

An Algorithm for Processing Vital Sign Monitoring Data to Remotely Identify Operating Room Occupancy in Real-Time

Yan Xiao, PhD*, Peter Hu, MS*, Hao Hu, MS*, Danny Ho, MS*, Franklin Dexter, MD†, Colin F. Mackenzie, MB, ChB*, F. Jacob Seagull, PhD*, and Richard P. Dutton, MD*

*Department of Anesthesiology, University of Maryland, Baltimore, Maryland; and †Division of Management Consulting, Departments of Anesthesiology and Health Management & Policy, University of Iowa, Iowa City, Iowa

We developed an algorithm for processing networked vital signs (VS) to remotely identify in real-time when a patient enters and leaves a given operating room (OR). The algorithm addresses two types of mismatches between OR occupancy and VS: a patient is in the OR but no VS are available (e.g., patient is being hooked up), and no patient is in the OR but artifactual VS are present (e.g., because of staff handling of sensors). The algorithm was developed with data from 7 consecutive days (122 cases) in a 6 OR trauma center. The algorithm was then tested on data from another 7 consecutive days (98 cases), against patient in- and out-times captured by OR

surveillance videos. When pulse oximetry, electrocardiogram, and temperature readings were used, OR occupancy was correctly identified 96% (95% confidence interval [CI] 95%–97%) and OR vacancy >99% of the time. Identified patient in- and out-times were accurate within 4.9 min (CI 4.2–5.7) and 2.8 min (CI 2.3–3.5), respectively, and were not different in accuracy from times reported by staff on OR records. The algorithm's usefulness was demonstrated partly by its continued operational use. We conclude that VS can be processed to accurately report OR occupancy in real-time.

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Managers of operating rooms (OR) and of units upstream and downstream of the OR (e.g., ambulatory surgical, intensive and postanesthesia care units) seek real-time information about OR occupancy to make decisions about managing OR workflow and coordinating resources. These decisions include when to move cases, how to assign staff, when to schedule add-on cases, when to prepare patients for the OR, and how to prioritize room cleanups (1). Nursing and anesthesia staff typically record patient in- and out-times by hand on multiple separate paper and electronic records, based on different time sources (e.g., the OR clock, the monitor clock, and individual wrist-watches). OR managers spend time each day physically walking about the suite and making estimates about the time each case will finish. Considerable effort is expended in collecting and communicating perioperative

information (2). Automated technology [e.g., electromechanical systems that record OR times without human intervention, as imagined in (3)] offers the potential to facilitate prompt and correct OR management decisions by providing accurate data in real-time.

Patients are typically connected to OR vital signs (VS) monitors soon after entering the OR and disconnected just before departure. Such monitors are increasingly linked by computer networks and are remotely accessible. The value of remotely accessible VS in monitoring the progress of anesthesia has been recognized (4). However, no methods have been reported to exploit networked VS to identify OR occupancy in real-time. Herein, we describe an algorithm that can be used in an automated system for reporting and recording OR occupancy based on networked VS. We then report the accuracy of the algorithm when evaluated in a 6 OR suite.

Methods

We developed a VS processing algorithm to identify OR occupancy, defined by three questions: a) Is a specific OR occupied by a patient? b) When did the patient enter the OR? c) When did that patient exit the OR? The site for development and testing was a 6 OR suite in a trauma center with networked VS and continuous surveillance video that provided a "gold standard" for determining

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Address correspondence and reprint requests to Yan Xiao, PhD, Human Factors and Technology Research, Department of Anesthesiology, University of Maryland, Baltimore, 685 W. Baltimore St., MSTF 534, Baltimore, MD 21201. Address e-mail to yxiao@umaryland.edu.

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OR occupancy. All data collection procedures were approved by the IRB (with exemption of patient and staff consent) and hospital administration.

Selection of VS Sources for Processing to Identify OR Occupancy

Several factors disassociate networked VS availability from OR occupancy at a given time. Such disassociation can result in two types of errors in identifying OR occupancy. *False occupancy* occurs when artifactual VS appear while no patient is in the OR. *False vacancy* occurs when no VS are available while the patient is in the OR. False vacancy always occurs at least for a brief episode between when the patient enters the OR and VS are first available, and between when VS are last available in the OR and the patient's physical departure. Although lengths of such episodes vary, they are usually short because of patient monitoring standards (5). Errors caused by these episodes cannot be remedied by algorithms processing VS data regardless of how good they are. However, if the episodes are short (e.g., <5 min), the patient in- and out-times identified by the algorithm may still be considered sufficiently accurate.

False occupancy and false vacancy may be reduced by remedying two types of problems in VS (illustrated in the Appendix). *Gaps* in VS occur while the patient is in the OR because of transient absence of electronic monitoring (e.g., during patient repositioning and sensor reconnection) or artifacts in monitoring data (e.g., from cautery). *False readings* occur while the patient is not in the OR (e.g., artifacts caused by monitors left on and sensors being handled by staff).

Remedies rely in part on using combinations of VS sources. For example, to enhance the sensitivity of detecting OR occupancy, electrocardiogram (ECG) and pulse oximetry (SpO₂) readings can be used in conjunction to ameliorate gaps in VS presence in either source. Selection of combinations of VS sources was based on characteristics of availability, gaps, and false readings from archival data. To maximize the applicability of the algorithm, we limited VS sources to the most frequently used monitors, and did not use waveform data.

Algorithm for VS Processing

A three-step algorithm was developed to process VS from selected sources (details are in the Appendix).

In the first step, VS are validated and combined. Readings from each VS source are coded as PRESENT when they are received from that VS source and they are clinically valid. The following ranges were considered clinically valid: $10 \leq \text{heart rate} \leq 200$ beats/min, $40 \leq \text{systolic blood pressure} \leq 300$ mm Hg, and $10 \leq \text{temperature} \leq 50^\circ\text{C}$.

In the second step, VS data are cleaned. Specifically, the algorithm was constructed to clean transient changes in VS presence based on VS received over a period of time (defined by two parameters as in the Appendix). If relatively

long periods are used, there would be greater accuracy when OR occupancy is reported, but longer lags in the algorithm's reporting that OR occupancy status has changed. After completion of the second step, the algorithm can display the identified occupancy status for each OR.

In the third step, patient in- and out-times are estimated based on changes in the identified OR occupancy (see the illustration in the Appendix). Gaps and false readings remaining from the second step can create short artifactual cases. Thus, they are removed automatically based on the assumption that the duration of a case or a turnover will always be longer than a few minutes. For example, patient repositioning produces a 4-min gap in VS and thus breaks up a single case into 2 at the end of the second step, but is recombined in the third step to reduce the number of artifactual cases.

In implementation, the first step was not seen by viewers. The identified occupancy for each OR from the second step was displayed. The identified patient in- and out-times were displayed when the identified OR occupancy status changed, and were revised when adjustment occurred in the third step. Viewers saw for every OR when the current case started (and how long the case had been running) and when the last case had finished (and how long the OR had been unoccupied).

Phase I of Study: Optimization of Algorithm Parameters

The algorithm has four parameters (two for the second step and two for the third step) to be chosen during phase I of the study. VS were collected continuously from all 6 ORs over 7 consecutive days, during which 122 surgical cases were performed (mean \pm SD of case length: 2.8 ± 1.5 h).

VS from the 6 ORs were obtained by BedMaster data capturing software (Excel Medical Electronics, Inc., Palm Beach, FL) running on a personal computer attached to the OR monitor network at 6-s intervals. Using the VS data, VS sources and algorithm parameters were selected.

To optimize the algorithm parameters, a gold standard was needed for patient in- and out-times, which were obtained by reviewing OR surveillance video records in the form of low-resolution images (100×75 pixels) taken every 6 s. United States official time was used as the standard reference time. The difference in the clock time of the VS processing computer and the standard reference time was compensated in patient in- and out-time calculation. Optimal values of algorithm parameters were determined based on the following three measures (formula details in the Appendix). False vacancy rate: the ratio of the total time of falsely identified vacancy to the total time of actual cases. False occupancy rate: the ratio of the total time of falsely identified occupancy to the total time of the OR being empty. Case identification ratio: the ratio of algorithm-identified cases

Table 1. Characteristic of Vital Signs (VS) for Phase I^a Data (122 Cases)

Monitors ^b	First ^c	Last ^d	Patient in to VS presence (min) ^e	VS absence to patient out (min) ^f	VS presence during case ^a	Gap lengths (s) ^g	False reading lengths (s) ^h
ECG	20.5%	11.5%	5.6 (1.7, 15.8)	7.5 (2.4, 22.6)	88 ± 8%	18 ± 23	18 ± 8
SpO ₂	71.3%	82.8%	4.1 (0.8, 12.7)	1.7 (0, 10)	90 ± 9%	79 ± 93	19 ± 12
ABP	7.4%	4.1%	5.2 (0.9, 54.9)	3.8 (0.1, 17)	19 ± 36%	36 ± 49	36 ± 46
TEMP	0.8%	1.6%	24.8 (9.3, 55.4)	21.1 (5.9, 61.8)	59 ± 23%	11 ± 10	6 ± 0
ECG+SpO ₂			3.9 (0.8, 11.9)	1.7 (0, 7.4)	94 ± 5%	17 ± 18	19 ± 12
ECG+SpO ₂ +TEMP			3.9 (0.8, 11.9)	1.7 (0, 6.3)	94 ± 4%	16 ± 11	19 ± 12
ECG+SpO ₂ +ABP			3.8 (0.8, 11.9)	1.7 (0, 6.3)	94 ± 5%	18 ± 18	19 ± 14

^a Phase I data were collected for selection of VS sources and for optimizing algorithm parameters.

^b ECG = electrocardiogram. SpO₂ = pulse oximetry. ABP = arterial blood pressures. TEMP = temperature. “+” = logical “or” of reading presence from any of the multiple monitor sources.

^c Percentage of cases in which the monitor readings were first present after the patient entered the OR.

^d Percentage of cases in which the monitor readings were last present before the patient left the OR.

^e Values are median (5th percentile, 95th percentile). The distributions were positively skewed (towards left).

^f Values are mean + SD of percentages of time of monitor reading presence. The cases in which no readings were present at all were not included.

^g Values are mean + SD.

to actual cases. A ratio >1 means that more cases were identified than actual cases, caused by breaking up cases in the second step of the algorithm. A ratio <1 means that cases were missed, caused by efforts to remove gaps by the third step of the algorithm.

Phase II of Study: Evaluation Testing

In phase II, we evaluated the algorithm’s accuracy in real operations. Identified OR occupancy and patient in- and out-times were displayed at the OR central desk to all OR personnel in real-time.

VS were collected over another 7 consecutive days. During this phase, actual patient in- and out-times for 1 OR between 12:30 AM Sunday and 12:30 PM Monday were not available because of image capturing problems. During that period, there were 4 cases in this OR. The remaining 94 cases were used in evaluation of the algorithm (mean ± SD of case length: 2.6 ± 2.3 h).

The accuracy of identifying cases was assessed by the false vacancy rate, false occupancy rate, and case identification ratio. Artifactual cases remaining after VS processing were investigated by examining the low-resolution images. Confidence intervals (CIs) for the false vacancy and occupancy rates were calculated using Fieller’s result for the statistical distribution of the ratio of two correlated random variables (6). The percentage impact of applying phase I optimization to the data from phase II was calculated using Clopper-Pearson CI for proportions (7). All CIs were calculated at 95%.

For comparison of the accuracy of the algorithm to nurse-reported patient in- and out-times, the latter was obtained from operational records (“OR Between-Time Reports”). So that the accuracy of the algorithm’s identified times was meaningfully compared with that of staff reported times in real ORs, the study allowed staff to collect patient in- and out-times in their usual methods (such as by checking timing sources of convenience or by recollection some time afterward). In that the absolute errors followed two-parameter log

normal distributions by Lilliefors’ test, related CIs were calculated by Cox’s method (8).

Results

Selection of VS Sources

Networked VS readings from 5 monitors were available: ECG, SpO₂, noninvasive arterial blood pressure (NIBP), temperature, and arterial blood pressure. Because >60% of NIBP readings were at a frequency of every 5 min or longer, NIBP was not considered further. SpO₂ was first available in 71% and last available in 83% of the cases (Table 1). Because the combined presence (logical “or”) of ECG, SpO₂, and temperature resulted in the smallest number of false readings and gaps, they were selected for VS processing. The majority of gaps and false readings after combining were <1 min (Fig. 1). For 45% of the cases, there were no gaps at all.

Phase I of Study: Optimization of Algorithm Parameters

Without optimization of the data collected in phase I, the false vacancy rate was 4.89%, false occupancy rate 0.12%, and case identification ratio 2.39 (i.e., 139% more cases were identified than actually occurred). The case identification ratio was highly sensitive to the parameters of the second step of the algorithm (Fig. 2).

There was a trade-off between the false vacancy and false occupancy rates. The minimum false vacancy rate of 4.5% was achieved with a false occupancy rate of 0.39%. The minimum false occupancy rate of 0.003% was achieved with a false vacancy rate of 5.4%. To settle the trade-off, we minimized the combined false occupancy and false vacancy rates. At this point, the false vacancy rate was 4.58%, the false occupancy rate was 0.02%, and the case identification ratio was 1.01 (2 more cases were identified than were actually performed). With the third step of the algorithm, the case

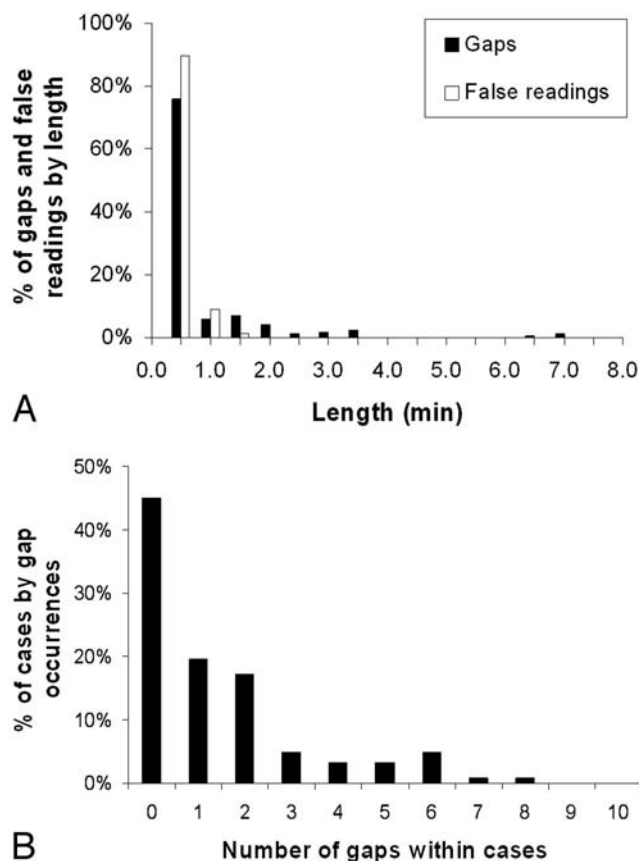


Figure 1. Distribution of gaps and false readings in phase I data. a, Distribution by length of gaps and false readings. b, Distribution by number of gaps within cases.

identification ratio was 1.00 (i.e., identified cases matched the actual cases).

Phase II of Study: Evaluation Testing

The false vacancy rate was 4.2% (CI 3.5%–5.2%) and false occupancy rate 0.19% (CI 0.12%–0.31%). In other words, OR occupancy was correctly identified 96% (CI 95%–97%) and OR vacancy >99% of the time. The case identification ratio was 1.03. No cases were missed. Of the 3 artifactual cases, 2 occurred during an 8-h operation and 1 in a 17-h operation. Examination of images indicated that both operations were spinal surgery. All three artifactual cases occurred when the patients were changed between the supine and prone positions.

The phase I optimization did improve performance. The data collected in phase II had 120 gaps during actual cases with a total duration of gaps of 112 min. Of 189 artifactual cases, 111 were caused by case break ups and 78 by false readings. Applying the parameters optimized during phase I resulted in removal of 93% of the 120 gaps (CI 87%–97%) and 54% of the 112 min of false vacancy caused by gaps.

The mean absolute errors in the algorithm's identified times were 4.9 min for patient in-times (CI 4.2–5.7

min) and 2.8 min for patient out-times (CI 2.3–3.5 min) (Fig. 3). The absolute errors did not differ statistically from the absolute errors in staff reported times, the means of which were 4.3 (CI 3.7–5.1) min for patient in-times and 3.7 (CI 2.8–5.0) min for patient out-times.

Outliers in the algorithm's identified times occurred when the patient entered the OR but staff postponed attachment of networked OR monitors, and when the operation was completed and OR monitors were detached but the patient remained in the OR for a prolonged period of time while connected to portable transport monitors.

The algorithm with optimized parameters has now been implemented and operational for >12 mo. Displayed OR occupancy information is continuously used by the OR personnel, as indicated in part by the volume and immediacy of service calls received when the display was not available.

Discussion

To assess the originality of the algorithm reported herein, we conducted searches in Medline using two combinations of Medical Subject Headings terms: "operating rooms" and "monitoring, physiologic," and "operating rooms" and "information systems" for published reports from 1966 to 2004. None of the 377 returned records were related to identification of OR occupancy through VS processing.

Despite frequent disruptions and artifacts in VS, the accuracy of identifying OR occupancy through processing VS was demonstrated in a trauma suite. The dynamic nature of the trauma OR workload (short and long cases; sick and healthy patients; frequent disruptions in the planned OR schedule) both provided maximal possible challenges in testing the algorithm and offered greatest use to the OR staff if it proved accurate. For the purpose of replacing human input of patient in- and out-times in operational records as opposed to the purpose of supporting day of surgery OR management, however, the errors in case identification may be too frequent.

The main benefit of the algorithm lies in the identification of patient in- and out-times for real-time OR management. The absolute errors in the algorithm-identified patient in- and out-times were not statistically different from those in staff recorded times (0.6 minutes more and 0.9 minutes less, respectively). Nevertheless, we suspect that the algorithm's advantage is not limited solely to being automatic. We believe that the accuracy of algorithm-identified patient in- and out-times would improve when staff are educated that the algorithm works whenever monitors are in place, and that the identified times will be used for operational decision-making.

Only one VS combination was implemented in the studied trauma suite. Although temperature readings were

Figure 2. The case identification ratio in relation to the parameters in the second step. Closer to 1 is better. Gap bridging and false reading filter values (horizontal plane) are defined in the Appendix as “confirmed in” and “confirmed out” durations. Increase in these two parameters reduced the amount of artifactual cases caused by false readings during case turnovers and by gaps breaking up cases.

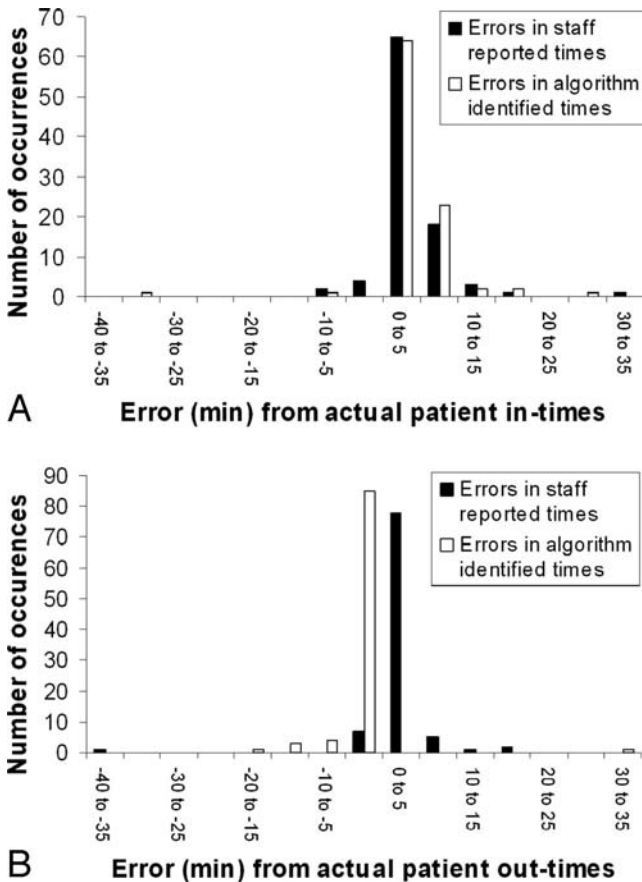
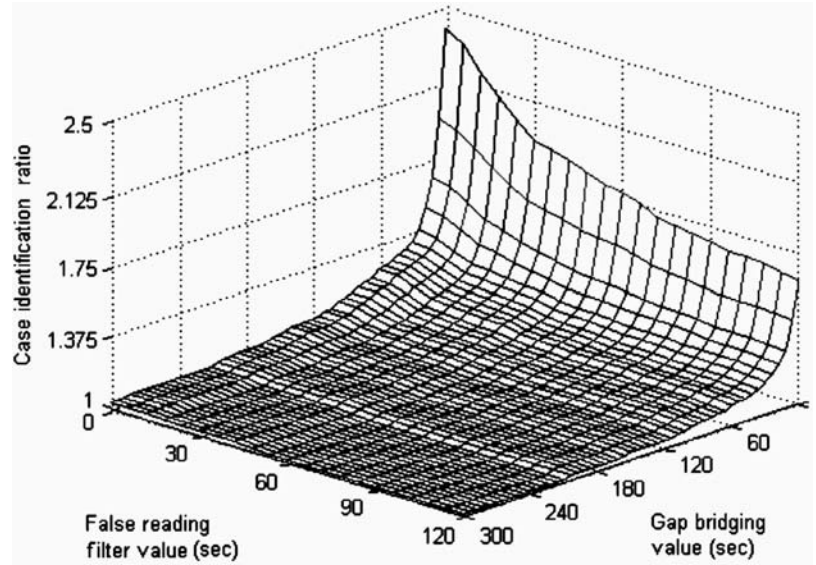


Figure 3. Errors in identifying patient in-times (a) and out-times (b), comparing algorithm-identified times with staff reported times.

present late (26 ± 14 minutes) after the patient in-time, they helped slightly in reducing gaps (Table 1). Different combinations may be used in different surgical suites (e.g., “pediatric” and “cardiac” rooms), based on the patient population served and the local anesthesia practice. The

methods described herein may be used in the selection of VS combinations at other suites. Furthermore, the logical “or” operations used in combining VS in our study may be changed to a weighted “or” operations to consider differences in reliability of VS sources. Other implementation considerations would include trade-offs between false occupancy and false vacancy when optimizing algorithm parameters. The algorithm did not provide a way to resolve the trade-offs. Decisions based on false occupancy would leave ORs under-utilized. Similarly, decisions based on false vacancy would lead to attempts to commit a case when ORs are not available, potentially resulting in over-utilization (staff staying late). The cost of these two types of decisions would be similar in terms of OR efficiency (1), although OR managers may have additional trade-off considerations.

Users of the implemented algorithm in the studied surgical suite have become dependent on the displayed OR occupancy information, as they now have access to real-time information when making decisions (1). One OR manager reported that he relied on the identified patient in-times to establish the expectation of when a case would likely be finished and thus to prioritize the tasks of getting the next cases ready, exactly as suggested by (1). Another OR manager reported that she used the identified patient out-times to follow up on the rooms that were unoccupied for more than half an hour.

The algorithm described herein can be used to implement a system to provide real-time OR occupancy data with no human input and low cost. We anticipate five areas of applications of the algorithm in OR management. a) Decision-making on the day of surgery is well understood but relies on real-time data (1). The algorithm described herein can be used in the management of many ORs, with information distributed through computer networks to provide real-time information on which ORs are occupied

currently and on patient in- and out-times in each OR. b) The OR occupancy information may be used to automatically update patient tracking systems (9). c) Graphical displays may be used throughout the perioperative processes, perhaps integrated with OR schedules and with prediction of surgical durations based on historical data (1,10). d) Automatic alerts may be implemented to notify providers of changes in OR occupancy status. e) The algorithm may be used to establish accurate OR workload data, which are the basis of OR efficiency calculations to allocate OR time and schedule cases. The fact that systems with the algorithm function passively, and do not depend on the collection of any patient or staff identifying information, may enable wide use of such algorithms in a variety of settings.

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Appendix: The Algorithm

The algorithm was designed to remove gaps and false readings that may occur when vital signs (VS) are accessed through networked operating room (OR) monitors, as illustrated in Figure 4(A). The algorithm assumes that time is discretized at an interval Δ , at which networked VS are sampled. In our implementation, $\Delta = 6$ sec.

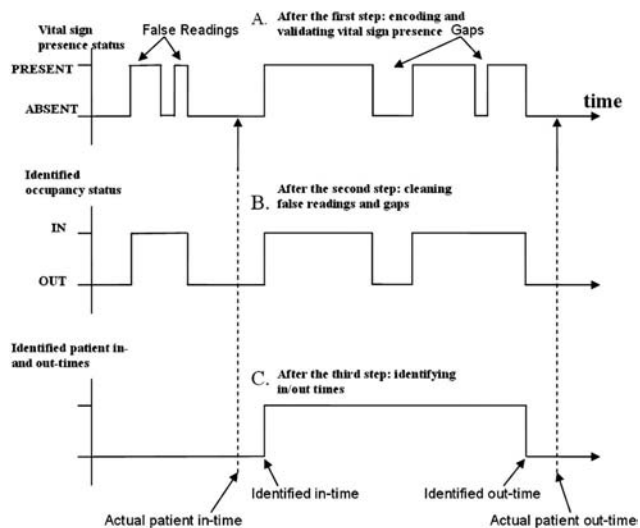


Figure 4. An illustration of the algorithm to process vital signs (VS) received from networked operating room (OR) patient monitors to identify OR occupancy. Top (A): Encoded VS availability, with false readings (PRESENT status when no patient is in the OR) and gaps (ABSENT status when a patient is in the OR). Middle (B): Identified OR occupancy status after the algorithm's second step (bridging short gaps and filtering short false readings). Bottom (C): Identified patient in- and out-times, after the algorithm's third step (deletion of short cases and turnovers).

The first step is to validate and encode combinations of readings from the selected VS sources into $S_k = \{\text{PRESENT, ABSENT}\}$ at time k .

The second step is to bridge short gaps and filter short false readings as illustrated in Figure 4(B). This step is defined by two parameters, P and G . $P \cdot \Delta$ is the filtering threshold and the "confirmed in" duration, during which VS are present consistently. Similarly, $G \cdot \Delta$ is the bridging threshold and the "confirmed out" duration, during which VS are absent consistently. The second step produces an identified OR occupancy status $S'_k = \{\text{IN, OUT}\}$, which is used during time $[k \cdot \Delta, (k + 1) \cdot \Delta)$ to display OR occupancy status. The second step may be represented by the following pseudo-code. IN = 1, OUT = 0, PRESENT = 1, and ABSENT = 0.

```

IF (  $\sum_{i=k-G+1}^k S_i$  ) = 0 THEN //If patient OUT status is confirmed
     $S'_k = \text{OUT}$  //set OR as vacant
ELSE IF (  $\sum_{i=k-P+1}^k S_i$  ) = P THEN //If patient IN status is confirmed
     $S'_k = \text{IN}$  //set OR as occupied
ELSE
     $S'_k = S'_{k-1}$  //signal fluctuating, keep last value
ENDIF
    
```

The third step is to identify patient in- and out-time based on the time series of the identified OR occupancy $\{S'_i, i = 0, \dots, k\}$. To remove artifactual cases and prevent case breakups, short IN and OUT blocks are deleted (illustrated in Figure 4(C)). The third step is defined by two parameters, M and D . IN blocks with durations less than $M \cdot \Delta$ and OUT blocks with durations less than $D \cdot \Delta$ are ignored, and previously identified patient in- and out-times are correspondingly revised. The third step may be represented by the following pseudo-code.

```

IF  $\hat{k}_n(\text{out}) = \text{Nil}$  THEN //If out-time for the nth case is not defined
    // (i.e., case identified as unfinished)
    //  $\hat{k}_n(\text{out})$ : identified out-time for the nth case.
    IF  $S'_k = \text{OUT}$  THEN //but if OR now identified as vacant
        //  $S'_k$ : identified occupancy status at time  $k$ 
        IF  $k - \hat{k}_n(\text{in}) > D$  THEN //And if IN block sufficiently long
            //  $\hat{k}_n(\text{in})$ : identified in-time for the nth case
             $\hat{k}_n(\text{out}) = k - G$  //Patient out-time identified, with correction of delays caused by cleaning (G)
        ELSE //The last IN block is too short to be a case
    
```

```

n = n - 1 //delete the last short IN
           block
           //n: current case number
ENDIF
ENDIF
ELSE //IF patient out-time for the
      nth case is defined
      //(i.e., last case identified as
      finished)
      //but if the OR now
      identified as occupied
IF S'k = IN THEN //If out-time for the nth case
                 is not defined
                 //(i.e., case identified as
                 unfinished)
                 //kn(out): identified out-time
                 //And if the last OUT block
                 sufficiently long.
                 n = n + 1 //Increment case number n;
                           a new case has started
                           kn(in) = k-P //Patient in-time identified
                                       for the new case,
                                       //with correction of delays
                                       caused by cleaning (P)
                           kn(out) = Nil //Set identified patient out-
                                       time undefined
ELSE //The last OUT block too
      short to be a case turnover
      kn(out) = Nil //Set patient out-tiem for the
                    nth case undefined
                    //(i.e., delete the OUT block)
ENDIF
ENDIF
ENDIF

```

The parameters P and G were optimized over historical values in a chosen period by minimizing the false vacancy rate (R_{FV}) and false occupancy rate (R_{FO}). During the same period, actual patient in and out-times were collected through analyzing OR video images for each case. Let N be the total number of actual cases in the period, and $k_i(\text{in})$ and $k_i(\text{out})$ the actual patient in- and out-times for the i^{th} case.

During all cases [$k_i(\text{in}), k_i(\text{out})$], $i = 1, \dots, N$, OUT values in $\{S'_k\}$ were falsely identified OR vacancy (i.e., the patient was in the OR, but the algorithm determined that the patient was out). R_{FV} was defined as the ratio of the total time of false vacancy to the total time of actual cases (note that IN was defined as 1 and OUT as 0):

$$R_{FV} = \frac{\sum_{i=1}^N \left(\sum_{j=k_i(\text{in})}^{k_i(\text{out})} (1 - S'_j) \right)}{\sum_{i=1}^N (k_i(\text{out}) - k_i(\text{in}))}$$

During all case turnovers [$k_i(\text{out}), k_{i+1}(\text{in})$], $i = 1, \dots, N - 1$, IN values in $\{S'_k\}$ were falsely identified OR occupancy (i.e., the OR was empty, but the algorithm determined that a patient was in the OR). R_{FO} was defined as the ratio of the total time of falsely identified occupancy to the total time of the OR being empty:

$$R_{FO} = \frac{\sum_{i=1}^{N-1} \left(\sum_{j=k_i(\text{out})}^{k_{i+1}(\text{in})} (S'_j) \right)}{\sum_{i=1}^{N-1} (k_{i+1}(\text{in}) - k_i(\text{out}))}$$

The algorithm's parameters M and D were optimized by making case identification ratio (R_{ID}) closest to 1. R_{ID} was defined as the ratio of algorithm-identified cases (N') to actual cases (N). An R_{ID} value greater than 1 meant that more (i.e., artifactual) cases were identified than actual cases, which was caused by breaking up cases or false readings. An R_{ID} value less than 1 meant that cases were missed.

$$R_{ID} = \frac{N'}{N}$$

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