

Artifact Removal for Intracranial Pressure Monitoring Signals: A Robust Solution with Signal Decomposition

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Abstract—Intracranial Pressure (ICP) monitoring signal collected in Neuro Intensive Care Units often contains large amount of artifacts. The artifacts not only directly lead to false alarms in automatic Intracranial Hypertension (IH) alert systems, and they also severely contaminate the characteristics of the underlying signal, which makes accurate forecasting of impending IH impossible. Therefore, in this paper, we propose a novel solution to effectively remove artifacts from ICP monitoring signals. The proposed method effectively detects artifacts by decomposing the ICP monitoring signal with Empirical Mode Decomposition (EMD) method. An iterative filtering method is also proposed to extract artifacts from the decomposed components of ICP signals. The proposed filter is *robust*. That is, the parameters of the iterative filter are estimated with *robust statistics*, which ensures the performance of the proposed filter will not be unduly affected by artifacts. The detected artifacts are then imputed based on the Auto-Regressive Moving Average (ARMA) model to preserve the original characteristics of the ICP signal. The effectiveness of the proposed artifact removal method is experimentally justified based on the ICP monitoring signals of 59 patients.

I. INTRODUCTION

Intracranial Pressure (ICP) refers to the internal pressure of our skulls. For patients in Neuro Intensive Care Units (NICUs), especially traumatic brain injury patients, continuous ICP monitoring is extremely crucial to prevent secondary brain damages caused by Intracranial Hypertension (IH) [1]. In NICUs, ICP monitoring currently relies solely on visual inspections by neuro-clinicians and nurses; and ICP controlling interventions are treated on patients, only after prolonged ICP elevations are observed. The current approach is human-intensive, prone to errors, reactive and inefficient. Automatic alerts for onsets of IH and effective forecasting models to predict impending episodes of IH are greatly desirable. However, the continuous ICP monitoring signals, which are recorded in real NICU environments, are often contaminated by artifacts. The artifacts can be caused by multiple factors, such as movement of patients, connection error, faults in monitoring system, human error, etc. Artifacts directly lead to high false alarm rates in automatic IH alert systems. Artifacts also contaminate the characteristics of the underlying data, which makes accurate forecasting of impending IH impossible. Therefore, in this paper, we propose a novel solution to effectively remove artifacts from

ICP monitoring signals.

In 30 years of ICP related research [2], many works [3,4,5] have been focusing on the prediction of impending IH episodes. However, achieved prediction accuracy is still unsatisfactory. One of the reasons is that the removal of artifacts in ICP signals has yet been effectively addressed.

For artifact removal, low-pass filtering is the most conventional method. Low-pass filter is only applicable to stationary signals, whose frequency spectrum is consistent over time. However, stationarity, in general, does not hold for ICP monitoring signals. Adaptive filtering [6] is a more advanced filtering method. The turning of adaptive filters requires a referencing signal, but this referencing signal is not available in the case of ICP monitoring. Independent Component Analysis (ICA) has also been applied for artifact removal in biomedical signals. ICA decomposes signals based on the assumption that the signal is the summation of multiple statistical independent components. This assumption may apply for signals, such as ECG [7] & MEG [8], but it does not hold in ICP signals. Wavelet transformation has been demonstrated to be effective for artifact removal in biomedical signals [6], but optimum performance can only achieved with appropriate choice of basis function.

In this paper, we propose to effectively detect artifacts by decomposing the ICP monitoring signal with Empirical Mode Decomposition (EMD) [9] method. Due to its self-adaptiveness and high efficiency, EMD recently has been widely used in the analysis of non-stationary non-linear signals. An iterative filtering method is further proposed to extract artifacts from the decomposed components of ICP signals. The proposed filter is *robust*, i.e. parameters of the iterative filter are estimated with *robust statistics* [10]. Unlike classical statistical methods, the performance of robust statistics will not be unduly affected by artifacts and outliers. The detected artifacts are then imputed based on the Auto-Regressive Moving Average (ARMA) model to preserve the original characteristics of the ICP signal.

II. PROBLEM DEFINITION

In NICUs, ICP levels are invasively measured with a fibre-optic intraparenchymal gauge (Codman and Shurtleff, Taynham, MA). Collected ICP monitoring signals are often contaminated by a considerable amount of artifacts. Based on our study, on average, 5% of data points in the collected ICP signals are contaminated by artifacts; and, in the worse case, more than 20% of signals can be contaminated. Figure 1 (a) shows an example of ICP monitoring signal.

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This work was supported by the SERC grant 092-148-0067 of Agency for Science, Technology and Research, Singapore.

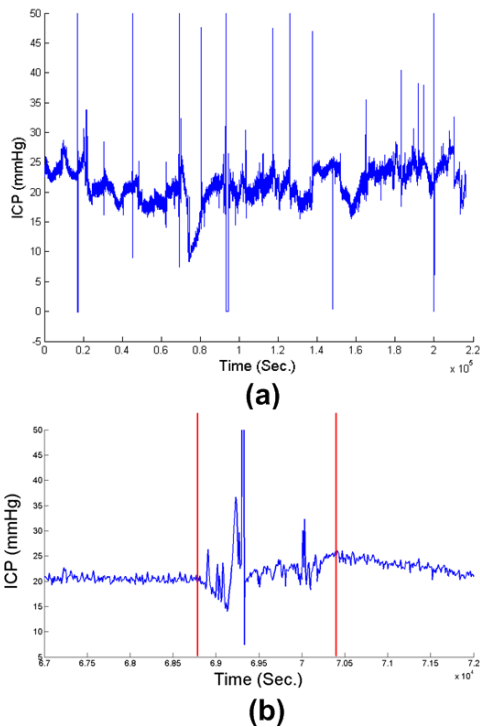


Figure 1 (a) Artifacts in ICP monitoring signal. (b) An example of artifact episode.

To remove artifacts from ICP monitoring signals, first and foremost, it requires accurate **artifact detection**. As illustrated in Figure 1 (a), the artifacts can be visually identified as tall and sharp “spikes”. These spikes are recognized as artifacts, because they indicate rapid and dramatic oscillations of ICP levels, which, as advised by neuroclinicians, are physiologically impossible. Moreover, as highlighted in Figure 1 (b), an artifact is not formed with just one or two data points but instead a cluster of them. We name the cluster of artifact data points an “artifact episode”. An artifact episode can be defined by its “location” and “width”. Therefore, the objective of artifact detection is to accurately identify the locations and widths of artifact episodes. The second task of artifact removal is then **artifact imputation**. Artifact imputation aims to impute data points of identified artifact episodes with appropriate values, so that original characteristics of the underlying signal are preserved.

III. ARTIFACT REMOVAL

To address the two main tasks in artifact removal, the proposed method is composed of two components: the artifact detection component and the artifact imputation component.

A. Artifact Detection

The objective of artifact detection is to identify the locations and widths of artifact episodes in ICP monitoring signals. In this subsection, we first discuss the observations we have made by decomposing the non-stationary ICP signals based on the Empirical Mode Decomposition III.

(EMD). A robust filter is then proposed to extract artifact data points from the decomposed components of ICP signals. Combining the results of EMD and robust filtering, an iterative artifact detection method is proposed.

Empirical Mode Decomposition

As shown in Figure 1 (a), ICP signals are non-stationary: evolving trends are observed, and, moreover, trends vary from time to time. Due to the non-stationarity of ICP signals, filters in both frequency and time domains cannot be directly applied to extract artifacts. To address this problem, we propose to decompose the ICP monitoring signal into more stable components based on Empirical Mode Decomposition (EMD).

EMD recently has been widely applied for the analysis of non-stationary time-series data, ranging from financial stock prices [11] to biomedical signals [12]. EMD decomposes the non-stationary time-series signal into a finite and often small number of Intrinsic Mode Functions (IMF). An IMF is defined in [11] as any function having the same number of zero-crossing and extrema, and also having symmetric envelopes defined by the local maxima, and minima respectively.

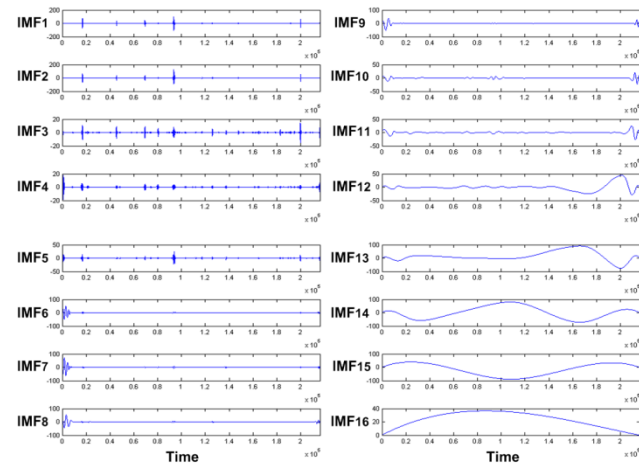


Figure 2 Decomposed intrinsic mode functions (IMFs) of the ICP signal shown in Figure 1(a).

As shown in Figure 2, with EMD, the ICP monitoring signal shown in Figure 1(a) is decomposed into 16 IMFs. More importantly, we have made the following observations over the decomposed IMF components:

- I. After decomposition, the evolving trends in the original ICP signal are removed from the high frequency IMF components (IMF₁₋₈). As a result, filtering techniques can now be applied to the high frequency IMF components to extract artifact episodes.
- II. Large magnitude oscillations in the 1st IMF component are effective indicators for the locations of artifact episodes. As graphically demonstrated in Figure 3 (a), large magnitude oscillations in the 1st IMF component perfectly align with all the artifact episodes in the original ICP signal. Based on the 1st IMF component, although we can

effectively identify the locations of artifact episodes, we tend to underestimate the widths of artifacts episodes. However, as shown in Figure 3 (b), we discover that: a more accurate width estimation can be achieved by iteratively “growing” (expanding) the initial width estimated from the 1st IMF component based on the subsequent IMF components.

Inspired by the above observations, we propose to first identify the locations of artifact episodes and obtain the initial estimation of their widths based on the 1st IMF component (Observation II). We then iteratively “grow” the estimated widths based on subsequent IMF components (Observation III). In addition, by decomposing the ICP signal into IMFs, it now allows us to employ time domain filters to extract artifact data points from IMF components (Observation I). In particular, a robust 3σ filter is used.

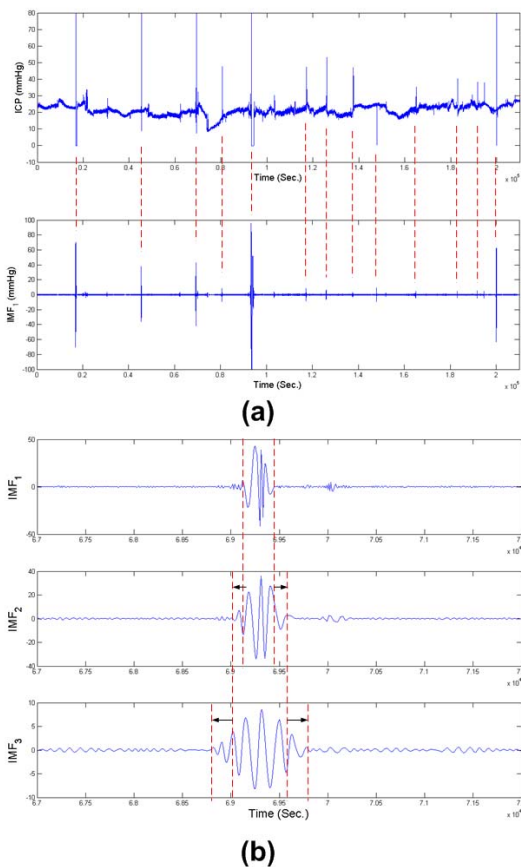


Figure 3 (a) Comparison between original ICP signal and its 1st IMF component. (b) Iterative estimation of the width of artifact episode.

Robust Filtering

A robust 3σ filter is employed to extract artifact data points from decomposed IMF components. In theory, the 3σ filter works very simply: any data point, whose value is outside of the 3σ region, is considered as an artifact. However, in practice, the actual value of standard deviation, σ, is always unknown. Thus, the challenge is: how to accurately estimate σ based on the collected data that is contaminated by artifacts?

Conventionally, the “sample standard deviation” is the

most common estimation of σ, and it is formally defined as:

$$\sigma_{\text{sample}} = \sqrt{\frac{1}{N-1} \sum_{i=1}^N (x_i - \mu_{\text{sample}})^2}$$

where {x₁, ..., x_N} is collected time-series data and μ_{sample} refers to the “sample mean”. However, both sample mean and standard deviation are not robust against artifacts. As graphically demonstrated in Figure 4, uncontrolled bias can be introduced to the sample mean and standard deviation by the presence of artifacts.

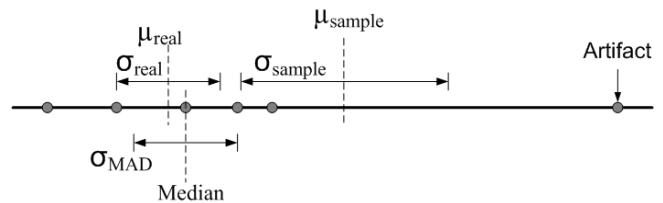


Figure 4 A graphical example to illustrate the robustness of mean absolute deviation (MAD) based estimation of σ, σ_{MAD}, in comparison with sample standard deviation, σ_{sample}.

To ensure the robustness of the proposed method, we propose to estimate σ with the “Mean Absolute Deviation” (MAD). For a univariate time-series {x₁, ..., x_N}, MAD is the median of the absolute deviations from the data’s median, and it is mathematically defined as:

$$MAD = \text{median}_i(|x_i - \text{median}_j(x_j)|)$$

where median_j(x_j) refers to the data median. Based on MAD, σ is estimated as:

$$\sigma_{\text{MAD}} = K \times MAD$$

where K ≈ 1.4826 if we assume the data is Gaussian. σ_{MAD} is a robust estimation of σ with 50% as *break-down point*, which means the bias of the estimation is bounded as far as the amount of artifacts is less than 50% of the overall data size [10].

Proposed Method

Inspired by the observations from EMD-based signal decomposition, and making use of the robust 3σ filter, a novel method is proposed to effectively extract artifact episodes from ICP monitoring signals. The flow of the proposed method is graphically demonstrated in Figure 5.

The proposed method is composed with 3 major steps. Step 1 decomposes the ICP monitoring signal into Intrinsic Mode Functions (IMFs) based on the Empirical Mode Decomposition (EMD). In Step 2, the proposed robust 3σ filter is applied to the 1st IMF component to separate artifact data points from the normal ones. This step not only effectively identifies the locations of artifact episodes but also provides an initial estimation of their widths. Step 3 then aims to iteratively refine the width estimations based on the subsequent IMF component, {IMF₂, ..., IMF_k}. Take IMF₂ as an example. As shown in Figure 3 (b), given the initial width estimation from IMF₁, the robust 3σ filter is applied to IMF₂ to detect artifact data points around the “neighbourhood” of the initial estimated width window. The

estimated width will then “grow” to cover the newly detected artifact “neighbours”. This process will repeat iteratively on subsequent IMF components until the estimated width stops “growing”.

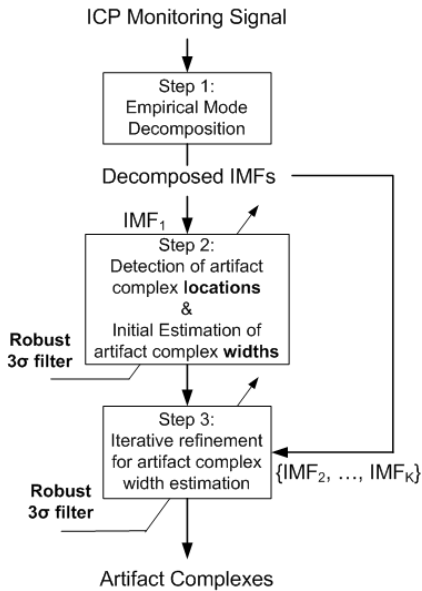


Figure 5 Proposed artifact detection method.

B. Artifact Imputation

After artifacts are detected from the ICP monitoring signal, the next question is: how should we deal with the detected artifacts?

The most straightforward approach is to simply discard the detected artifact data points. However, this approach severely destroys the time information of the signal. In ICP monitoring, the time information is extremely crucial for clinical tasks, such as diagnosis of patients’ physiological status and understanding of patients’ treatment response. We propose to impute the detected artifact episodes based on the Auto-Regressive Moving Average (ARMA) model.

ARMA model is an effective tool to understand and predict values of a stationary time-series signal. (Theoretical details of the ARMA model can be referred to [13].) Considering the entire time-series, the ICP monitoring signal is non-stationary. However, stationarity is still observed within small segments of the signal. According to our study, we found that the widths of artifact episodes are usually very small (on average, less than 10 mins/60 data points). Therefore, it is reasonable to assume stationarity, and ARMA is applicable to impute the values of detected artifact episodes.

IV. RESULTS & DISCUSSION

The proposed artifact removal method is empirically evaluated with the collected ICP monitoring signals of 59 patients, who were admitted to the NICU of National Neuroscience Institute, Singapore, between January 2009 to December 2010. Basic statistics of the selected patients’ data are summarized in Table 1. The ICP levels of the selected

patients are continuously monitored for more than 24 hours. Measured ICP levels were sampled and recorded every 10 seconds with a bedside computer system. Artifact episodes in the collected ICP monitoring signal were manually annotated and verified by experts. The annotated artifact episodes are used as the ground truth for the performance evaluation.

Statistics	Readings
Size of Samples	59
Avg. Monitoring Length (Hr.)	203.5
Avg. No. of Artifact Episodes	25.9
Total No. of Artifact Episodes	1532

Table 1 Basic statistics of the selected patients’ data.

The performance of the proposed artifact detection method is evaluated based on how well it identifies the locations of artifact episodes and how accurately it estimates their widths.

For artifact episode location identification, on average, the proposed method achieves 100% precision and 73.6% recall. 100% precision implies that no useful signal is misclassified as artifact by the proposed method. However, the recall of the proposed method is comparatively lower indicating that a number of artifact episodes are missed. As shown in Figure 6, the misses are mainly caused by the masking effect of the “tall” artifacts, whose magnitudes are abnormally large. This limitation can be effectively addressed by repeating the proposed detection method for multiple iterations. As demonstrated in Figure 6, after performing the 2nd iteration, most of the artifact episodes have been identified. However, identifying artifact episodes with multiple iterations of the proposed method introduces higher computational overheads. To achieve the best trade-off between performance and computational cost, the optimum number of iterations needs to be determined. We will further investigate this in our future work.

The overall detection performance of the proposed method is measured with the F score, where

$$F = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

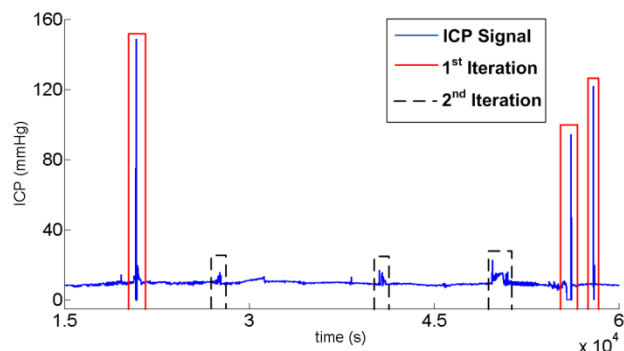


Figure 6 Performance comparison between 1st and 2nd iterations of the proposed artifact detection method. Artifact episodes detected in the 1st iteration are highlighted in solid red lines, and new artifact episodes detected in the 2nd iteration are highlighted in black dotted lines.

For the proposed detection method, F is calculated to be 0.848, which indicates that the proposed method is effective in identifying artifacts episodes from ICP signals.

For width estimation, the proposed method, on average, achieves 82% of accuracy. Moreover, we observe that our method tend to overestimate the width of artifact episodes. Thus, more fine-tuning is still required for the proposed method, and we will address it in our future work.

After artifact episodes are detected, we propose to impute the artifact data points based on the ARMA model. As demonstrated in Figure 7, the ARMA model significantly outperforms the linear regression model, a commonly used imputation method, in preserving the data characteristics of the underlying signal. Figure 7 also graphically illustrates that, compared with the proposed method, low-pass filters are not effective solutions to remove artifacts from ICP monitoring signals.

In this study, the AR and MA order of the ARMA model is set to 20, based on the partial auto-correlation study. Selecting the optimum order of the ARMA model can further improve the performance of artifact imputation. Thus, this issue will be further investigated in details in our future works.

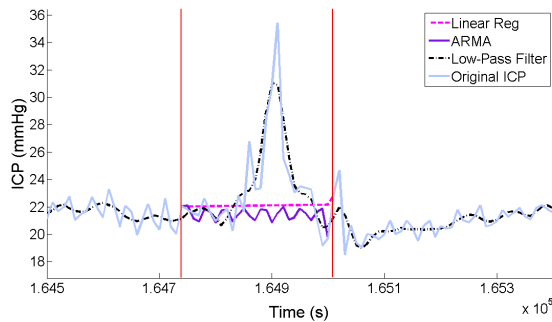


Figure 7 Performance comparison between the ARMA model, the linear regression model and a low-pass filter. The low-pass filter is implemented using Equiripple FIR filter with Passband = 0.015Hz, Stopband = 0.020Hz and Attenuation = -60dB.

V. CONCLUSION

In this paper, we have proposed a novel solution to effectively remove artifacts from ICP monitoring signals. Artifact removal involves two main tasks: artifact detection and artifact imputation.

To effectively detect artifact episodes from the ICP monitoring signal, we proposed to decompose the non-stationary non-linear ICP signal into Intrinsic Mode Functions (IMFs) based on Empirical Mode Decomposition. Useful properties are observed in the decomposed IMF components. Inspired by the observed properties, we proposed an effective method to accurately identify the locations of artifact episodes and iteratively estimate their widths with a robust filter. Instead of classical statistical tools, parameters of the proposed robust filter are estimated using robust statistics, which ensures the performance of the proposed filter will not be unduly affected by artifacts.

Finally, the detected artifact data points are imputed based on the ARMA model to preserve the characteristics of the underlying ICP signal.

The effectiveness of the proposed artifact removal method is experimentally justified based on the ICP monitoring signals of 59 patients. However, one limitation of the proposed method is observed. In the presence of “tall” artifacts with abnormally large magnitudes, due to their masking effect, the proposed method may miss the relatively “shorter” artifacts. We have demonstrated that this limitation can be effectively addressed by repeating the proposed detection method for multiple iterations. Detailed solution for this limitation will be further investigated in our future work.

ACKNOWLEDGMENT

The authors would like to thank the staffs at Neuro-ICU of National Neuroscience Institute, Tan Tock Seng Hospital, Singapore, especially Dr. Beng Ti Ang & Dr. Nicolas King, for their advices and help with patient data collection.

REFERENCES

- [1] P. Jones, P. Andrews, S. Midgley, S. Anderson, I. Piper, J. Tocher, A. Housley, J. Corrie, J. D. Slattery, “Measuring the burden of secondary insults in head-injured patients during intensive care,” *Journal of neurosurgical anesthesiology*, 6 (1):4-14, 1994.
- [2] R. Allen, “Time series methods in the monitoring of intracranial pressure,” *Journal of Biomed. Eng.*, 5: 5-18, 1983.
- [3] X. Hu, P. Xu, S. Asgari, P. Vespa, M. Bergsneider, “Forecasting ICP elevation based on prescient changes of intracranial pressure waveform morphology,” *IEEE Tran. on Biomed. Eng.*, 57(5):1070-1078, 2010.
- [4] M. James, C. Cristina, A. Mateo, E. Miles, L. Susanna, S. Robert, Brahm G. “Precursors to rapid elevations in intracranial pressure,” *EMBC*, 3977-2980, 2001.
- [5] M. Swiercz, Z. Mariak, J. Krejza, J. Lewko, P. Szydluk, “Intracranial pressure processing with artificial neural networks: prediction of ICP trends,” *Acta Neurochirurgica*, 142:401-406, 2000.
- [6] D. B. Keenan, and F. H. Wilhelm, “Adaptive and wavelet filtering methods for improving accuracy of respiratory measurement,” *Biomed. Sci. Instrum.*, vol. 41, 2005, pp. 37-42.
- [7] C. A. Joyce, I. F. Gorodnitsky, M. Kutas, “Automatic removal of eye movement and blink artifacts from EEG data using blind component separation,” *Psychophysiology*, 41(2), 313-325, 2004.
- [8] V. Ricardo, S. Jaakko, J. Veikko, H. Matti, O. Erkki, “Independent component approach to the analysis of eeg and meg recordings,” *IEEE Tran. on Biomed. Eng.*, 47(5):589-593, 2000.
- [9] N. E. Huang, Z. Shen, S. R. Long, “The empirical mode decomposition and Hilbert spectrum for nonlinear and non-stationary time series analysis,” *Proc. Roy. Soc. Lond. A*, 454:903-995, 1998.
- [10] J.H. Peter, “Robust statistics,” *Wiley*, 1981.
- [11] N. E. Huang, M-L Wu, W. Qu, S. R. Long, S. S. P. Shen, J. E. Zhang, “Applications of Hilbert–Huang transform to non-stationary financial time series analysis,” *Applied Stochastic Models in Business and Industry* 19: 245–268, 2003.
- [12] S. Liu, Q. He, R. X. Gao, P. Freedson, “Empirical mode decomposition applied to tissue artifact removal from respiratory signal,” *EMBC*, 3624-3627, 2008.]
- [13] P. J. Brockwell and R. A. Davis, “Introduction to Time Series and Forecasting (2nd Edition)”, Springer, 2002.