Biomedical Signal Processing and Control 28 (2016) 19–26

Contents lists available at ScienceDirect

Biomedical Signal Processing and Control

journal homepage: www.elsevier.com/locate/bspc

Noise reduction in intracranial pressure signal using causal shape manifolds

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ARTICLE INFO

Article history:
Received 8 August 2015
Received in revised form 3 January 2016
Accepted 15 March 2016
Available online 30 April 2016

Keywords:
ICP
Intensive care
Traumatic brain injury
Manifold learning
Noise reduction

ABSTRACT

We present the Iterative/Causal Subspace Tracking framework (I/CST) for reducing noise in continuously monitored quasi-periodic biosignals. Signal reconstruction of the basic segments of the noisy signal (e.g. beats) is achieved by projection to a reduced space on which probabilistic tracking is performed. The attractiveness of the presented method lies in the fact that the subspace, or manifold, is learned by incorporating temporal, morphological, and signal elevation constraints, so that segment samples with similar shapes, and that are close in time and elevation, are also close in the subspace representation. Evaluation of the algorithm's effectiveness on the intracranial pressure (ICP) signal serves as a practical illustration of how it can operate in clinical conditions on routinely acquired biosignals. The reconstruction accuracy of the system is evaluated on an idealized 20-min ICP recording established from the average ICP of patients monitored for various ICP related conditions. The reconstruction accuracy of the ground truth signal is tested in presence of varying levels of additive white Gaussian noise (AWGN) and Poisson noise processes, and measures significant increases of 758% and 396% in the average signal-to-noise ratio (SNR).

1. Introduction

Intracranial pressure (ICP) is defined as the pressure inside the skull and is a marker of the brain's ability to compensate for cerebral pathophysiological changes. Although intraventricular catheters and intraparenchymal sensors are widely used for ICP monitoring, their invasiveness presents considerable risk to the patient, and therefore are only used when the risks associated with a pathological increase in ICP outweighs those associated with its invasive monitoring. Clinically, ICP is a fundamental physiologic parameter that, if elevated, can lead to a pathological reduction in cerebral blood flow and possible herniation of the brain, resulting in irreversible brain damage or death if left untreated. Currently, the ICP signal is used to diagnose dangerous increases in average pressure (computed using a moving average) and helps guide treatment with recommendation based on ICP greater than 20 mmHg for more than 5 min [1]. Although the average ICP is monitored in modern clinical environments, subsequent higher-order analysis on the ICP pulse waveform often requires complex processing, expert annotations, and corrections due to egregious noise introduced during measurement from electronic equipment, electrode transients, displacement of the sensor, or even the patient shifting their posture. Such conditions make it difficult for real-time monitoring software to properly interpret ICP waveform data (Fig. 1).

The conventional approach to noise reduction is to filter the input signal. When noise is constrained to particular frequencies, such as 60 Hz tonal noise, we can retrieve most of the desired signal by applying bandstop (notch-type) filters. In the general case, when a model of the desired signal's spectral content is known, along with an estimate of the noise distribution, adaptive filtering may be used to construct a mean-square optimal filter [2]. However, the problem is more challenging when noise has a spectral density which overlaps significantly with that of the desired signal. Channel estimation is fickle in this application, because biosignals are not easily constructed from band-limited primitives. Specifically, it is increasingly difficult to identify a generic noise-floor when the relevant spectral content of the signal is not entirely known.

Another popular approach to the broadband noise problem is to estimate the original signal by assuming some stochastic mixing process. A mixture model uses knowledge of the expected degradation to estimate the most likely values for the originally transmitted signal [3]. When the number of possible source-transmitted symbols is relatively low and discretized, expectation maximization (EM) and maximum a posteriori estimation (MAP) algorithms can

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http://dx.doi.org/10.1016/j.bspc.2016.03.003
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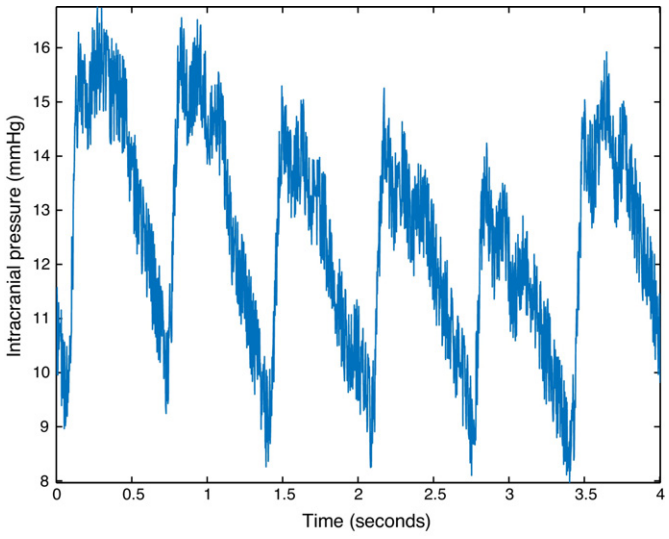

Fig. 1. Illustration of a typical intracranial pressure signal (ICP) recorded in clinical conditions. ICP typically exhibits significant noise on its envelope that challenges its morphological analysis.

be used to estimate the most likely source-transmitted symbol, although an initial characterization of both the source and noise distributions is required.

In the case of ICP waveform, the number of possible pulse shapes is not finite and assigning a discrete estimate from a bank of reference signals is not an optimal solution to preserve patient-specific features. Moreover, a static characterization of the noise distribution is not always possible in clinical environments, since degradations may vary between sites and may be introduced from a combination of sources (including patient movement, sensor displacement, electronic noise, type of sensor) in varying proportion. To tackle this problem, we present a method for reducing noise in continuously monitored quasi-periodic biosignals without prior knowledge of the noise distribution. Noise is reduced by reconstructing an estimate of the original signal from a mixture of reference signals. The references are selected by searching the closest neighbors of an input sample in a reduced dimensional space. By tracking the position of consecutive samples in the subspace, causal correction transformations can be iteratively applied to the collected data stream.

There has been significant interest in modeling the morphology of the ICP waveform [4–9]. One of the main findings of those studies is to characterize the relationship between the average ICP value and the signal morphology (up to the beat level). By clustering the morphology of the waveform for various levels of ICP, as we will illustrate later in this paper, it can be observed that the ICP waveform at the beat level has shape features that vary along with the ICP. Based on this strong correlation between the ICP value and signal morphology, we introduce a modified nonlinear subspace learning algorithm to accent this correlation by warping the learned subspace to reflect constraints about time, morphology, and average ICP. The intuition behind the algorithm is that the level of ICP implicitly constraints the possible waveform morphologies which can be used to refine the denoising process.

The structure of this paper is as follows: we first present the dataset and the ground truth used during our experimental evaluation in Sections 2.1 and 2.2. The mechanics of the Iterative/Causal Subspace Tracking (I/CST) is presented in Section 2.3, ending with the formulation of a simple I/CST implementation (Algorithm 1). The performance of this implementation is evaluated for ICP signals in Section 2.4 and the results presented in Section 3. This work results in a noise reduction framework capable of real-time performance, which enables a more reliable analysis of continuous waveform characteristics, as discussed in Section 4.

2. Methods

2.1. Data source

The dataset originated from the University of California, Los Angeles (UCLA) Medical Center, with approval from the institutional review board (IRB) for use in this study. This is a retrospective study on patients who were being treated for various intracranial pressure related conditions including idiopathic intracranial hypertension, Chiari syndrome, and slit ventricle patients with clamped shunts. A total of 60 patients were considered for this study and their ICP and electrocardiogram (ECG) signals were recorded continuously. ICP was sampled continuously at 400 Hz using an Codman intraparenchymal microsensor (Codman and Schurtleff, Raynaud, MA) placed in the right frontal lobe. An expert researcher retrospectively identified intracranial hypertension (IH) episodes and annotated the time of the elevation onset, elevation plateau, and invasive cerebrospinal fluid drainage in each patient recording. Within our cohort, 30 patients did not present any IH episodes and were excluded from the study. An additional 5 patients were excluded due to signal drop and artifacts that did not let the expert identify IH episodes with a high level of confidence. A total of 70 IH episodes were extracted from the ICP signal of the remaining 25 patients. Each segment included 20-min of data, capturing the transition from a state of normal (0–20 mmHg) to elevated ICP (>20 mmHg). The segments were time-aligned such that they contain 15 min of data before the plateau and 5 min after.

2.2. Pre-processing and ground truth

Individual ICP pulses were first extracted from each 20-min recording using a correlation of ICP with R-wave peaks in the ECG signal [10]. Because this method is dependent only locally on the R-wave peaks, the segmentation is sufficiently accurate and largely invariant to heart-rate variability [11]. The extracted pulses were distilled into 3 variables: (1) amplitude and length normalized vector containing pulsatile information, (2) mean value of the original pulse, and (3) starting time-index of the pulse relative to the elevation plateau.

The normalization is necessary because pulses extracted by the segmentation may differ in length, and require a consistent size to facilitate morphological comparisons of the form $||x_i - x_j||$. As such, each segmented ICP pulse s_i was normalized to a fixed-length vector $x_i \in \mathcal{R}^n$ taking values between 0 and 1, and placed into a matrix of vector samples $X \in \mathcal{R}^{m\times n}$. If the length of the pulse s_i was larger than the chosen length $n = 500$, the extra values at the end of the pulse were ignored. If the pulse was smaller than n, the last value $s_i[end]$ was repeated to fill the vector. As written formally,

$$x'_i(j = 1, \ldots, n) = \begin{cases} s_i[j] & \text{if } j \leq n \\ s_i[end] & \text{otherwise} \end{cases} \quad (1)$$

$$x_i(j = 1, \ldots, n) = \frac{x'_i - \min(x'_i)}{\max(x'_i) - \min(x'_i)} \quad (2)$$

An idealized ICP signal is then generated by accumulating similar beats and computing their average. The notion of similarity is subject to change here and is largely dependent on the intended application. In our tests, for example, beats are clustered based on their relative-time index (i.e. by binning the pulses starting within every 3 s interval). This strategy, however simple, preserves a notion of morpho-temporal locality in the ICP signal, a property that is exploited in the tracking algorithm (Section 2.3.2). Finally, to