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Artifact Correction with Robust Statistics for Non-Stationary Intracranial Pressure Signal Monitoring

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Abstract

To enhance ICP monitoring of Traumatic Brain Injury (TBI) patients, much research effort has been attracted to the development auto-alarming systems and forecasting methods to predict impending intracranial hypertension episodes. Nevertheless, the performance of the proposed methods are often limited by the presence of artifacts in the ICP signal.To address this bottleneck, we propose novel artifact correction methods. A scale-based filter is proposed to identify the artifacts. For the proposed filter, instead of classic statistics, robust statistics is employed to estimate the scale parameter. Thus, our proposed methods are robust against undesirable influences from artifacts. Since the ICP signal is non-stationary, non-stationary signal processing techniques, the empirical mode decomposition (EMD), wavelet transformation and median filter, are also employed. The effectiveness of proposed methods are evaluated experimentally. Experimental results demonstrate that, with the proposed artifact correction methods, significant performance gains can be achieved.

1. Introduction

Intracranial pressure (ICP) is defined as the internal pressure in the skull. During the patient's stay in neuro-critical care, ICP is the most crucial physiological signal for Traumatic Brain Injury (TBI) patient monitoring [1]. When ICP rises above the safe region, it is medically referred as an episode of intracranial hypertension. Intracranial hypertension may lead to direction brain damages and indirect damages due to insufficient oxygen and nutrition supply to the brain.

To enhance ICP monitoring of TBI patients, in the last 30 years, much effort [1] has been spent in the development auto-alarming systems and forecasting methods to predict impending intracranial hypertension episodes. Nevertheless, the performance of the proposed methods are often limited by the presence of ar-

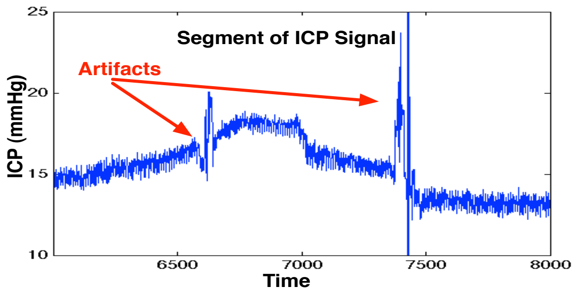

Figure 1: *An segment of ICP signal with artifacts.*

tifacts in the ICP signal. As illustrated in Figure 1, due to the complicated environment of neuro-critical care, ICP monitoring signal is often contaminated with artifacts. Since the artifacts are much stronger compared to the signal, they can impair the performance of auto-alarming systems by causing false alarms and can also jeopardize forecasting models by introducing undesirable biases. However, in the literature, not much work has studied the artifacts in ICP signals. To address this gap, we propose an artifact correction method based on robust filtering and non-stationary signal processing techniques.

2. Signal Characteristics & Problem Definition

The task of artifact correction consists of two subtasks: ***artifacts detection*** and ***artifacts imputation***. The *detection* task is to identify artifacts from the contaminated signal; the *imputation* task then replaces the detected artifacts with imputed values so to reconstruct the original characteristics of the signal. This paper focuses more on the detection task, because accurate artifact detection is the prerequisite for effective artifact correction.

Artifacts in ICP signals are often caused by environmental factors in the neuro-critical cares, e.g. adjustment of bed angles, movement of patients, shift of sensors, etc. As can be observed from Figure 1, the artifacts are segments of signals, which oscillate over extremely large *scales* (variants) that are physiologically impossible. Suppose the ICP signal consists of an innovation process, u_t, an i.i.d white noise, where $u_t \sim N(0, \sigma_0^2)$. An artifact can then be interpret as a segment of i.i.d noise, v_t, where $v_t \sim N(0, \sigma_1^2)$ and $\sigma_1^2 >> \sigma_0^2$.

Since an artifact can be modeled as noise with an abnormally large *scale* parameter σ_1^2, we propose to detect artifacts with a *scale*-based filter. Instead of classic statistics, robust statistics [2] is employed to ensure the estimation of the *scale* parameter will not be unduly biased due to the existence of artifacts.

We also observe that the ICP signal is non-stationary, and preprocessing is necessary before filtering can be applied to identify artifacts. In the literature, three popular non-stationary signal processing techniques are empirical mode decomposition (EMD) [3], wavelet transformation [4] and median filter. Based on these three processing techniques., three artifact detection approaches are proposed. To decide on the most effective approach, the strengths and weakness of the proposed approaches are evaluated and compared both theoretically and experimentally .

3. Proposed Method

3.1 Artifact Detection

3.1.1 Robust MAD Filter

We observe that artifacts in the ICP signal can be approximately modeled as a segment of i.i.d white noise with an abnormally large *scale* parameter. Inspired by this observation, a *scale*-based filter is proposed to identify the artifacts. The idea is simple: data points that are abnormally far away (w.r.t. the *scale* parameter) from the "main crowd" are likely to be artifacts. To develop the filter, an accuracy estimation of the *scale* parameter is necessary. However, this task can be challenging in the presence of artifacts.

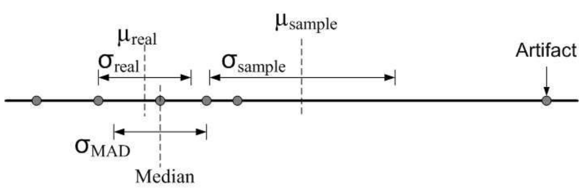

Figure 2: *Comparison between estimations based on classic statistics and robust statistics.*

In conventional statistics, the *scale* parameter is usually estimated with the sample variants. However, as graphically demonstrated in Figure 2, the sample variant estimation is not robust against artifacts. It introduces unbounded bias in the presence of extremely large artifacts. Filters developed based on the sample variant estimation suffer from the "marking effect", where large artifacts will "mask out" small artifacts and make them undetectable.

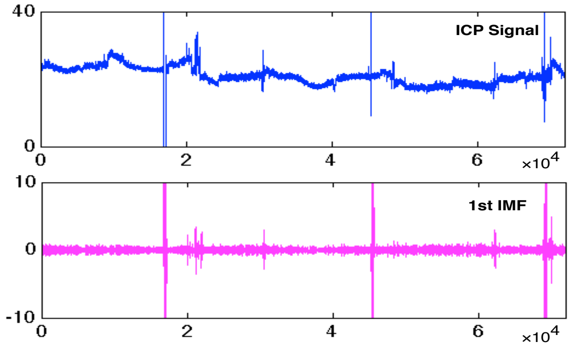

Figure 3: *Comparison between ICP signal and its 1st IMF component.*

To address this challenge, we estimate the *scale* parameter with the *Median Absolute Deviation* (MAD), a robust estimator. MAD is formally defined as

$$MAD_n = n \times med_i |x_i - med_j x_j| \qquad (1)$$

where n is a constant, and $n = 1.4826$ assuming the artifacts follow Gaussian distribution. Among all *scale* estimators, MAD has the highest tolerance against artifacts, and its influence function is bounded with the sharpest possible bounds [5]. The biggest advantage of MAD is that it is simple and easy to compute. To identify artifacts, we compute a score for each data point x_i.

$$score = \frac{|x_i - med_j x_j|}{MAD_n} \qquad (2)$$

Data points whose scores exceed a cutoff point are then classified as artifacts. In the proposed method, the cutoff point is set to be 3. The proposed MAD filter can be seen as the robust version of the well-known 3σ filter.

3.1.2 Empirical Mode Decomposition Approach

Empirical Mode Decomposition (EMD) [3] is an empirical process that decomposes a signal into multiple components called the *Intrinsic Mode Functions* (IMFs). Each IMF component represents a unique mode of oscillation imbedded in the data, which contains no complex riding waves. As illustrated in Figure 3, we observe that, after decomposition, the large amplitude oscillations in the 1st IMF component align perfectly with the artifacts in the original ICP signal. This finds us an effective indicator to locate the artifacts.

Inspired by these observations, based on EMD we propose to extract artifacts from the ICP signals in two steps. (Details of this approach is discussed in our previous work [**?**].)

Step 1 With the proposed robust MAD filter, locate the

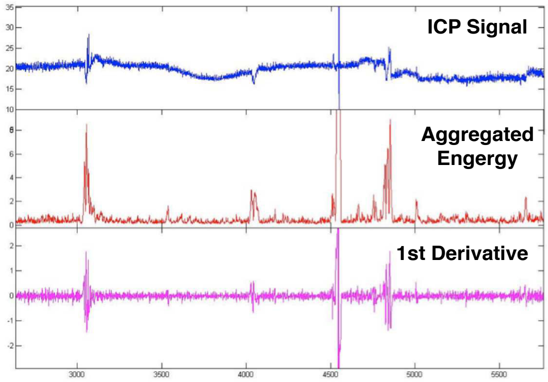

Figure 4: *Comparison among ICP signal, aggregated energy from wavelet transformation and its 1st derivative.*

positions of artifacts based on the 1st IMF component.

Step 2 Iteratively "grow" the full segments of artifacts based on subsequent IMF components.

The strength of the EMD approach is that, unlike other transformations, e.g. wavelet transformation, EMD is adaptive with the basis of the decomposition automatically derived from the signal. However, since EMD is a empirical process, it can be computationally "expensive". In addition, since the number of IMF components is signal dependent and is not controllable, the computational time can grow unbounded.

3.1.3 Wavelet Transformation Approach

Wavelet transformation is basically an adjustable window Fourier spectral analysis with the general definition as:

$$W(a, b; X, \psi) = |a|^{-1/2} \int_{\infty}^{-\infty} X(t)\psi^*(\frac{t-b}{a})dt \quad (3)$$

where $\psi^*(.)$ is the basis wavelet function, a refers to the dilation factor and b refers to the translation of the origin. Equivalently, the ratio $1/a$ denotes the frequency scale and b indicates the temporal location of an event. The physical meaning of wavelet transform can be simply interpreted as: $W(a, b; X, \psi)$ measures the "energy" of signal X at frequency scale $1/a$ and $t = b$.

In our proposed approach, the Haar wavelet basis function is employed to detect sudden transition in the underlining signal. Based on wavelet transform, the detection approach is composed with three steps:

Step 1 Transform the ICP signal into "energy" based on Haar wavelet.

Step 2 Aggregate the transformed "energy" across different scales. As shown in Figure 4, artifact segments in the ICP signal will cause obvious impulses in the aggregated energy, which can be used as indicators for artifact detection.

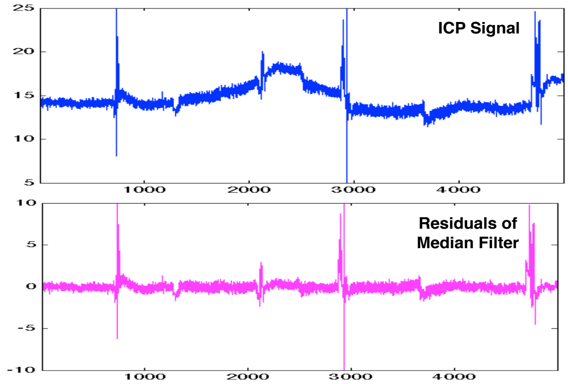

Figure 5: *Comparison among ICP signal and the residuals of median filter.*

Step 3 Calculate 1st derivative of the aggregated energy, and apply the proposed MAD filter to identify artifact segments.

With the Haar basis function, the wavelet transform approach is very sensitive to sudden changes in the signal, which is ideal for artifact detection. Moreover, superior to windowed Fourier transform, the wavelet transform maintains a uniform resolutions across all scales. It is also computationally "cheaper" than the EMD approach. However, as its weakness, the performance of the wavelet transform approach greatly relies on the right choices of the basis function.

3.1.4 Median Filter Approach

Median filter is a simple but effective tool that can be used to extract the trend component from a non-stationary signal. Since it is based on the median operation, the median filter is also a robust process that are sturdy against undesirable influence of artifacts. Give a time series $X(n)$, the outcome of a k-order median filter, $T(n)$, is defined as:

$$T(n) = \begin{cases} \text{if } k \text{ is odd :} \\ median\{X(n-\frac{k-1}{2}), \cdots, X(n+\frac{k-1}{2})\} \\ \text{if } n \text{ is even :} \\ median\{X(n-\frac{k}{2}), \cdots, X(n+\frac{k}{2})\} \end{cases} \quad (4)$$

Let $X(n)$ denote the original ICP signal. The median filter based artifact detection approach is proposed as follows.

Step 1 Apply median filter on $X(n)$ and obtain the trend component $T(n)$.

Step 2 Calculate the residual component $R(n) = X(n)-T(n)$. Figure 5 demonstrates that the residual component of median filter is also an effective indicator for artifacts in ICP signals.

Step 3 Apply the proposed MAD filter on $R(n)$ to identify artifact segments.

The most attractive strength of the median filter approach is its simplicity, which makes it a very attractive solution for online applications. Moreover, the median filter is a robust process that maintains stable performance in the presence of artifacts. On the other hand, the weakness of the median filter approach is that, to maximize its effectiveness, appropriate order k is necessary. In our case, the order k is set to 50 based on our statistical survey on the characteristics of artifacts in the ICP signals.

3.2 Artifact Imputation

After artifact segments are identified, detected artifacts are imputed based on the Autoregression Integrated Moving Average (ARIMA) model. Artifact segments are usually very short segments of signals. Within short segments, we observe that the ICP signal follows some ARMA-like behaviors. Thus, we choose the ARIMA model, which not only captures the characteristics of ARMA but, with its differentiating step, is also capable to normalize non-stationarity in signals. The order of ARIMA is optimized based on the *Akaike* information criterion.

4. Experimental Evalution

The proposed artifact correction methods are tested on the recorded ICP signals of 82 TBI patients, who were admitted in between 2007 to 2010. The selected patients were monitored for at least 12 hours. The effectiveness of the proposed artifact correction approaches are evaluated based on their achieved performance gain in ICP signal forecasting. The ARIMA model with AIC order selection is employed to forecast the ICP signal. The standard forecasting approach that has no artifact correction features is used as a comparison benchmark. The forecasting horizon is set as 15 mins, which is recommend by neurosurgeons to enable meaningful diagnostic applications. The forecasting performance is measured in terms of the Mean Square Error (MSE), Relative Absolute Error (RAE) and Forecasting Error (FER) [6]. The average computational time for each approach is also compared.

Table 1 summarizes the performance comparison results. It is observed that all three proposed approaches achieve significant performance gains. Among all, the EMD approach achieves the best gains. However, as expected, it requires a longer computational time. This makes it a more suitable method for offline analytic applications rather than online applications. For online diagnostic or prognostic applications, we recommend the median filter approach, for it is computationally efficient and, at the same time, achieves satisfactory performance gains.

	G_{MSE}	G_{RAE}	G_{FER}	Time(sec)
EMD	24.7%	9.07%	13.6%	312
Wavelet	21.8%	5.4%	8%	57
Median Filter	24.6%	10.2%	6.6%	24

Table 1: *Performance comparison. The standard forecasting approach without artifact correction features is used as a comparison baseline. G_{MSE}, G_{RAE} and G_{FER} refer to the achieved performance gain in Mean Square Error (MSE), Relative Absolute Error(RAE) and Forecast Error(FER). Time then refers to the average computational time of various approaches.*

5. Conclusion

In this paper, artifact correction methods are proposed to enhance ICP signal monitoring of TBI patients. Based on our observation, a *scale*-based filter was proposed to identify the artifacts. Moreover, to ensure the performance of the proposed filter will not be unduly influenced by artifacts, robust *scale* estimator, MAD, was employed. We also observed that the ICP signal is non-stationary. Therefore, three artifact detection approaches were proposed based on three non-stationary signal processing techniques, namely the EMD, wavelet transformation and median filter. The detected artifacts were then imputed based on the ARIMA model with AIC order selection.

The strengths and weakness of the proposed approaches were investigated and compared both theoretically and experimentally. According to our study, all three proposed approaches achieve significant performance gains. But, for online diagnostic or prognostic applications, we recommend the median filter approach, for it is computationally efficient and, at the same time, achieves satisfactory performance gains.

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