Proceedings of the 28th IEEE
EMBS Annual International Conference
New York City, USA, Aug 30-Sept 3, 2006

A Simple Non-physiological Artifact Filter for Invasive Arterial Blood Pressure Monitoring: a Study of 1852 Trauma ICU Patients

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Abstract— **Invasive arterial blood pressure (BP) is a vital sign in hemodynamic monitoring of trauma intensive care unit (ICU) patients. Continuous BP analysis can potentially provide additional information about patient status, predict morbidity and mortality, and automatically populate electronic nurse charting systems than intermittent monitoring. Challenges to routine application in the ICU include integration of complex physiological data collection systems, artifacts, missing data, and the various clinical interventions that may temporarily corrupt the BP signal. We have developed and previously described SIMON (Signal Interpretation and MONitoring), a physiological data collection system in the Trauma ICU at Vanderbilt University. In order to extract useful information from continuous arterial line BP monitoring, it is necessary to remove non-physiological artifacts. In this setting, potential artifacts appear to be caused by resonance, over-damping, and data transmission. We designed a simple filter to identify various sources of non-physiological artifacts using statistical signal processing techniques. We implemented the filter to arterial invasive BP signals of 1852 trauma patients throughout their length of ICU stay. After filtering, the power of BP measures to predict hospital death was enhanced. Therefore, we concluded that our strategy of removing non-physiological artifact was simple, fast and useful for an accurate assessment of BP measures in trauma patients.**

I. Introduction

While technology has expanded the spectrum of physiologic parameters available in the intensive care unit (ICU), interpreting these parameters remains largely a manual process. The SIMON (Signal Interpretation and MONitoring) project began at the Vanderbilt University Trauma Center in 1998 and captures physiologic data every 1 to 4 second continuously, aiming to provide more information about trauma ICU patient than conventional processes. Our previous work demonstrated that reduced heart rate variability was associated with mortality and morbidity in trauma ICU patients [1-4]. Arterial blood pressure (BP) emerged as our next most important parameter.

Increases in long term BP variation have been associated with worsening hypertension, cardiovascular risk and end organ damage in hypertensive patients [5;6], while decreases in short term BP variation has been associated with severity of neurological injury and brain death in acute brain injury children [7;8]. Our preliminary results showed that decreased short-term blood pressure variation, but *not* central tendency, was correlated with an increased mortality in trauma ICU patients [9]. For this and other reasons, continuous rather than intermittent BP monitoring is important in this group of patients.

Arterial invasive BP is of interest primarily in critical care, when the maintenance or restitution of physiologic homeostasis is vital. It reflects the general physiologic state of the whole organism, and includes systolic, diastolic, mean arterial and pulse pressure components (SAP, DAP, MAP, PP). These can be measured continuously via catheter-transducer systems in systemic arteries through the length of ICU stay for each patient. Other methods of BP measurement (*e.g.* Doppler, cuff) are not as reliable as arterial line in critical care patients for various reasons [10]. As a result, arterial catheterization (*i.e.* insertion of a tubular device into a blood vessel for injecting or withdrawing fluids for diagnostic or therapeutic purposes) is routine practice in critical care.

Computerized analysis of continuous invasive arterial BP signal may benefit computerized decision support for morbidity and mortality. Arterial catheterization can be used for BP waveform analysis, direct BP level control, and BP time series analysis. However, it is rarely applied in ICU setting. The reasons are mainly problems in the integration of complex systems, the presence of artifacts and missing data during data collection, and the involvement of clinical interventions, as summarized in Ref [11].

Our ultimate goal is toward early diagnosis of morbidity and mortality of ICU patients by developing mathematical and statistical tools for BP analysis. We hypothesize that new measurements based on dense BP data capture may supplement intermittent readings as “new vital signs”. The integration of the complex data collection system has been accomplished [1]. It continuously captures 13 important physiological parameters (including heart rate, blood pressure, tissue perfusion pressures, arterial & venous oxygen saturations, cardiac index, end diastolic volume index, and *etc*.) from all ICU beds since December 2000. However, the invasive pressure monitoring was subject to non-physiological artifacts due to inappropriate catheter positioning, the presence of clot or air bubble, flushing, etc. A simple, fast filter that can be used clinically would potentially improve the usefulness of densely-captured BP data.

However, BP filter design was challenging because:
(1) There is no BP measurement more accurate than arterial line which could serve as a reference or “gold standard”;

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(2) The only data immediately available were recordings of integer SAP, DAP, MAP, and PP, captured unevenly every 1-4 seconds;
(3) The BP waveform, which is essential to tell the presence of resonance or over-damping, was not available for this project;
(4) Physicians were unable to tell precisely if artifact existed simply by retrospectively inspecting continuous recordings of SAP, DAP and PP.

Despite the challenges, we proposed a statistical filter of BP signal which can potentially improve the usefulness of desnsely-captured BP data.

II. METHOD

A. Data Collection

Arterial line BP data were collected in the trauma ICU of Vanderbilt University Medical Center (VUMC) from Philips bedside physiologic monitors [2]. From December 2000 to November 2004, the physiological data from 3187 trauma patients were collected, of which 1852 patients had arterial line BP data to form our study population. Clinical data such as hospital death were collected from the database of the Trauma Registry of the American College of Surgeons (TRACS) [4]. In this study population, 308 patients died.

B. Source of Non-physiological Artifacts

The main sources of non-physiological artifact include resonance and over-damping [12]. They are two related, but opposing, phenomena. On one hand, resonance of the monitoring system may lead to exaggeration of systolic peak. Resonance usually happens when the catheter is long, narrow-bore and of high-compliance. On the other hand, over-damping tends to diminish the perceived oscillation and results in an artifactual decrease in SAP and an artifactual increase in DAP, thus causes a minimal PP [13]. Over-damping may occur after several days of catheterization when catheter tip is blocked or kinked. When over-damping is spotted, the nurse performs a flush test to be certain that over-damping is present, and replaces the catheter if necessary. Other less dominant factors include different dispositions of the catheter tip and data collection/transmission, which are characterized by an abrupt and brief change in BP. The artifacts should be removed prior to analysis because they are indeed erroneous.

The top panel of Figure 1 shows an example of BP signals corrupted by non-physiological artifact.

C. Filter Design

Based on suspected artifact patterns in BP measurement, physiologic norms, and clinical experience, we defined BP data to be non-physiological artifact if: (1) BP values were out of range of 30-250 mmHg for SAP and 15-200 mmHg for DAP; (2) brief abrupt BP change of 15 mmHg or more for SAP and 10mmHg or more for DAP within 10 second and return equally abrupt to baseline; or (3) over-damping was defined as the presence of pulse pressure PP = SAP-DAP < 10 mmHg, an arbitrary and loose cutoff. It was challenging to distinguish over-damping from extremely low but physiologic pulse pressure by only looking at time series of BP signals (without other information about the patient such as BP waveform, neurological stability, intervention) in order to keep the filter simple and clinically applicable. One of our basic rules of filter design was to remove least amount of data possible.

BP data beyond the physiologic ranges of 30-250 mmHg for SAP and 15-200 mmHg for DAP were first removed. Then we adapted the algorithm of artifact removal for fetal heart rate data developed at University of Virginia [14] to remove the abrupt change of BP due to the similar feature of the artifact. Basically, within each 5 minute interval, BP data points were identified as abrupt artifacts if they were either:

(1) 3 folds of interquartile range beyond its median or
(2) 15mmHg for SAP or 10 mmHg for DAP beyond median value when interquartile range is zero, *i.e.* the variability of the data was minimal.

Finally, in order to identify BP data when over-damping was present, we developed automatic algorithms to detect the beginning and end of over-damping. Each pulse pressure recording first went through a two-step low-pass-filter with a cut-off frequency f_c = 1/15Hz from trial and error in order to remove small jitters:

$$y(i) = x(i\text{-}1)^* \rho + x(i)^*(1\text{-}\rho),\ i = 1, 2,\ldots N$$
$$z(i) = y(i\text{+}1)^*\rho + y(i)^*(1\text{-}\rho),\ i = N, N\text{-}1,\ldots 1$$
$$\text{where } \rho = 2\text{-}cos(2\pi f_c)\text{-}[(2\text{-}cos(2\pi f_c))^2\text{-}1]^{1/2}$$

Filtered points with values less than 10 mmHg and the number of consecutive point of at least 8 were picked as potential over-damping sites. Since over-damping may develop gradually or intermittently, the PP data were scanned from the potential over-damping sites forward and backward in time until local maxima greater than 25th percentile value were reached. They were identified as beginning and end of over-damping, and the data segment between them were removed, while the remaining data were kept as the version before over-damping filter.

D. Evaluation

Evaluating the efficacy of the BP filter was challenging. Ideally, a controlled study should be conducted by manually inspecting and marking the portion of clinically diagnosed artifact by an expert clinician, and assessing the extent a filter can capture by producing a false negate and positive rates. Unfortunately, this process is difficult and time-consuming. Another option is to use the non-invasive cuff pressure as a reference, which is simple and readily available. However, cuff pressure is not measured continuously, and not sufficiently accurate [10] as a reference signal.

We applied an alternative way to assess the effect of our filter indirectly. The reasoning was that, ultimately,

measures of BP quantified from the filtered signal would be developed and statistical models would be established to assess the association and predictive ability of these measures to mortality and morbidity. Artifact tends to ruin the potential correlation structure. Therefore, logistic regression models were developed to investigate the effect of simple BP measures and hospital death with as opposed to without filtering.

Logistic regression is a statistical model for making predictions when the dependent or outcome variable, **Y**, is binary, while the predictive variables can be continuous and discrete [15]. We define **Y** = 0 or 1, with 1 denoting the occurrence of death, and a vector of **X** is predictive variables. Then a logistic regression model is in a formula of $C(\mathbf{Y}|\mathbf{X}) = \text{Prob}\{\mathbf{Y}=1|\mathbf{X}\} = 1/(1+\exp(-\mathbf{XB}))$, where $\mathbf{XB} = \beta_0+X_1\beta_1$, if there is only one predictor variable. Maximum likelihood estimation (MLE) was applied to estimate the two parameters β_0 and β_1 in the model [16]. Denote the binary response and the probability of the response of the ***i***th subject as Y_i and P_i, respectively, and we can define the likelihood function of an observed Y_i as $L_i = P_i^{Y_i}(1-P_i)^{1-Y_i}$. The joint likelihood **L** of all responses Y_1, Y_2, …Y_n is the product of all likelihood L_i, for i = 1, 2,…, n. The MLE of parameter **p** is the **P** at which **L** reaches maximum, that is, $d(\log\mathbf{L})/d\mathbf{P}=0$, where $P = 1/(1+\exp(-\beta_0+X_1\beta_1))$, so we obtain MLE estimate of the parameters β_0 and β_1.

We collected 180 million data points, representing 132 thousand hours of data collection from 1852 trauma patients. BP measures included median as measure of central tendency, and difference between 90th and 10th percentiles as measure of variation for each non-overlapping 5-minute interval. So, for BP signals before and after the filter, two logistic regression models were established, one using median (50th percentile) and another using 90th-10th percentile of BP within each 5-minute interval as predictor X. For comparison, the log likelihood ratios (*i.e.* the odds that a given test would be expected in died as opposed to lived) were computed by taking log of the ratio of the maximum value of the likelihood function as a measure of the predictive power. Not rigorously speaking, given the same number of patients, the larger the likelihood ratio, the better odds that the predictive variable distinguishes the died from the lived.

III. Result

We removed non-physiological artifact of BP data for all 1852 patients who were under arterial BP monitoring. The filter was fast. For a patient whose BP signals lasted 200 hours, the filter process took less than 30 second. Figure 1 is an example showing BP signals before and after the filter. It shows an over-damping of several hours which ended up a new catheter. In addition, brief and abrupt artifacts were removed effectively.

Overall, an average of 3.15% of SAP data and 3.27% of DAP data were identified as non-physiological and removed. This percentage was in the range consistent with physicians' experience. The majority of the artifact filtered was due to the over-damping (Table 1). Note the proportion was same for SAP and DAP because both of them were filtered at the site of over-damping.

However, the distribution of the number of points filtered was far from even. For example, for those patients with short length of ICU stay, little or no over-damping occurred, while those who stayed longer, had more episodes of over-damping.

Despite the small amount of data filtered, the effect was enormous and the power of predicting death was enhanced considerably after filter. The results from logistic regression modeling using 90th-10th percentile as predictor were significant and log likelihood ratios increased from 1500 to 5000 for SAP and 1100 to 7100 for DAP, respectively, before and after filter. The results from using median as predictor remained non-significant before or after filter, and thus were not informative in evaluating filter performance.

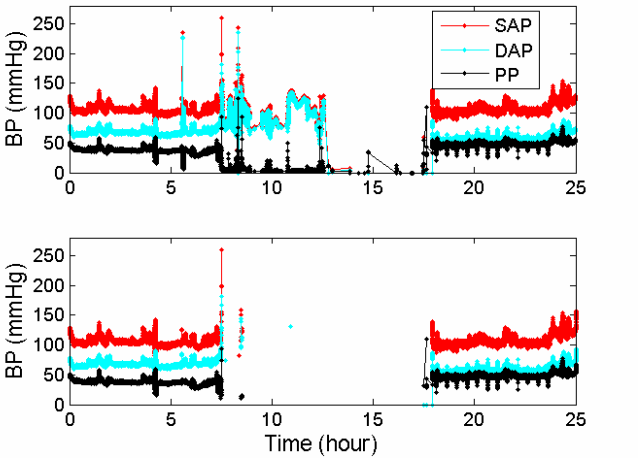

Figure 1: An example of artifact removal from one patient. Top panel is raw BP data, and bottom panel is data after filter. At hour 8, over-damping occurred, characterized by an abrupt drop of pulse pressure below 10mmHg. It happened at the end of ICU day 2. The nurse changed a new catheter at this time and the BP signals became free from over-damping again. At hour 5.5, there is a brief abrupt increase lasting 4 second in both SAP and DAP (top panel), and it is removed by the filter (bottom panel). We can see that the filter effectively removed the non-physiological portion of the data for later analysis. Notice that the seemingly "abrupt" change of SAP and DAP at hour 7.5 actually lasted 3.5 minute and thus is not deemed as artifact. SAP = systolic arterial pressure; DAP = diastolic arterial pressure; PP = pulse pressure; ICU = intensive care unit.

Table 1. Average proportion of Blood pressure data filtered stratified by sources of artifact and patient outcome

Source of Artifact	SAP Filtered (%)	DAP Filtered (%)
Out-of-range	0.27	0.27
Brief abrupt change	0.26	0.38
Over-damping	2.63	2.63

IV. Conclusion

We have developed a simple and fast filter based on a large amount of retrospective data from invasive BP monitoring. It appears to be effective as evidenced by our statistical modeling of mortality. Retrospectively correlating data before and after filtering, with morbidity and mortality, is a useful way to assess artifact rejection and filter performance. However, rigorous evaluation of such filters remains challenging.

Acknowledgment

We would like to thank R. Donahue, and NT Mowery, LR Waitman, AE Williams, R. Shiavi and RJ Brychta for support.

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