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Calculation of the Mean Pressure with Less Delay for Real-Time Clinical Monitoring

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***Abstract*— The mean of cardiovascular pressure signals is an important metric in patient monitoring applications for many types of diseases and injuries. It is typically calculated with a moving average of 3–8 s of the pulsatile signal. This method of calculating the mean introduces a delay of 1.5–4 s. We demonstrate that an FIR filter with coefficients calculated with a least squares error (LSE) estimator can reduce this delay without a clinically significant impact on the accuracy of the displayed signal. Preliminary results with intracranial pressure signals show that the delay can be completely eliminated with a maximum root-mean-square error of approximately 1 mmHg. Reduction or elimination of this delay could permit patient monitors to display the mean in real time and permit clinicians to respond to acute events more rapidly.**

I. Introduction

Patient monitors used in acute care applications calculate many summary metrics of the physiologic signals that are monitored. For pressure signals such as the arterial blood pressure, pulmonary arterial pressure, central venous pressure, and intracranial pressure, one of the most important metrics is the mean pressure. The "mean pressure" is a clinical misnomer because it generally refers to the signal trend, rather than the mean value of the signal.

The mean pressure can be defined as the average value of the pressure signal over the duration of each cardiac cycle. This definition, however, is not used in patient monitors and fluctuates with the respiratory cycle. Instead, the mean pressure is generally accepted as a measure of the trend of the pressure signal that excludes the pulsatile component due to the cardiac and respiratory cycles. In most clinical research applications and in some commercial patient monitors, the mean pressure is calculated with a 3–8 s moving average of the pressure signal. The moving average is a special case of a finite impulse response filter with coefficients that are all equal.

From a clinical perspective, this presents a problem for patient care because rapid and significant changes in the patient's actual clinical condition (e.g., hypotension, cardiac arrest, intracranial hypertension) will precede any changes displayed on the patient monitor. Potentially, this can cause a clinically significant delay in diagnosis and treatment.

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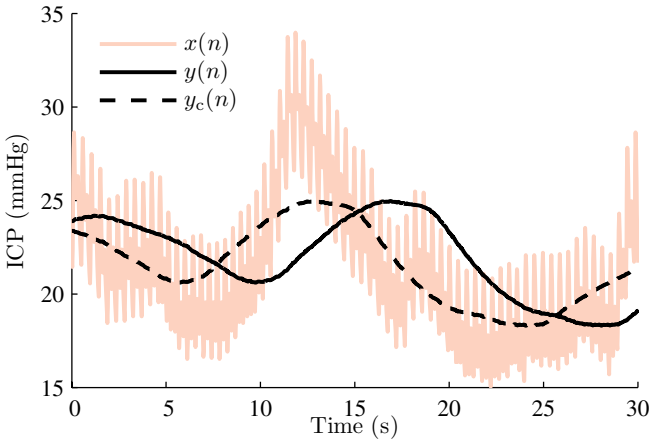


Fig. 1. Example of an intracranial pressure signal $x(n)$, its centered mean y_c, and the mean as displayed on patient monitors $y(n)$.

In this paper we focus on intracranial pressure (ICP) signals. Complications arising from traumatic brain injury (TBI) can cause intracranial hypertension, resulting in cerebral ischemia. Elevated ICP is associated with worse outcomes [1], [2], and clinicians closely monitor mean ICP through invasive monitoring techniques. Generally, therapy is designed to maintain the mean ICP below a critical threshold of 20 mmHg.

Fig. 1 shows an 8 s moving average estimate of the mean ICP. The centered mean is also shown in this figure and is defined as a symmetric moving average of the ICP signal. The centered mean cannot be calculated in real time because it requires knowledge of 4 s of the past and 4 s of the future values of the signal. Our objective is to demonstrate that an FIR filter with appropriate coefficients can reduce or eliminate this delay without significantly compromising accuracy.

Other investigators have attempted to predict and anticipate acute intracranial hypertensive episodes in TBI [3]–[5]. Our aim differs from this previous work in that our primary aim is to estimate the mean ICP, rather than predict acute events.

II. Filter Design

Our approach to this design is to use archived clinical data to estimate the optimal linear filter coefficients to estimate the true mean ICP with less delay than the moving average. With the archived data we can actually calculate the true mean since future values of the pressure signal are known.

Throughout this paper we use an 8 s moving average as our standard of comparison.

A. Target Signal Computation and Prediction

The 8 s moving average of the unfiltered ICP signal, $x(n)$, is defined as

$$y(n) = \frac{1}{M_0} \sum_{k=0}^{M_0-1} x(n-k), \tag{1}$$

where M_0 is the filter length in samples, determined by the sampling frequency, f_s. For an eight-second window,

$$M_0 = f_s \times 8. \tag{2}$$

The signal $y(n)$ represents the mean ICP displayed on patient monitors. It is delayed by 4 s from the centered mean ICP, defined as

$$y_c(n) \triangleq \frac{1}{M_0} \sum_{k=-(M_0-1)/2}^{(M_0-1)/2} x(n-k). \tag{3}$$

Our objective is to reduce this delay by predicting $y(n)$ from past and present values of the unfiltered ICP signal $x(n)$. Our estimate can then be expressed as

$$\hat{y}_p(n) = \sum_{k=0}^{M-1} c_k\, x(n-p-k), \tag{4}$$

where $\hat{y}_p(n)$ is an estimate of $y(n)$ calculated at time $n-p$ and c_k is the kth filter coefficient. The variable p is called the prediction horizon. Complete elimination of the delay corresponds to a prediction horizon of $p = (M_0-1)/2$ samples.

B. Least Squares Error Estimation

We used the method of least square error (LSE) estimation to build FIR filter coefficients c_k for a variety of prediction horizons p. To prevent edge conditions from biasing the estimates, we limited the range of the target signal from $n = M_0 + p_m$ to $n = N-1$, where N is the number of samples of $x(n)$ in the archived signal and p_m is the maximum value of p considered. The LSE filter coefficients are given by

$$\boldsymbol{c}_{\mathrm{ls}} = (\boldsymbol{X}^H \boldsymbol{X})^{-1} \boldsymbol{X}^{\mathrm{T}} \boldsymbol{y}, \tag{5}$$

where $\boldsymbol{X}$ is the input data matrix and $\boldsymbol{y}$ is the target signal vector.

We combined the data from multiple patients into a single composite data matrix and target vector,

$$\boldsymbol{X} = \begin{bmatrix} x_1(M_m-1) & \cdots & x_1(0) \\ \vdots & \ddots & \vdots \\ x_1(N_1-p_m) & \cdots & x_1(N_1-p_m-M_m) \\ x_2(M_m-1) & \cdots & x_2(0) \\ \vdots & \ddots & \vdots \\ x_2(N_2-p_m) & \cdots & x_2(N_2-p_m-M_m) \\ x_3(M_m-1) & \cdots & x_3(0) \\ \vdots & \vdots & \vdots \end{bmatrix}, \tag{6}$$

where the subscripts represent the patient index. Likewise, the target vector is given by

$$\boldsymbol{y} = \begin{bmatrix} y_1(M_m-1+p_m-1) \\ \vdots \\ y_1(N_1-1) \\ y_2(M_m-1+p_m-1) \\ \vdots \\ y_2(N_2-1) \\ y_3(M_m-1+p_m-1) \\ \vdots \end{bmatrix}. \tag{7}$$

C. Validation and Performance Metric

The only critical user-specified parameter in this application is the filter length M. Values that are too small or too large will decrease the accuracy, in general, due to excessive bias or variance of the estimate. Large filter lengths also increase the computational costs and cause longer transient responses to artifact.

Clinically, the critical tradeoff is between accuracy and reduction in the delay. We selected the root mean square error (RMSE) as our performance metric in this application. It is defined as

$$\mathrm{RMSE} \triangleq \sqrt{\frac{1}{N_a} \sum_{k=p_m+M_m-1}^{N-p_m} [y(n) - \hat{y}_p(n)]^2}, \tag{8}$$

where

$$N_a = N - 2p_m - M_m + 2 \tag{9}$$

is the number of terms included in the sum. The units of the RMSE are the same as that of the quantity being estimated, and it can be understood as a coarse approximation of the standard deviation of the error.

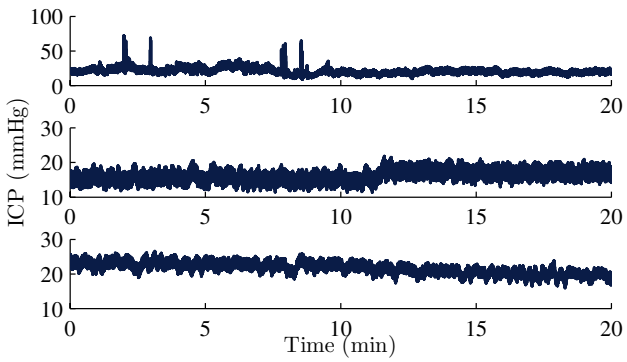
III. Results and Discussion

We used a composite data matrix of three 20 min ICP signals ($f_s = 125$ Hz) obtained from separate TBI patients in the pediatric ICU at OHSU (Fig. 2(a)). We examined the accuracy tradeoffs calculating the RMSE for various filter lengths at three prediction horizons: $p = 2$ s, $p = 4$ s, and $p = 6$ s. As shown in Fig. 2(e), the gain in performance for filter lengths greater than $M = 1250$ samples (10 s) is insignificant and may increase the variance of the estimate. We used this filter length in all subsequent analysis.

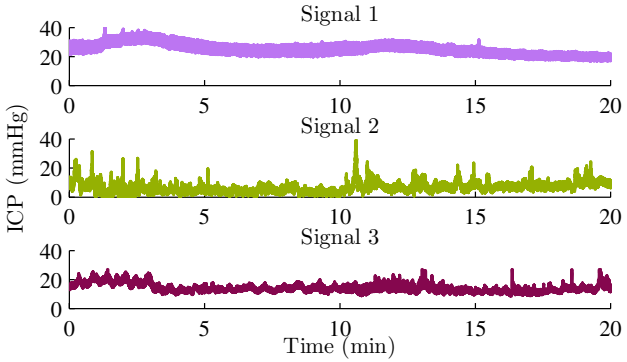
In addition to the training data used to estimate the filter length and coefficients, we also assessed the performance on test data obtained from three other patients. The test data are shown in Fig. 2(b).

A. Performance on Training Data

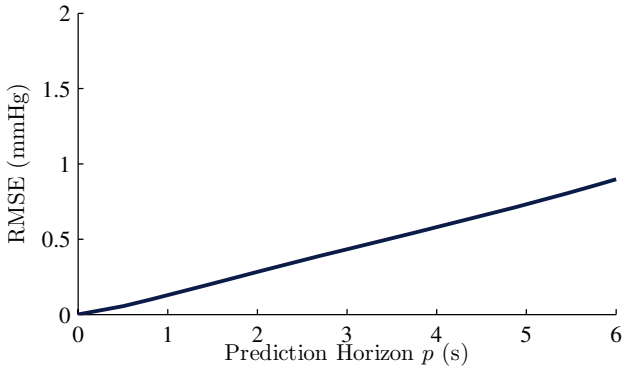
Fig. 2(c) shows the RMSE over a range of prediction horizons, defined as p in (4). The estimator can calculate the moving average mean ICP exactly when p = 0 samples, and the error increases monotonically as the estimator tries to predict further into the future. Fig. 2(g) shows a comparison



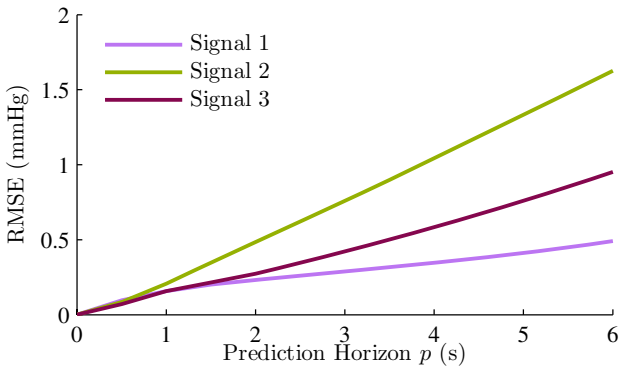
(a) Training signals



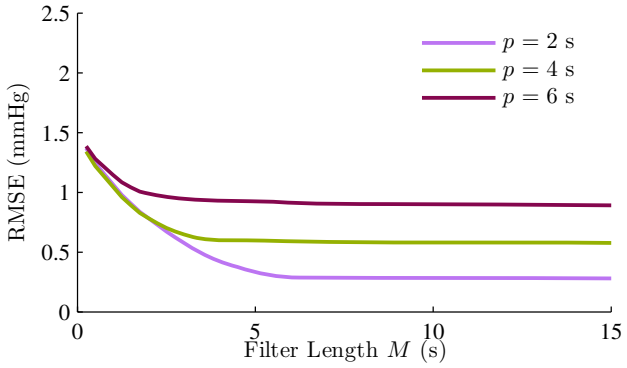
(b) Test signals



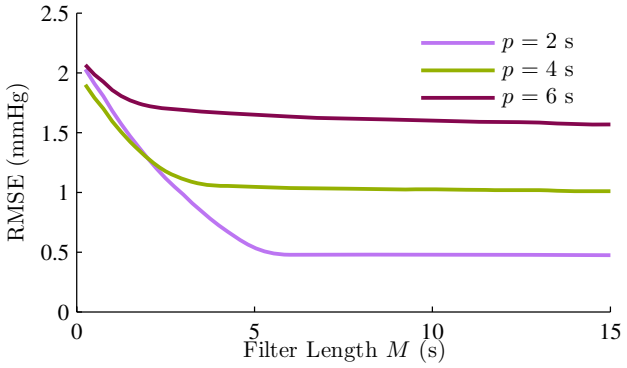
(c) Sweeping prediction p on composite training signal



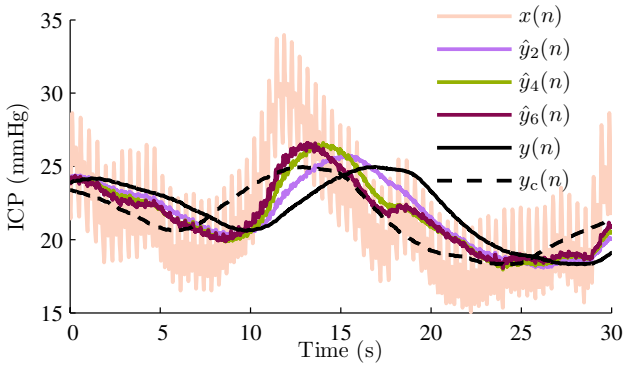
(d) Sweeping prediction p on training signals



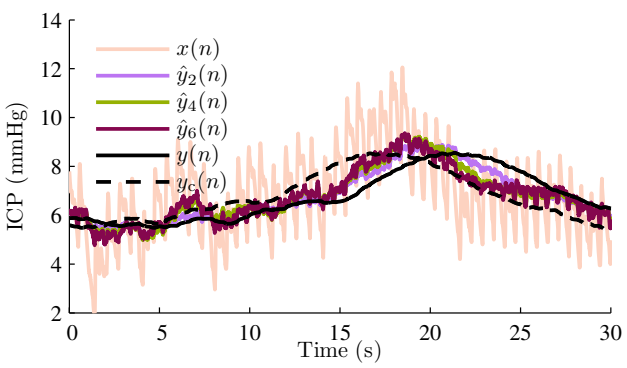
(e) Sweeping filter length M on composite training signal



(f) Sweeping filter length M on test signal 2



(g) Performance example on composite training signal



(h) Performance example on test signal 2

Fig. 2. (a) Training signals used to estimate the filter coefficients. (b) Test signals used for performance assessment. (c) RMSE versus prediction horizon p on the training signals (filter length $M = 10$ s). (d) RMSE versus prediction horizon p on each of the test signals (filter length $M = 10$ s) . (e) Error versus filter length in composite training signal. (f) Error versus filter length on test signal 2. (g) Example of estimates on a training signal. (h) Example of estimates on test signal 2.

of the ICP $x(n)$, the centered mean $y_c(n)$, the moving average mean $y(n)$, and $\hat{y}_p(n)$ for $p = \{2, 4, 6\}$.

The predicted means clearly have less delay than the moving average mean. They are also able to track fluctuations in the baseline trend better than the centered or moving average means. The example shown in Fig. 2(g) suggests that the 8 s moving average may actually oversmooth and miss clinically significant elevations in the ICP. The predicted estimates are less smooth and better able to track significant changes in the ICP, but they do not attenuate fluctuations at the cardiac frequency as much as the moving average. These fluctuations at the cardiac frequency are < 1 mmHg and not clinically significant.

B. Performance on Test Data

We tested the LSE estimator on 20 minute ICP epochs from three patients (Fig. 2(b)). The RMSE versus prediction p appears in Fig. 2(d). The performance on the three test signals varied considerably. The RMSE reached a threshold of 1 mmHg with a prediction horizon of 3 s for test signal 2, but exceeded p =6 s for test signal 3. This is due to the rapid increases in ICP that occurred in test signal 2.

Fig. 2(d) suggests we can eliminate the delay ($p = 3$–4 s) with a maximum error of approximately 1 mmHg. An error of this magnitude is acceptable for most clinical monitoring applications.

IV. Discussion and Conclusion

Our preliminary results with 20 min records from six patients suggest that FIR filters are able to estimate the mean pressure with less delay and better tracking of short-term fluctuations in pressure signals than the conventional moving average estimates widely used in research and clinical patient monitors.

The results also seem to indicate we can forecast the mean ICP two seconds into the future with only 2 mmHg of error. This is less remarkable than it might appear because most of the time the mean ICP is stable and predictable. This results in a low RMSE, even if the estimator cannot track or predict rapid increases in the mean ICP. These events do not occur frequently, but are important clinically.

The development of an optimal estimator of the mean value of pressure signals is hampered by a precise definition of the "mean". It may be possible to use conventional FIR lowpass filter designs to track the clinically significant fluctuations with more accuracy and less delay. Further studies with larger data sets are necessary to determine the most suitable tradeoffs between the ability to track significant fluctuations (e.g., slew rate), attenuation of the respiratory and cardiac components (i.e., stopband attenuation), robustness to artifact, passband flatness, and delay.

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