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ORIGINAL RESEARCH

Error-checking intraoperative arterial line blood pressures

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Abstract

Electronic medical records now store a wealth of intraoperative hemodynamic data. However, analysis of such data is plagued by artifacts related to the monitoring environment. Here, we present an algorithm for automated identification of artifacts and replacement using interpolation of arterial line blood pressures. After IRB approval, minute-by-minute digital recordings of systolic, diastolic, and mean arterial pressures (MAP) obtained during anesthesia care were analyzed using predetermined metrics to identify values anomalous from adjacent neighbors. Anomalous data points were then replaced with linear interpolation of neighbors. The algorithm was then validated against manual artifact identification in 54 anesthesia records and 41,384 arterial line measurements. To assess the algorithm's effect on data analysis, we calculated the percent of time spent with MAP below 55 mmHg and above 100 mmHg for both raw and conditioned datasets. Manual review of the dataset identified 1.23% of all pressure readings as artifactual. When compared to manual review, the algorithm identified artifacts with 87.0% sensitivity and 99.4% specificity. The average difference between manual review and algorithm in identifying the start of arterial line monitoring was 0.17, and 2.1 min for the end of monitoring. Application of the algorithm decreased the percent of time below 55 mmHg from 4.3 to 2.0% (2.1% with manual review) and time above 100 mmHg from 8.8 to 7.3% (7.3% manual). This algorithm's performance was comparable to manual review by a human anesthesiologist and reduced the incidence of abnormal MAP values identified using a sample analysis tool.

Keywords Intraoperative blood pressure · Arterial line pressure · Algorithm · Artifact identification

1 Introduction

In many electronic medical records, intraoperative arterial line blood pressure readings are routinely stored in analyzable form. In principle, such highly detailed data sets represent a tremendous opportunity for investigation. However, research on perioperative management of blood pressure has often focused more on preoperative and postoperative phases [1], and relationships between intraoperative blood pressure and perioperative outcomes have largely been limited to qualitative examination of time-averaged pressures [2–4].

One potential barrier to quantitative analysis of intraoperative blood pressure data is the high rate of artifacts from arterial line monitoring. These artifacts may be due to multiple causes including physical perturbations, calibration procedures, blood sampling, and electrocautery. Previous studies quantitatively examining intraoperative blood pressure have sidestepped the difficulty of identifying and removing artifacts by averaging hemodynamic data over lengthy intervals, setting thresholds beyond which a reading is assumed to be artifactual, or implementing rudimentary algorithms to remove obviously false data [5]. In this paper, we propose an algorithm to automate the identification and interpolation of arterial line blood pressure traces, thereby permitting more widespread analysis of hemodynamic data sets.

2 Methods

The error checking algorithm was implemented in R version 3.1.2, and takes as input minute-by-minute readings of systolic, diastolic, and mean arterial pressures (MAP) blood

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pressures (Online Resource 1). In the first step, the intraoperative period during which the arterial line pressure transducer was recording is isolated by removing leading and tailing values of NA from each trace (Fig. 1). In the second step, tunable parameters for determining whether a change between consecutive pressure readings was large are defined. We used $\delta_s = 8,\ \ \delta_d = 5,\ \ \delta_m = 6$ mmHg when working with systolic, diastolic, and MAP pressures, respectively. Because initial placement of the arterial monitoring line generates a large amount of artifact, the third step is to determine the start of the period where the arterial catheter has been stably placed. Call the earliest time point remaining after trimming NA values s. Let the systolic, diastolic, and MAP pressures at time s be denoted S_s, D_s, and M_s, respectively. Five criteria are applied to check if the pressures were within a physiological window (indicating intra-arterial location) and stable (filtering out placement artifacts). First, S_s must be between 40 and 260 mmHg. Second, D_s must be between 20 and 140 mmHg. Third, the pulse pressure must be at least 15 mmHg. Fourth, $s+1$ or $s+2$ must satisfy the first three criteria. Fifth, the change in pressure between time s and $s+1$ must be $< 2\delta$, or the change in pressure between time s and $s+2$ must be $< 2\sqrt{2}\,\delta$, in at least two of the three pressure traces. If these five criteria are satisfied, then s is taken as the beginning of the time interval during which the arterial line was stably placed. If they are not satisfied, we delete S_s, D_s, and M_s, increase s by 1, and recheck the five criteria, iterating until the start point is found. The fourth step is to determine the end of the period with a stably placed arterial catheter, e, using similar criteria.

In the fifth step, Q is computed as

$$Q = \frac{1}{e-s+1}\sum_{t=s}^{e}\frac{M_t - D_t}{S_t - D_t}$$

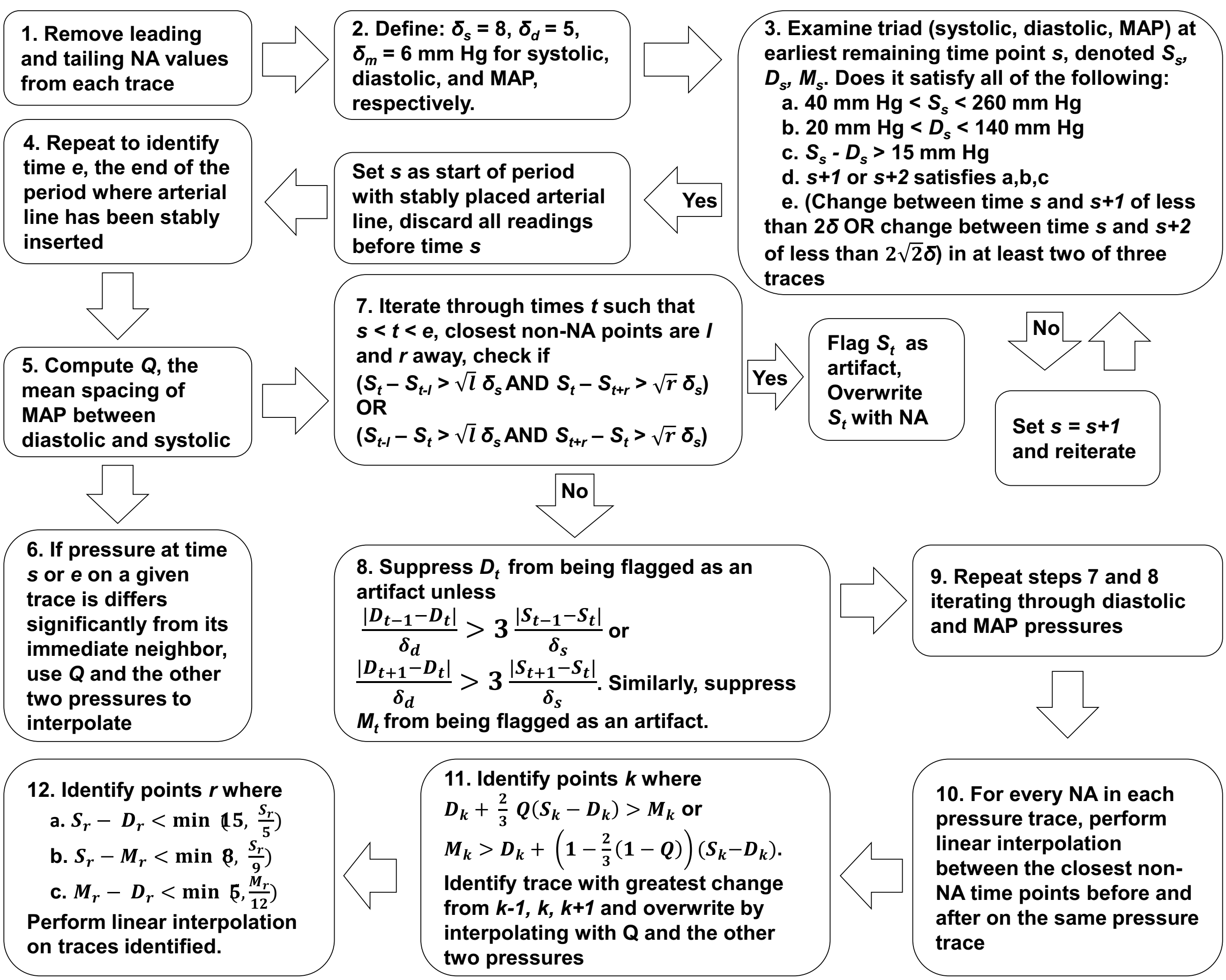

Fig. 1 Flowchart of automated intraoperative arterial line blood pressure error-checking algorithm. Graphic was created in powerpoint

This represents the mean spacing of MAP between the diastolic and systolic pressures across all time points t such that $s \le t \le e$, and is used later for interpolation.

Next, each pressure trace is examined individually and every minute-by-minute pressure reading is iterated through sequentially and checked if it is close to its immediate neighbors. Step 6 handles the cases where pressure at time s or e on a given trace differs significantly from its immediate neighbor. Suppose $|S_s - S_{s+1}| > \delta_s$. Then S_s^*, the interpolated value corresponding to S_s as denoted by the superscript asterisk, would be computed as

$$S_s^* = D_s + \frac{M_s - D_s}{Q}$$

The other cases with pressures at time s or e differing significantly from immediate neighbors on the systolic, diastolic or MAP pressure traces are handled with comparable algebra. Step 7 iterates through systolic pressures at times t where $s < t < e$. Suppose l and r are such that S_{t-l} and S_{t+r} are the closest non-NA points flanking S_t. If $S_t - S_{t-l} > \sqrt{l}\,\delta_s$ and $S_t - S_{t+r} > \sqrt{r}\,\delta_s$, or $S_{t-l} - S_t > \sqrt{l}\,\delta_s$ and $S_{t+r} - S_t > \sqrt{r}\,\delta_s$, then S_t is detected to be an artifact and is overwritten with NA. The square root of time was chosen as a scaling factor for δ because mean random walk distance from origin is proportional to the square root of time. If S_t is not detected as an artifact, in step 8, D_t is suppressed from being detected as an artifact unless

$$\frac{|D_{t-1} - D_t|}{\delta_d} > 3\frac{|S_{t-1} - S_t|}{\delta_s}$$

or

$$\frac{|D_{t+1} - D_t|}{\delta_d} > 3\frac{|S_{t+1} - S_t|}{\delta_s}$$

Using similar criteria, M_t is also suppressed from being detected as an artifact. Step 8 prevents false positives in artifact detection by increasing the detection threshold at times exhibiting high non-artifactual variability. In step 9, steps 7 and 8 are repeated iterating through diastolic and MAP points.

Step 10 is to interpolate values for each NA in the three pressure traces. Let t be such that S_t is NA, let p be the latest non-NA systolic pressure before t, and let q be the earliest non-NA systolic pressure after t. Linear interpolation is performed by computing

$$S_t^* = \frac{q-t}{q-p}S_p + \frac{t-p}{q-p}S_q$$

In step 11, the three pressure traces were cross-referenced for internal consistency of relative spacing. Suppose time k satisfies $M_k < D_k + \frac{2}{3}Q(S_k - D_k)$ or $M_k > D_k + \left(1 - \frac{2}{3}(1-Q)\right)(S_k - D_k)$. Then either D_k, S_k or M_k is artifactually high or low. The artifact-containing trace is identified as the trace with largest sum of the unsigned distances from time $k-1$ to k and k to $k+1$. The artifactual pressure at time k was interpolated using Q as per step 6. Finally in step 12, the absolute spacing between pressures was examined. Points r were identified where the systolic was less than $\min\left(15, \frac{S_r}{5}\right)$ mmHg above diastolic, the systolic was less than $\min\left(8, \frac{S_r}{9}\right)$ mmHg above MAP, or the MAP was less than $\min\left(5, \frac{M_r}{12}\right)$ mmHg above diastolic. Each point r was replaced using linear interpolation as per step 10.

To test and validate performance of the above algorithm, de-identified blood pressure data was used with approval by the Institutional Review Board of the University of Chicago (17-0541). The validation dataset consisted of the 78 surgical procedures at the University of Chicago Hospitals between 08/28/2017 and 09/01/2017 for which arterial line monitoring was performed and stored in the electronic medical record. 54 of these records comprising 41,384 minute-by-minute measurements had continuous monitoring with no interruption of 5 min or greater. Records were manually reviewed for start and end times and artifacts to validate the algorithm, additionally taking into account procedural annotations such as drug administration and incision times not used by the algorithm. Examples used in figures were taken from older procedures to be visually representative of the various artifact modes encountered.

3 Results

The raw arterial line blood pressure traces often contained artifactual perturbations consisting of an elevated or depressed reading at a single minute, without any abnormalities to the minutes before or after. Whether at the beginning of a pressure trace (Fig. 2, single asterisk), in the middle (double asterisk), or involving multiple traces (triple asterisk), the error-checking algorithm identified the artifact using a combination of pressure change between minutes on an isolated trace and the relative spacing between systolic, diastolic, and MAP pressures at every time point.

In a second example the algorithm avoids erroneously smoothing during time intervals that exhibit high variability. Even when the diastolic pressure appears to have artifactual elevations at the asterisked times when viewed in isolation, the marked peaks are not identified as artifacts due to the explanatory concurrent systolic pressure elevations which lasted several minutes (Fig. 3). Notably, the algorithm is able to reconstruct pressure readings over densely perturbed periods of time in a manner comparable to human review (Fig. 4).

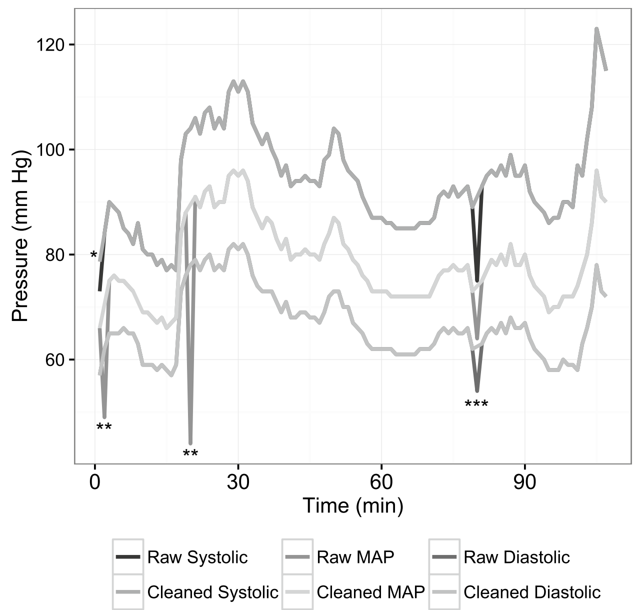

Fig. 2 Example illustrating the algorithm's ability to identify and interpolate artifactual fluctuations in pressure readings at isolated time points. Systolic, diastolic, and MAP pressures are plotted over intraoperative monitoring time before (raw) and after (cleaned) running error-checking algorithm. Asterisks indicate artifacts that were corrected at the beginning of a pressure trace (single asterisk), middle of a pressure trace (double asterisk), or span multiple traces (triple asterisk). Graphic was created in R

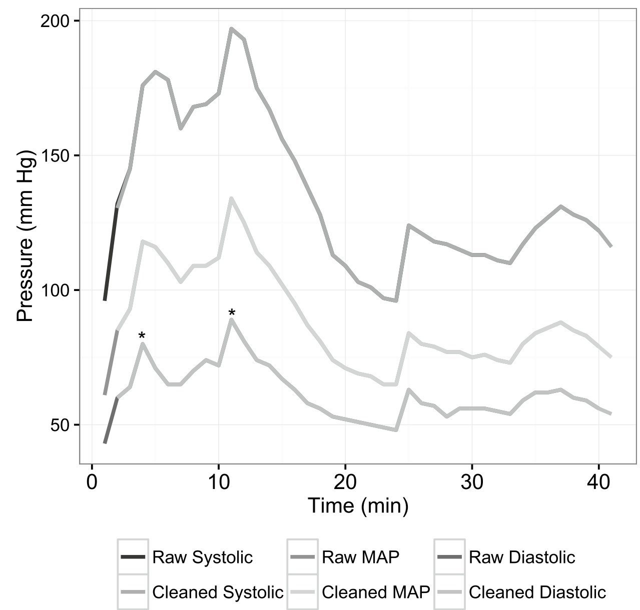

Fig. 3 Example illustrating the algorithm's ability to avoid falsely correcting true elevations by cross-referencing the three pressure traces against one another. Systolic, diastolic, and MAP pressures are plotted over intraoperative monitoring time before (raw) and after (cleaned) running error-checking algorithm. Asterisks indicate regions which may appear artifactual when diastolic pressure was examined in isolation, but was not flagged as artifact due to comparable simultaneous changes in systolic pressure which occurred more smoothly. Graphic was created in R

In total, manual review by a human anesthesiologist found 509 (1.23%) pressure readings to be artifactual (Table 1). Of those, the algorithm identified 443, giving a sensitivity of 87.0%. The algorithm also flagged 256 points which the human considered to be non-artifactual, out of 40,875 total non-artifactual points, giving a specificity of 99.4%. Many points flagged by the algorithm but not the human were in regions of alternating high and low readings, in which the true blood pressure was ambiguous. In these situations the human opted to not flag any readings as artifactual.

Performance of the algorithm in discriminating between "true" hemodynamic swings and artifact was assessed by analyzing hemodynamic data from first 15 min of cases where blood pressure changes due to induction, laryngoscopy and intubation were anticipated. Of the 2392 minute-by-minute pressure readings in the first 15 min of each operation, the algorithm flagged 80 of the 88 pressures deemed to be artifactual on manual review, for a sensitivity of 91%. It also flagged 43 of the 2304 pressures found to be non-artifactual on manual review, for a specificity of 98%.

Identification of start and end times of the intraoperative time period of accurate monitoring, when the arterial line had been stably placed, was also benchmarked against human review. Across the 54 cases, the average unsigned distance between algorithm and human-identified start

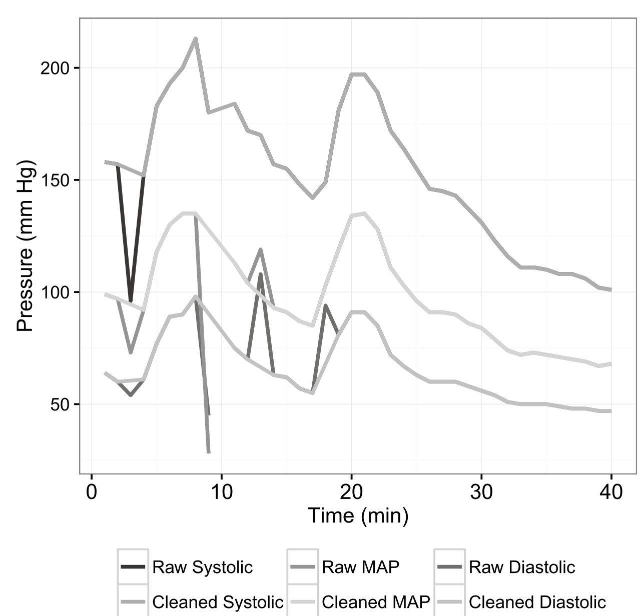

Fig. 4 Example illustrating the algorithm's ability to error-check and interpolate arterial blood pressure data densely laden with artifacts. Systolic, diastolic, and MAP pressures are plotted over intraoperative monitoring time before (raw) and after (cleaned) running error-checking algorithm. Graphic was created in R

Table 1 Number of arterial line pressure readings identified as artifact versus non-artifact by algorithm, compared to identification by human review across a set of 54 procedures comprising 41,384 minute-by-minute pressure readings

	Artifact (human)	Non-artifact (human)	Total
Artifact (algorithm)	443	256	699
Non-artifact (algorithm)	66	40,619	46,085
Total	509	40,875	41,384

times was 0.17 min (SD of 0.61), and between end times was 2.1 min (SD of 5.1).

To examine the impact of the algorithm on sample metrics potentially used to characterize intraoperative blood pressure, we analyzed the dataset before and after application of the algorithm or human review and calculated the percent of time spent with MAP > 100 mmHg or < 55 mmHg across the 54 patients. Over the 41,384 minute-by-minute measurements used for validation, raw data identified that 8.8% of intraoperative time was spent with MAP > 100 mmHg, and 4.3% of intraoperative time was spent with MAP < 55 mmHg. After the algorithm was applied, the interpolated data found 7.3% of intraoperative time being spent with MAP > 100 mmHg, and 2.0% of intraoperative time being spent with MAP < 55 mmHg. In comparison, the manually reviewed data found 7.3% of intraoperative time being spent with MAP > 100 mmHg, and 2.1% of intraoperative time being spend with MAP < 55 mmHg.

4 Discussion

In this paper we describe an algorithm able to identify arterial blood pressure readings likely to be erroneous, and perform interpolation. Validation with a large dataset of 42,860 pressure readings against manual review demonstrated high sensitivity as well as specificity. Moreover, the points of disagreement most often occurred in regions of higher blood pressure variability where the human reviewer was unable to clearly identify hemodynamic data as real or artifactual. As such, the algorithm's performance in identifying artifact is comparable to a human anesthesiologist manually inspecting the same dataset.

While algorithms for correcting artifacts in other potentially comparable types of data such as intraoperative body temperature have been described [6], intraoperative arterial line blood pressure data are sufficiently different that these existing algorithms are not applicable. First, arterial blood pressures have much higher variability over the course of an operation than variables such as temperature, and aggressive smoothing approaches to hemodynamic data would actually create artifacts by excessively smoothing the data. Second, the three interrelated blood pressure traces present the opportunity for cross-referencing, allowing more accurate differentiation of true blood pressure changes from artifacts. Current algorithms do not take full advantage of this property [5, 7].

Automated error-checking and interpolation of intraoperative arterial line blood pressures permits large scale analyses of hemodynamic data previously limited by concern for artifact. For example, during laryngoscopy and intubation a large spike in sympathetic tone can occur with concomitant hemodynamic changes. In contrast to normotensive individuals where blood pressures may rise by 20–30 mmHg, pressures in patients with untreated hypertension can be much greater [8]. However, large volume automated case analysis of this phenomenon is often limited because separating such "true" pressure swings from artifacts is difficult and smoothing techniques used for temperature data [5] may partially blunt such changes. Our algorithm, however, effectively captured this change. In addition, our algorithm performed similarly to human artifact screening, and machine analysis of our dataset after application of our algorithm demonstrated reductions in abnormal data consistent with screening by humans. Our algorithm thus has the potential to enable more accurate analysis of intraoperative hemodynamic data previously restricted due to artifact and may allow a better understanding of how intraoperative hemodynamic information affects perioperative outcomes.

Compliance with ethical standards

Conflict of interest Dr. Tung receives a salary as Executive Editor for Critical Care and Resuscitation for the journal of Anesthesia & Analgesia. Charles Du and Dr. Glick declare that they have no conflict of interest.

Ethical approval All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards. For this type of study formal consent is not required.

Informed consent No identifying information was collected.

References

1. Lonjaret L, Lairez O, Minville V, Geeraerts T. Optimal perioperative management of arterial blood pressure. Integr Blood Press Control. 2014;7:49–59. https://doi.org/10.2147/IBPC.S45292.
2. Kheterpal S, O'Reilly M, Englesbe MJ, Rosenberg AL, Shanks AM, Zhang L, Rothman ED, Campbell DA, Tremper KK. Preoperative and intraoperative predictors of cardiac adverse events after general, vascular, and urological surgery. Anesthesiology. 2009;110(1):58–66. https://doi.org/10.1097/ALN.0b013e318190b6dc.
3. Wang NY, Hirao A, Sieber F. Association between intraoperative blood pressure and postoperative delirium in elderly hip

fracture patients. PLoS ONE. 2015;10(4):e0123892. https://doi.org/10.1371/journal.pone.0123892.
4. Reich DL, Bennett-Guerrero E, Bodian CA, Hossain S, Winfree W, Krol M. Intraoperative tachycardia and hypertension are independently associated with adverse outcome in noncardiac surgery of long duration. Anesth Analg. 2002;95(2):273–7.
5. Salmasi V, Maheshwari K, Yang D, Mascha EJ, Singh A, Sessler DI, Kurz A. Relationship between intraoperative hypotension, defined by either reduction from baseline or absolute thresholds, and acute kidney and myocardial injury after noncardiac surgery: a retrospective cohort analysis. Anesthesiology. 2017;126(1):47–65. https://doi.org/10.1097/ALN.0000000000001432.
6. Sun Z, Honar H, Sessler DI, Dalton JE, Yang D, Panjasawatwong K, Deroee AF, Salmasi V, Saager L, Kurz A. Intraoperative core temperature patterns, transfusion requirement, and hospital duration in patients warmed with forced air. Anesthesiology. 2015;122(2):276–85. https://doi.org/10.1097/ALN.0000000000000551.
7. Stapelfeldt WH, Yuan H, Dryden JK, Strehl KE, Cywinski JB, Ehrenfeld JM, Bromley P. The SLUScore: a novel method for detecting hazardous hypotension in adult patients undergoing noncardiac surgical procedures. Anesth Analg. 2017;124(4):1135–52. https://doi.org/10.1213/ANE.0000000000001797.
8. Wolfsthal SD. Is blood pressure control necessary before surgery? Med Clin North Am. 1993;77(2):349–63.