Empirical Mode Decomposition-Based Method for Artefact Removal in Raw Intracranial Pressure Signals

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Introduction

The most common way of analysing the intracranial pressure (ICP) signal in clinical practice is by visually inspecting the presence of macro patterns and waveform abnormalities. However, this approach relies on the experience of the observer, and hence the outcome might not be consistent. Automated and standardized methods of detecting wave patterns are thus desired to enable better detection of ICP deviations for diagnostic and therapeutic purposes. However, ICP signals are often contaminated by artefacts and the presence of segments of missing values. Some of these artefacts can be observed as very high and short spikes with a physiologically impossible high slope and value. These spikes can be generated by different sources, e.g. connection errors and movement of the monitoring system during data collection [1]. The presence of these spikes reduces the accuracy of pattern recognition techniques because they mask the characteristic appearance of ICP patterns.

Several methods have been used to identify the presence of spikes in ICP signals, from signal thresholding [2] to wavelet analysis. Signal thresholding fails to work if the signal-to-noise ratio (SNR) is low or if the ICP rises in an unphysiologically short time. Techniques using low-pass filtering are not appropriate in the case of the ICP signal since they are non-stationary (i.e. statistical properties change over time), as shown in the top graph of Fig. 1, where trends varying in time can be observed [3]. Alternative non-linear methods are based on wavelet transformation, whose output performance is highly influenced by the choice of a basis function [4]. These basis functions are fixed, hindering their match with the nature of the input signal at a given time. To overcome this drawback, more recent papers decompose the signal using the empirical mode decomposition (EMD) method, where the mother functions are derived from the signal, making the decomposition adaptive [4, 5].

Therefore, in this paper we propose a modified EMD method for automatic spike removal in raw ICP signals. The method is adaptive in non-linear and non-stationary signals because it involves breaking down signals into different frequency modes without leaving the time domain. It relies on the principle that some of these modes, also referred to as intrinsic mode functions (IMFs), capture the noise in signals so no a priori information on the data is required. This is important because there is no a priori knowledge of noise, so no procedures can be fixed beforehand to decrease the contribution of noise in signals.

Methods

EMD Algorithm

Huang et al. [6] presented EMD as a sifting method for adaptively decomposing non-stationary signals into a finite number of IMFs. An IMF is described as a function with two requirements: first, the number of extrema must be equal to zero-crossing or differ mostly by one and, second, the mean value of its lower and upper envelopes is zero. The EMD algorithm used for IMF extraction is briefly described for a given input ICP signal $s(t)$ as follows:

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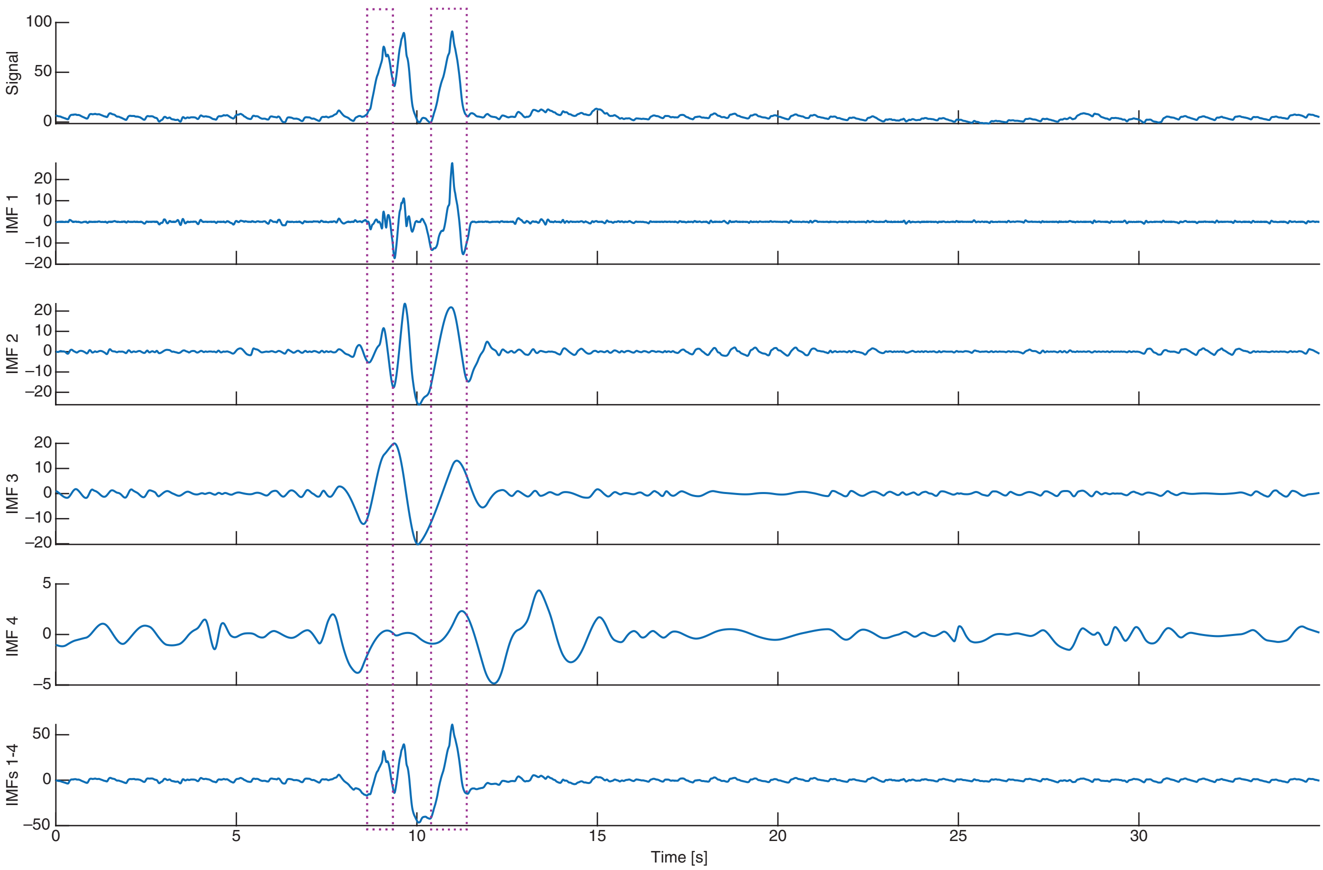

Fig. 1 Examples of peaks in ICP signals and IMF1–4

1. Find signal $x(t)$ extrema to which splines are fitted to generate both lower and upper envelopes. In the first iteration, $x(t) = s(t)$.
2. Calculate the arithmetic average of the two envelopes, $m(t)$.
3. Generate a candidate IMF $h(t)$ by subtracting the average envelope from the signal: $h(t) = x(t) - m(t)$.
4. If $h(t)$ is not an IMF according to the preceding requirements, then $x(t)$ must be replaced with $h(t)$ and steps 1–3 repeated. However, if $h(t)$ is treated as an IMF and the stopping criteria are not reached, the residue $r(t) = x(t) - h(t)$ is assigned to $x(t)$ and steps 1–3 are repeated. The stopping condition is usually a very small value to which the mean squared difference between the last two extracted successive IMFs is compared.

At the end of this iterative process, the original signal $s(t)$ can be expressed as the sum of all extracted IMFs plus the final residue. Note that the later an IMF is extracted, the lower will be its frequency content.

Proposed EMD-Based Algorithm

Spikes have a band-limited waveform, which implies that the frequency content is limited only to certain consecutive IMFs. *Band-limited* means that the frequency domain of the signal is zero beyond a certain finite frequency. The summation of the successive IMFs that contain part of a spike's dominant frequency would then help to temporally localize the spike event.

For localization and later removal of spikes from the ICP signal, we propose the following method:

1. Break down ICP signal into sixteen IMFs via EMD, as described above. Based on the physiological properties of the ICP signal as well as previous experiences by Feng et al. [7], breaking down the signal into 16 IMFs was considered the best trade-off between the signal length and computational time [8].
2. Spike detection from estimated IMFs.
3. Spike imputation in the original signal.

It must be noted that missing values are also randomly present in the ICP signal and they must be temporarily replaced with zeroes before EMD. In our monitored ICP signals, missing values are most likely due to sensor detachment during several minutes. Thus, temporal replacement by zeros during only the decomposition would not have any effect on higher frequency IMFs, which are the ones we are interested on for denoising. Instead, it will affect the low-frequency part, *i.e.* the local trend. Given the simplicity and lower computational time of this shortcoming and its ability to achieve an effective technical solution, it is preferred over the interpolation of values.

After decomposition, as visually demonstrated in Fig. 1, high amplitude oscillations in the first IMF align with the location of spikes in the ICP signal. Because the spikes have band-limited waveforms, dominant oscillations are found in various consecutive IMFs. Thus, a more effective event duration estimation is obtained when various successive IMFs are taken into account. In our case, only the location of peaks in IMF_{1-4} aligns with the location of peaks in the ICP signal, so summing these four IMFs enhances spike episodes: $IMF_{1-4} = \sum_{k=1}^{4} IMF_k(t)$. It is assumed then that the oscillations that build a spike are present in these four successive IMFs at the same temporal location as the signal artefact.

To identify the peaks in the summed IMFs, an adaptive thresholding approach is proposed (Fig. 2). ICP samples outside the bounded region in $[-P_{th}, P_{th}]$ will be identified as spikes. The threshold is determined based on the noise level in the summed IMFs: $P_{th} = \widehat{\sigma}\sqrt{2 \times \log L}$, where σ is the standard deviation of the signal and L the number of samples in the summed IMF [1]. Because σ is always unknown given the presence of artefacts in the signal, it must be estimated using e.g. the median absolute deviation: $\hat{\sigma} = \frac{MAD}{0.6745}$, where $MAD = Me\,|\,IMF_{1-4} - Me(IMF_{1-4})|$ [9]. If two identified spikes lie within a window of 0.4 s, the ICP samples between them are also treated as spike events. ICP spikes identified can either be removed or imputed with a moving average calculated over a sliding window of 10 s. An example of the results can be seen in Fig. 3.

Results

To both prove the non-stationarity of the signals and test the ability of the proposed method to detect spikes, real ICP signals are used. A total of 26 h are investigated from five different monitoring sequences. The Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test for stationarity is applied to selected artefact-free segments of increasing size [10]. With a 1-s window size, ICP signals are non-stationary with p-values around 0.03 for a significance level (critical alpha) equal to 0.05. Increasing window sizes reject the null hypothesis for the stationarity of the time series with even lower p-values (i.e. values close to 0.01).

To investigate the performance of the proposed algorithm, ICP segments containing unwanted dominant spikes are examined. Segments are visually inspected by an expert using a spike template. This template is established just for visual inspection purposes and is based on the determination of two spike characteristics: a duration shorter than 0.5 s and an abrupt ICP value increase. The artefact events visually

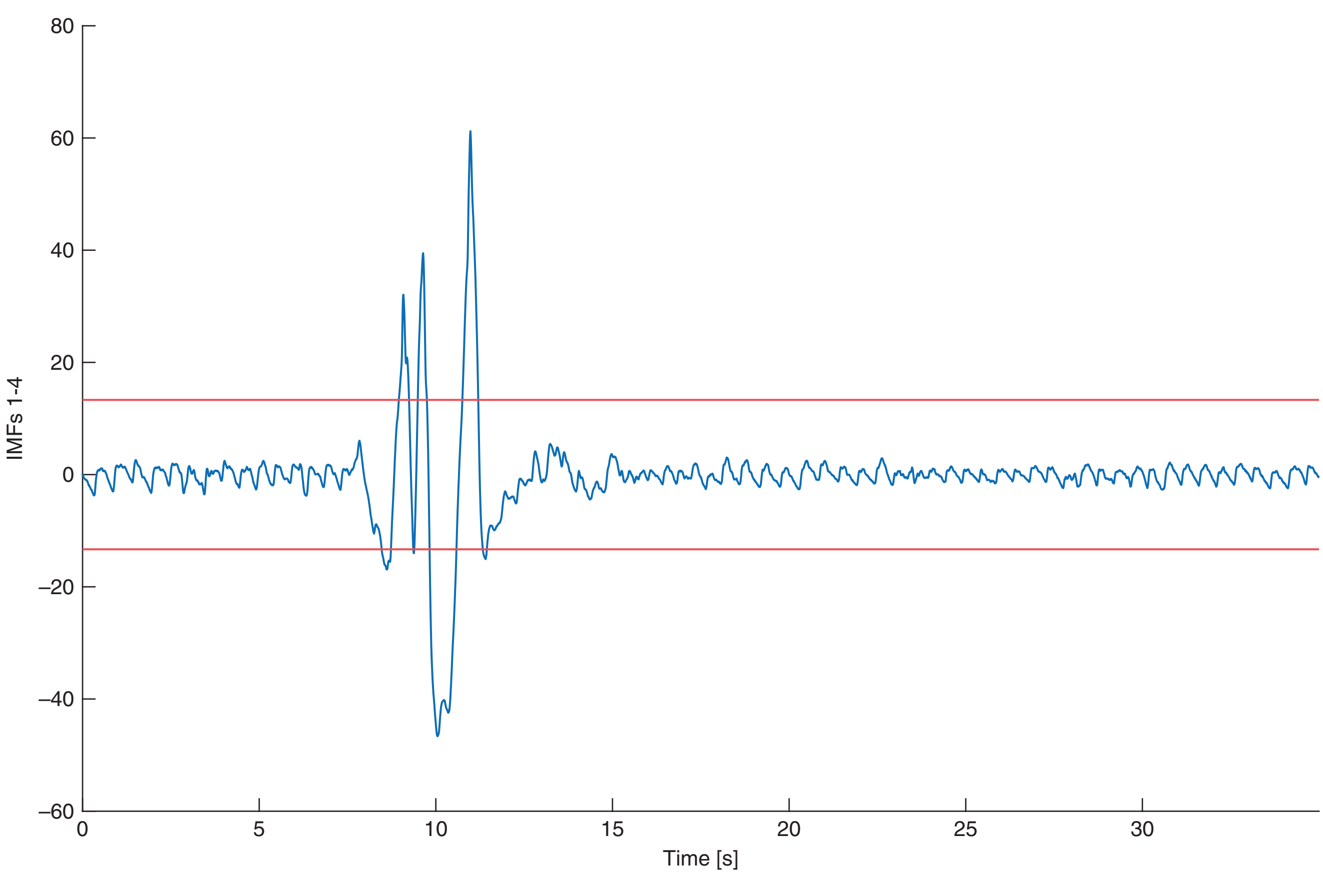

Fig. 2 ICP signals with lower and upper thresholds marked in red

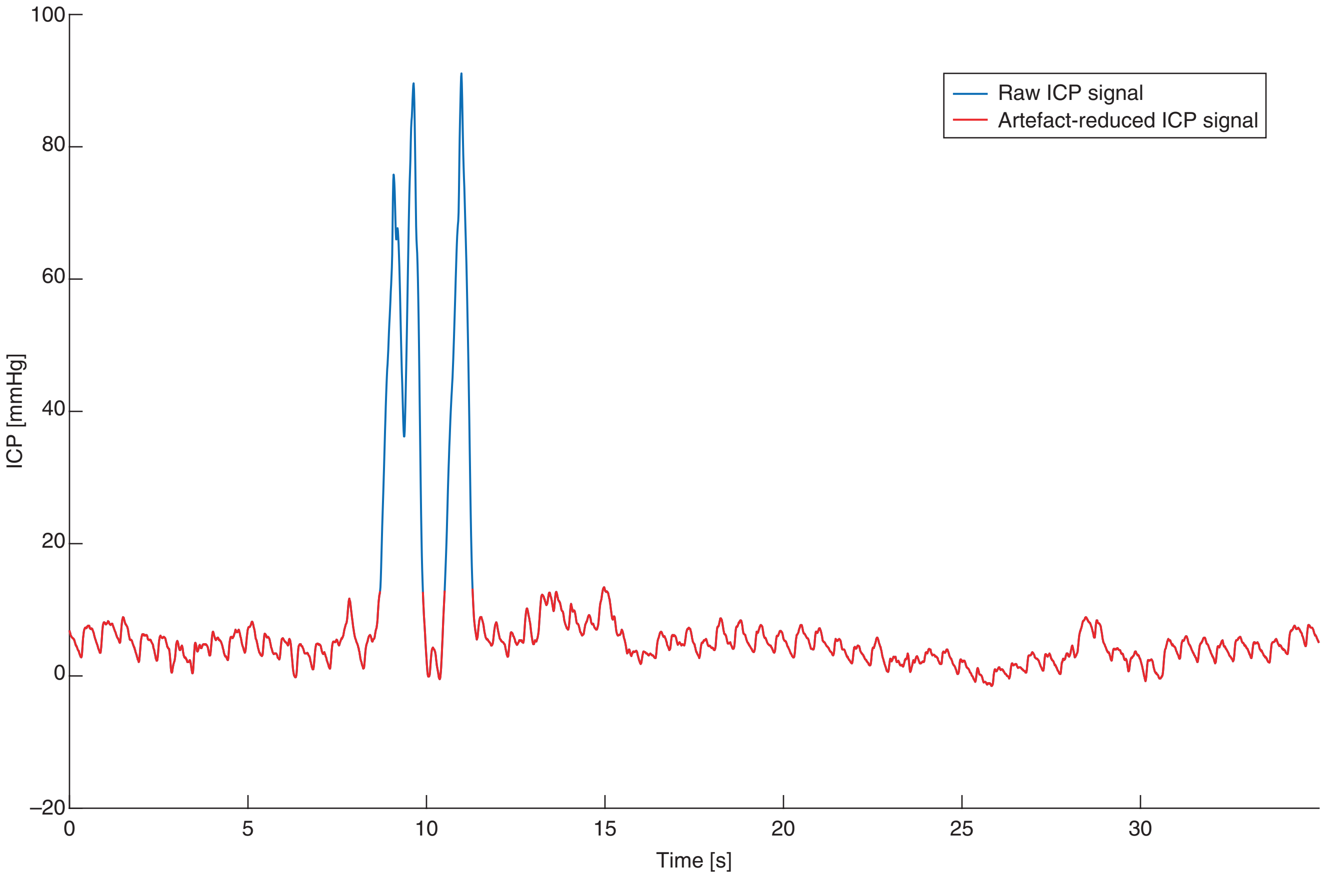

Fig. 3 Artefact-reduced ICP signal where detected spike has been removed

identified with the presence of the template are used as ground truth, and the ability of the method to identify them is then examined. The performance of the proposed method is quantified based on how well it estimates the location of the spikes using precision and recall metrics:

$$\text{precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \qquad \text{recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

where TP is the number of correctly identified spikes, FP is the number of spikes identified that were not spikes, and FN is the number of unidentified spikes. The goal is to get both values as close to 100% as possible. The proposed algorithm can detect spikes achieving an 84% precision and a 77% recall, given that TP = 114, FP = 21 and FN = 34.

Discussion

Results show that there are some artefact-free signal segments that are incorrectly classified as artefacts, given that the precision achieved is not 100%. The recall is lower, which shows that some artefact events are not identified. This is likely to be due to the magnitude of the episodes being smaller than the adaptive threshold P_{th} calculated. This limitation could be addressed by performing an additional spike identification iteration based on the slopes of the summed IMF peaks.

The algorithm also presents the drawback of not establishing a method to deal with the identified artefacts. We will further investigate this in our ongoing research, for which autoregressive moving average (ARMA) models [5] will be considered.

Conclusion

In this paper, a new methodology based on EMD is proposed for the removal of unphysiological spikes in clinical ICP signals, which is essential for correct patient evaluation and diagnosis in clinical practice.

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Conflict of Interest **The authors declare that they have no conflict of interest.**

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