y. Wang, "Removal of cardiac beat artifact in esophageal pressure measurement via a modified adaptive noise cancellation scheme," *Annals of Biomedical Engineering*, vol. 29, no. 3, pp. 236-243, 2001.

[7] N.E. Huang, "The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis," *Proc. R. Soc. Lond. A*, vol. 454, no. 1971, pp. 903-995, 1998.

[8] G. Rilling, P. Flandrin, and P. Goncalves, "On empirical mode decomposition and its algorithms," *IEEE-EURASIP workshop on nonlinear signal and image processing*. NSIP-03, Grado, Italy, 2003.

[9] E. Abdulhay, P Guméry, J. Fontecave, and P. Baconnier, "Cardiogenic oscillations extraction in inductive plethysmography: Ensemble empirical mode decomposition," *2009 31st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBS)*, Minneapolis, 2009, pp. 2240-2243.

[10] M. Shahbakhti, V. Khalili and G. Kamaee, "Removal of blink from EEG by Empirical Mode Decomposition (EMD)," *The 5th 2012 Biomedical Engineering International Conference*, Ubon Ratchathani, 2012, pp. 1-5.

[11] Z. Wu and N.E. Huang, "Ensemble Empirical Mode Decomposition: A noise-assisted data analysis method," *Advances in Adaptive Data Analysis*, vol. 1, no. 1, pp. 1-41, 2009.

[12] J. Zhang, R. Yan, R.X. Gao, and Z. Feng, "Performance enhancement of ensemble empirical mode decomposition," *Mechanical Systems and Signal Processing*, vol. 24, no. 7, pp. 2104-2123, 2010.