

Reactive Software Agent Anesthesia Decision Support System

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ABSTRACT

Information overload of the anesthesiologist through technological advances have threatened the safety of patients under anesthesia in the operating room (OR). Traditional monitoring and alarm systems provide independent, spatially distributed indices of patient physiological state. This creates the potential to distract caregivers from direct patient care tasks. To address this situation, a novel reactive agent decision support system with graphical human machine interface was developed. The system integrates the disparate data sources available in the operating room, passes the data through a decision matrix comprising a deterministic physiologic rule base established through medical research. Patient care is improved by effecting change to the care environment by displaying risk factors and alerts as an intuitive color coded animation. The system presents a unified, contextually appropriate snapshot of the patient state including current and potential risk factors, and alerts of critical patient events to the operating room team without requiring any user intervention. To validate the efficacy of the system, a retrospective analysis focusing on the hypotension rules were performed. Results show that even with vigilant and highly trained clinicians, deviations from ideal patient care exist and it is here that the proposed system may allow more standardized and improved patient care and potentially outcomes.

Keywords: medical, information system, computation, visualization, operating room, alarm

1. INTRODUCTION

Information overload of acute care practitioners is increasing due to the demands of technological advances and may threaten the safety of patients in the Intensive Care Unit (ICU) or under anesthesia in the operating room (OR). Over the years the number and complexity of equipment to control and monitor a patient's vital functions has increased considerably (i.e. vital sign monitors, therapeutic devices supporting/replacing organs, fluid, gas or medication administration devices) [1]. Modern anesthesia monitors are able to provide more than 20 periodic or

continuous traces regarding the status of the patient [4]. However, the alarms and visualization systems responsible for the effective management and utilization of these devices has lagged behind medical device technology [3]. In critical care settings, clinicians must continuously synthesize large amounts of real-time data to extract critical information describing the overall state of the patient and care necessary [6]. The number and complexity of devices and alarms monitoring patient physiologic parameters vie for the anesthesiologist's attention as the brain can only process and act on a certain amount of information at one time [1, 4, 5]. Additionally, concentration decreases as a function of time and intensity (amount of incoming information) and it can be very difficult to maintain perfect vigilance through a lengthy case [1]. Cooper et al. [2], studied human errors and equipment failures in anesthesia and performed a critical incident analysis. Their group found that 70% of critical incidents were due to human error (monitoring device use, fluid management, airway management, intravenous equipment use, drug administration, anesthesia machine use), and could have, or did lead to undesirable outcomes.

A key problem with these devices, that research has shown, is instead of alarms providing additional benefit about 90% of all alarms in critical-care monitoring are false positives, leading to potential distraction or desensitization [3, 5]. To prevent this scenario, many physiologic variable traces and alarms are commonly turned off to avert information overload [4]. In a study by Chambrin et al. [10], no medical action was taken for 72% of all the alarms. The positive predictive value was only 27%, and the specificity only 58%. The negative predictive value and the sensitivity were 99% and 97%, respectively. Therefore many false alarms can result and only a few may provide useful information to the anesthesiologist. Some activity not related to the physiologic state of the patient (sensor movement, accidental disconnections, etc) can result in a series of alarms [1, 3]. McIntyre et al. [7] found that 58% of the 789 anesthetists questioned, admitted to muting an alarm for a variety of reasons. These alarms generally use simple thresholds based on a single physiologic variable [9]. An alternative used to minimize the number of alarms is setting "safe limits"; however, this can result

in unnecessary deterioration of the patient's condition in the event of a true alarm [1, 3]. In a study by Imhoff et al. [12], 40% of all alarms resulted from patient manipulation. Meijler [13] analyzed 731 warnings generated by a statistical disturbance algorithm during cardiac surgery by linking them to the response of the anesthetist. Of these alerts 7% were useful, and 13% followed some intervention, and probably could have been predicted and eliminated. Kestin et al. [14] evaluated the significance of auditory alarms during routine anaesthetic management of 50 paediatric patients undergoing elective surgery. Five monitors with auditory alarms were used routinely: ECG, automatic blood pressure (BP), oxygen analyzer, pulse oximeter and ventilator low pressure (disconnect alarm). There was a mean of 10 alarms per case with an average frequency of one alarm every 4.5 minutes. The incidence of alarms varied little between the different phases of anesthesia and surgery. Of all alarms that sounded, 75% were spurious, i.e. caused by patient movement, interference or mechanical problems. Only 3% of all alarms indicated risk to the patient. O'Carroll [15] recorded a total of 1455 alarms during a three week period. Only 8 indicated a potentially serious threat to patient safety and consisted of one ventilator disconnect alarm and seven dysrhythmias. Lawless [11] found that the rate of true alarms in the pediatric ICU was about 10%, various procedures induced 27% of the alarms and 68% were truly false alarms. In another study about a third of all alarms originated from the ventilator, another third from the cardiovascular monitor, and 15% from pulse oximetry. Similar studies found pulse oximetry to cause over 40% of all false alarms. In patients with invasive blood-pressure monitoring, arterial BP alarms can also often be the leading cause of false alarms [3].

It can clearly be seen that alarms are necessary, but not in large numbers. False alarms coupled with the various common surgical distractions, and patient care tasks the anesthesiologist must perform, can make it easy to miss physiologic variable changes or diagnoses relying on historic sensor data (i.e. potential hypotension). Major improvements in improved display and alarm algorithms, incorporating decision support features, for operating room anesthesia and critical care patient monitoring are thus urgently needed [3].

There has been significant interest and success over the last two decades in the development of smart alarms and monitoring systems, rather than just displaying the raw data for anesthesiologists to interpret [4]. These new alarm methods need to fulfill a number of methodological criteria, such as robustness, real-time and online capabilities, methodological rigor and applicability to large patient populations. With the recent advances in artificial intelligence it is believed that the implementation of 'intelligent' monitoring and alarm systems can improve patient care [1]. It is believed that integrated intelligent monitoring systems are able to detect deviations and states that may not be noticed or recognized through periodic clinical observations alone and prevent adverse patient outcomes [1]. Univariate and multivariate methods have been proposed and investigated, mostly from the fields of statistics and artificial intelligence. Some have even shown encouraging results in clinical studies [3].

We have developed an intelligent agent (IA) architecture capable of integrating the data from various sources, such as electronics medical records (EMRs), patient monitors, anesthesia machines, etc. in University of Michigan Hospital operating rooms. The system provides a centralized graphical visualization of the physiologic state of the patient and performs basic decision support, by implementing expert rules captured from anesthesiologists. Using our custom developed data integration server we can perform various types of intelligent signal processing, visualization and alerting to implement and study the performance of artifact removal, classification/diagnosis, and decision support and prediction algorithms. There is no need for the anesthesiologist to scan for information from several pieces of equipment as data from a variety of monitors are combined using mathematical modeling and rule-based logic into meaningful statements about the functioning of specific organ systems. The system is capable of running on historic data as well as live patient information, enabling both retrospective and prospective studies.

This manuscript is divided into two parts: Section 2 presents the architecture of the system, while Section 3 and 4 provide a retrospective analysis of the potential hypotension alert.. A discussion is presented in Section 5, followed by a conclusion.

2. SYSTEM ARCHITECTURE

An intelligent agent system must make rational decisions and effect changes to their environment to achieve a specified goal. Rationality is especially important in the medical domain. A rational decision can be defined as a decision that would mimic that of an experienced physician if given the same facts. The goal of the agent is to improve a patient's state of health (environment). To enable rational decisions the agent must accurately perceive its environment through the integration, sensor selection and data cleaning from various heterogeneous data sources (i.e. electronic medical record, patient monitor, clinicians, etc). To achieve its goal the agent must be capable of effecting change to its environment (i.e. visual and acoustic alerts). Figure 1 illustrates this conceptual architecture of the agent system.

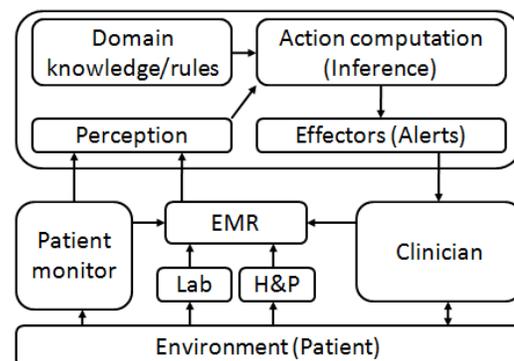


Figure 1. Reflex intelligent agent architecture for anesthesia supervision.

Knowledge about patient physiology and anesthesia care are encoded as mathematical equations and production rules. The system is designed in such a way as to provide supervisory support to the caregiver and not interfere or replace existing workflow

policies in the OR. A key aspect of agents is their communication ability, allowing them to share information with other agents and distributed hospital systems. Even though this is the first agent we have developed in this environment, it can be seen that many specialized agents can be developed, which function together to improve multiple aspects of patient care.

2.1. IA Perception

Figure 2 illustrates the practical implementation and network infrastructure of the agent system on the hospital network. The University of Michigan Hospital OR uses Solar 9000 monitors (General Electric Healthcare). These monitors pass data to a common data network (Unity Network, General Electric Healthcare), similar to other monitor systems. A software package (Monitor Capture Server, General Electric Healthcare) was used to capture the physiologic data broadcast over the network by the monitors. This package then logs the data to a SQL database (SQL Server, Microsoft Corporation, Redmond, WA) in a standard format every 10s. The University of Michigan hospital uses the Centricity EMR (General Electric Healthcare) to capture and store patient records (H&P), OR scheduling, anesthesia records, etc. The anesthesia record contains key surgical events (anesthesia start, incision, etc.), lab values, fluids, drugs and physiologic data from the patient monitor.

A multi-threaded Java based data integration server retrieves the current patient physiologic data using a SQL query through the JDBC connector every 2 seconds. A similar query is performed on the EMR to obtain surgical, treatment and lab information (data not recorded through the patient monitors) using stored procedures every minute. The patient monitor data and EMR data are integrated and cleaned depending on the characteristics of the source sensor and resulting data. When the

graphical display connects to the data integration server, it opens a TCP socket for mutual communication and the optimal set of data describing the patient state is sent to the client.

Certain surgeries utilize different sets of sensors, with multiple sensors measuring similar quantities (i.e. pulse oximeter heart rate and ECG heart rate). A sensor selection matrix, weighted by sensor category, is utilized to automatically select the best sensor sub-set for the calculation being performed. The weighting is determined from physician experience as to which sensor (if redundant sensors are available or alternate methods utilizing different data to calculate a similar metric) provides less measurement noise for a given situation. For example, depending on the surgery that is performed, blood pressure can be monitored in various ways. Figure 3 shows a 90 minute window comparing the systolic blood pressure, measured using a non-invasive cuff, and the invasive arterial (A-line) method. Typically, these methods are used independently. The A-line is only used, if necessary to ensure patient safety, since there are additional risk factors associated with puncturing an artery. However, there are cases where both are used or a very long interval (about 30min) cuff measurement is used along with the A-line. It is clear the A-line method provides a much higher sample rate, but can also be more susceptible to perturbations. This situation can be seen by the positive and negative going spikes in the figure, which could lead to false alarms. From Figure 3 the A-line measurement interval appears to be 1 minute, however in our system we are able to collect 10 second interval data directly from the patient monitor. A three point (or greater) median filter can be used to attempt to remove these spikes (which was unsuccessful for the large positive going spike), but can also introduce signal delays, which would not be acceptable if used in the BP cuff measurement scenario due to larger sampling intervals (typically 3-5 minutes). The need for robust sensor selection and conditioning can clearly be seen.

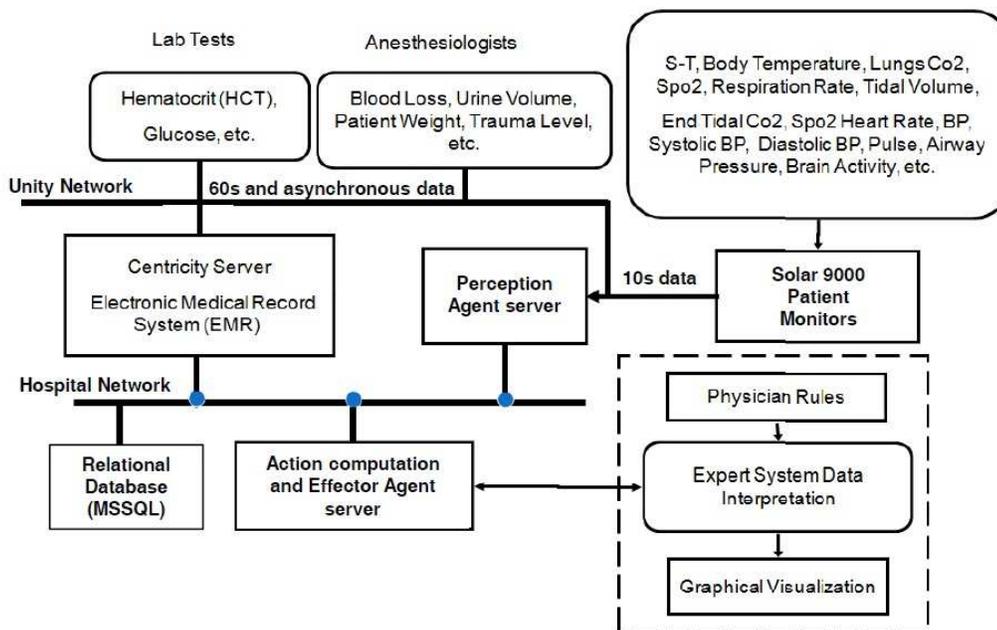


Figure 2. Data flow diagram and infrastructure of the clinical information system.

2.2. Action Computation

Production Rules are created for alerts, notifications and reminders. Alerts are based on sensor sub-sets selected from combinations of one or several monitor, EMR, or calculated variables that may potentially detect or predict adverse outcome if not addressed in a timely manner. Notification rules also contain normal, abnormal and marginal ranges for variables such as bispectral index (BIS), minimum alveolar concentration (MAC), systolic blood pressure (SBP), heart filling volume, end tidal (ET) CO₂, peak airway pressure (PAP), pulse oximeter oxygen saturation (SpO₂), body temperature, hematocrit (HCT), estimated HCT, glucose, positive end-expiratory pressure (PEEP) and creatine. All the rules and thresholds are based on well defined and agreed upon anesthesia practice.

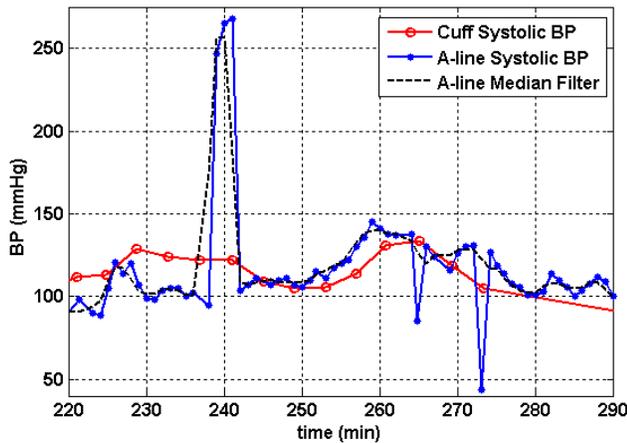


Figure 3: Comparison between measurement data obtained from invasive (A-line) and non-invasive (cuff) BP measurement methods.

Equation 1 provides an example of an equation used to predict a patient's estimated HCT [16]. Where, $b(t)$ is the estimated blood loss, taking into account any transfusions, h_0 is the last hematocrit measurement and h_i corresponds to the estimated hematocrit at time interval i . V is the estimated body volume calculated by multiplying the body weight by 70 ml. Equation 2 presents an example of one such rule for the "potential tension pneumothorax" alert. Reminders alert the physician to provide some treatment, remind them to perform certain duties, or highlight the current patient states. The normal range is defined for these variables which are shown green on the graphical display. Beyond the normal range (high risk) and marginal which are displayed with red and yellow respectively. All the alarms are listed in Table 1 and the specific threshold value used in the equations are configurable. There are 7 primary alerts in which physicians are most interested. Some of these are very uncommon (i.e. malignant hypothermia) and the system helps less experienced clinicians by suggesting this condition.

$$h(t) = h_0 / e^{b(t)/V} \quad (1)$$

$$P4: (\overline{SBP} < 60) \wedge (PAWP > 50) \wedge (PEEP > 20) \rightarrow \text{alarm4} \quad (2)$$

2.3. Visualization and Alerts

The patient state visualization system was developed using Adobe Flash (Adobe, CS 3.0) to draw the graphical interface and actionscript to implement the functionality. The interface integrates and displays the patient state, critical variables and generates alerts and alarms based on professional rules provided by experienced anesthesiologists. The system logs all alerts and alarms fired in a SQL database. Figure 4 (a) and (b) provide a screen shot of the visualization system monitoring a patient under general anesthesia in the OR. Patient registration number and patient name have been concealed for privacy. Fig 4 (a) shows a patient under normal conditions while Fig 4 (b) illustrates a patient with potential hypotension alert and low heart filling volume notification. These figures illustrate how quickly the patients physiological states can be assessed and cause for concern easily identified.

The graphical interface can be divided into two regions: on the left with the gray background is the case information, including: patient registration number, name, location, surgical duration, NPO time, estimated blood loss, body weight, third space loss. Third space loss and NPO time can be input into the interface for calculation of heart filling volume which is displayed as the area inside the heart that is filled. NPO defaults to midnight the night before surgery and surgical third space loss defaults to moderate. The main display area on the right can be divided into brain, lungs, heart and body. The "normalize volume" button zeros the offset used to calculate heart volume in spite of previous heart filling history.

All real-time variables displayed contain the corresponding measured value and time difference between the last update and current time (dt). If dt is too large, then the values displayed will be replaced with a message indicating the variable is no longer available (i.e. "No BP").

If an alert is fired, a clear message will appear together with the alarm tone to draw the attention of the physician. The "reset" button acknowledges all alarms that are currently activated. When an alarm is active, an alert tone is sounded once to attract the physician's attention. The physician can silence the alarm or resume it, by pressing the "silence" button. If the cause of the alarm is not addressed, the alarming tone will repeat automatically in a minute.

The color at the brain indicates the MAC, which is calculated by anesthesia agents, ET Sevoflurane, ET Isoflurane, ET Desflurane, ET nitrous and propofol rate [17]. If the neurological monitor is being used, the column of BIS to the left of the brain will change color and a message indicating the brain states will show up to the right of the brain (eg, BIS 40-60 is the normal range for general anesthesia, over 80 the patient may be awake).

The heart contracts with each beat and the lungs expand and retract with each breath. This provides a "live" alert that the physician can quickly observe and detect changes in heart rate and respiration rate. The trachea color indicates the PAP, and the color of the lung's border indicated the PEEP. A gauge inside the left lung indicated the ET CO₂ and the right lung shows SpO₂.

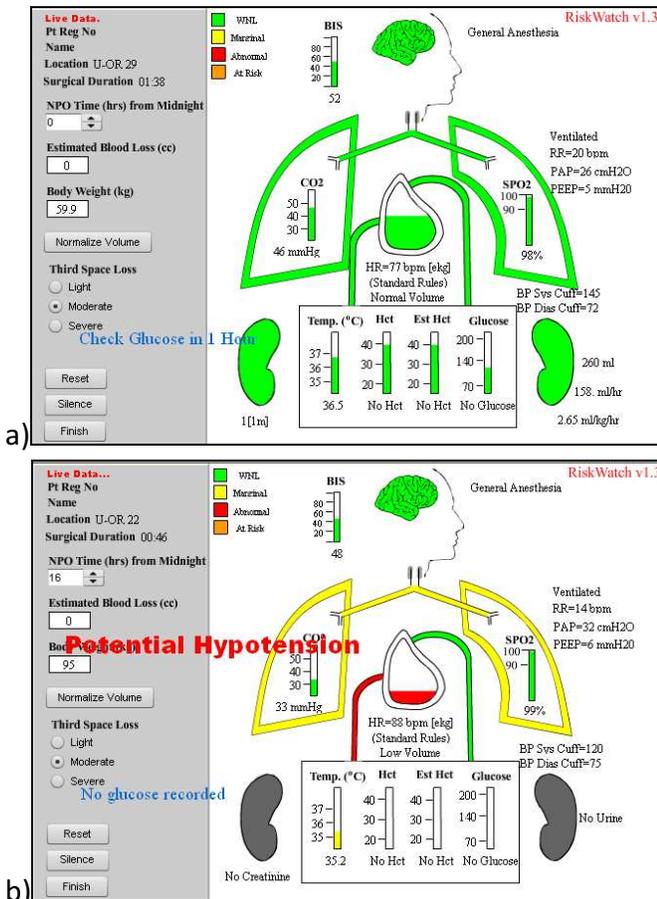


Figure 4. Visualization and user interface illustrating, a) Patient in stable condition, b) Interface showing adverse patient event.

The heart filling volume level (high, low and normal) will be determined using one of the 1-SPV, 2-CVP, 3-PADP, 4-PAWP measurement with priority in the indicated order depending on what physiologic data is available. Otherwise, it continuously calculates the fluid balance using standard rules [18]. Outgoing fluids are insensible loss with 4:2:1 rule according to patient weight, third space loss, and urine output. Incoming fluids contain blood, colloid, crystalloid by all the incoming and outgoing fluids. The color of aorta that is connected to the right of the heart indicates the SBP which determines the hypotension and hypertension states of patients.

On the bottom is the body part, containing the variables and lab values for the whole body. Temperature, hematocrit, estimated hematocrit and glucose are shown with color coded bars indicating whether they are within normal limits.

Creatinine and urine output are displayed below left and right kidneys respectively. If they are unavailable, the kidneys will turn gray. The three values beside the right kidney are urine output, per hour value and per hour per kilogram value.

The system can automatically configure alarms and display contextually by surgical milestone or time point in the database. The alerts only fire during the effective surgical time period: from patient verification to post anesthesia care unit bed requested. After bed requested, the heart and lungs will stop

moving and all the alerts are disabled. However, the notifications of variables are still displayed until the patient is moved out and transferred to PACU. At this point the system will automatically return to the login page.

All the alerts, notifications that exceed the normal limits as well as reminders generated during the surgery, are sent to the Java server which stores then in a SQL server for future analysis.

Table 1. Alerts, notifications and reminders.

#	ALARMS	#	ALARMS
1	Ischemia	13	Peak airway pressure
2	Bronchospasm	14	SpO ₂
3	Airway Disconnect	15	Body temperature
4	Tension Pneumothorax	16	Hematocrit
5	Cardiac Arrest	17	Estimated Hematocrit
6	Potential Hypotension	18	Glucose
7	Malignant Hyperthermia	19	PEEP
8	BIS	20	Creatinine (renal failure)
9	MAC	21	Glucose infusion
10	Systolic BP	22	Urine output
11	Heart filling volume	23	CO ₂ rebreathing
12	ET CO ₂	24	No BP cuff measurement

3. SYSTEM ANALYSIS

Once the system was operational, the next phase of the research was to evaluate the performance and fine-tune each rule. This data can be used to optimize the alerts and information provided to the clinician to enhance the system's accuracy, sensitivity, specificity and support of the physicians. A Java based rule processing engine using the same techniques as the clinical system was used to perform the retrospective data analysis processing. A large scale retrospective analysis of 60,000 general anesthesia cases was performed to develop a baseline for the analysis of the system's performance for classifying patient conditions and improving care. Cardiac and electroshock therapy (ECT) cases, cases with ASA 5 or 6, or patients younger than 18 years were not included.

This manuscript reports on the preliminary development and analysis of the potential hypotension alert rule. Using the results obtained from this analysis we are able to evaluate the performance of the potential hypotension alert and develop further hypotheses to optimize the alert algorithm. Our aim was to reduce the frequency and duration of hypotension, as well as lapses in BP measurement. A prospective trial will however still need to be performed to determine the actual effect on patient care and outcomes.

The advantage of studying the potential hypotension alert rule first is that it is one of the most common alerts, and the performance of the alert can be readily determined since the outcome is automatically recorded. This allows for a quality

dataset to be obtained from the EMR, without large amounts of time spent in manual chart reviews and analysis. Only general anesthesia cases with BP cuff measurements were utilized and each of the cases will be evaluated from the time of first BP to the last BP.

Our initial analysis was to determine the occurrence of delays or gaps in BP recording so that an idea of the impact of a BP measurement interval alert could be determined. It was hypothesized that gaps in measurement may lead to hypotension due to the lack for information being provided to the anesthesiologist. The standard of care is that a BP cuff measurement should be taken every 5 minutes, and the patient monitor is usually set to automatically take this measurement. However, due to patient care related distractions or other factors, this feature may not be set on the patient monitor or else the measurement interval may be lengthened. Intervals below 3 minutes tend to be avoided due to the potential injury to the patient from the continual palpitation of the measurement site. A “delayed” measurement is defined as no BP reading from 6-10 min and a “late” measurement is defined as no reading for greater than 10-15 min. We also determine the number of readings taken after an interval of 15 min.

Our second analysis attempted to gauge the impact a potential hypotension alert would have on treatment time. Increasing anesthetic agent concentration tends to reduce BP, therefore one of the more common treatments for hypotension is simply to lower the anesthetic concentration. Therefore, to determine time to treat, we measured the duration between the detection of hypotension and the adjustment of the anesthetic agent indicating treatment had begun. The concentration of anesthetic agent delivered to the patient and inspired is automatically recorded in the Centricity EMR. Only cases where isoflurane, sevoflurane or desflurane are used were evaluated as the inspired anesthetic agent concentration was used to determine time to treat a condition of hypotension. After hypotension was detected, a search was performed for a reduction of 0.1% of the inspired anesthetic agent as a sign that treatment has begun.

Finally, we used the available data to determine the predictive capability of the potential hypotension alert using a simple linear classifier as our benchmark. Figure 5 illustrates the operation of the rule and the analysis process used on the retrospective dataset. The classifier uses the most recent two non-invasive BP (NIBP) cuff measurements (A and B) and based on the slope, predicts the next SBP (C). If this prediction is below a certain BP threshold (D), the potential hypotension alert will be issued to the anesthesiologist. For each case the cuff SBP was plotted versus time and the next SBP predicted using a linear function. The predicted value was compared to a hypotension BP threshold and the determination made whether or not a potential hypotension warning should be executed. Thereafter, the measured SBP for the predicted interval was retrieved and compared to the hypotension threshold. A true positive or negative outcome could then be defined if both hypotension classifications were below or above the threshold respectively. A false positive was defined when a classification of potential hypotension is made and no hypotension resulted and visa versa for true negative classifications. Using this data the sensitivity,

specificity, positive and negative predictive performance metrics for the alert rule could be determined to characterize the classifiers performance. The hypotension threshold is adjusted and the resulting data was analyzed using a receiver operating characteristic (ROC) curve.

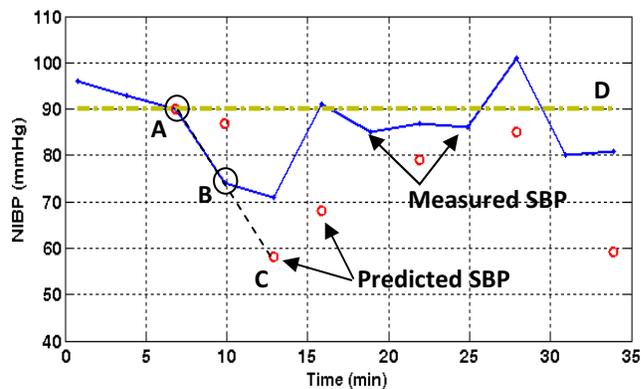


Figure 5: Analysis of potential hypotension alert rule for cuff blood pressure of a single case.

4. RESULTS

Table 2 provides the results of the BP measurement interval analysis. The cuff BP measurement should be taken at least every 5 minutes, however, as can be seen from Table 2, there are many events where the measurement interval is between 10-15 min, and even some with intervals longer than 15 min. It can easily be seen that since the physician does not know the patients BP for an extended period of time the potential exists for a serious situation to occur, such as hypotension. However, a more in depth analysis is necessary to determine the root causes of these measurement delays and whether any adverse events could occur as a result. In any event, if this situation were to occur during a case supervised by the reactive agent developed in this research, it is hoped the occurrence of this situation will significantly be reduced more in line with the requirements of standard practice. This will be achieved by the user interface will flashing the *dt* for BP when there is no measurement in more than 5 minutes and alerting the anesthesiologist that an action is required. This reminds the clinician to measure the BP regularly preventing the potential chance of missed hypotension or hypertension.

Table 2. Delayed BP measurement analysis.

BP measurement interval	6-10 min	10-15 min	>15min
Number of events	26,478	157,777	52,340

Table 3 summarizes the frequency and time to intervention under different hypotension alert thresholds. It can be seen that generally >90% of the hypotension events get treated within 10 minutes (or one BP cuff measurement) of the event detection. The number of cases decreases from 34,857 to 2,693 as the threshold varies from SBP<80 to SBP<40. It should be pointed

out that the SBP <80 rule occurs most frequently in the OR as 57% of patients have at least one SBP<80. Hypotension defined by a SBP<70 occurs in 30% of all cases. However, there are a number of cases that exhibit longer intervals of hypotension. Durations larger than 10 minutes occur in about 3-9% of events. However, these low ratios may be due to special situations and further investigation is necessary. Of course treatment will most likely not begin until the anesthesiologist receives a hypotensive BP measurement at which time the patient will already be hypotensive and could be deteriorating at a significant rate. Our hypothesis is that due to other patient care activities and the fact that generally only the last BP measurement is displayed on the patient monitor, it can be difficult for the anesthesiology to predict the BP decent or rate thereof ahead of time. Once hypotension is detected through a single measurement, the anesthesiologist would have to specifically request another BP measurement from the patient monitor to determine the rate of descent and course of treatment. This process could take 1-3 minutes depending on the situation before treatment commences. Providing a prediction of the onset of hypotension may allow for proactive treatment preventing the patient becoming “too hypotensive”.

Figure 6 provides a ROC curve illustrating the relative trade-offs of the potential hypotension linear classifier. The sensitivity or true positive rate (TPR) is plotted on the vertical axis, while inverse of the specificity or false positive rate (FPR) is plotted on the horizontal axis. TPR specifies the performance for classifying potential hypotension out of all the actual potential hypotension events. FPR specifies how many incorrect potential hypotension classifications occur out of all the normal BP. A FPR of 0 with a TPR of 1 would represent a prefect classification performance. The diagonal line C represents the line of no-discrimination, where a perfectly random guess would fall. Each circle in Figure 6 shows the TPR versus FPR for each BP threshold ranging from 52 mmHg (A) to 82 mmHg (B) in 2 mmHg steps. From this graph it can be seen that if the classifier runs for each measurement interval there are <5% false alarms (incorrectly predicted hypotension) generated, however there is about a 30% chance of correctly predicting the onset of hypotension in the next measurement interval (3-5min later).

5. DISCUSSION

The proposed system was required to have three major capabilities derived from our original hypotheses: 1) complete data capture and recording from all OR devices, 2) a single integrated graphical display to show critical patient data and 3) ability to generated alarms based on patient variables according to production rules. Based on the infrastructure of the information system in UM hospital, the system is able to retrieve all monitor records from the patient monitors, as well as EMR. The system is flexible and extensible in that new variables can easily be integrated and displayed. By encoding the knowledge of experienced anesthesiologists a more improved and standardized level of care can be delivered to patients undergoing surgery.

It is clear that if a BP measurement is missed, it can be difficult to quickly and accurately diagnose a serious event, such as hypotension. Even though a very high level of care is provided in the OR, it can be seen that the potential still exists for

extended periods of hypotension and large intervals between BP measurements.

A preliminary attempt to address this situation was undertaken, firstly through issuing an alert if the standard measurement interval is exceeded, and secondly a predictive blood pressure alert if it is suspected that the next BP will fall below a predetermined hypotension threshold. Even though the basic linear predictor performs fairly poorly, at the very least it provides an initial benchmark for future development, as well as providing doctors with a previously unavailable warning of an impending condition. By undertaking some further development along with prospective studies, these alerts will hopefully be shown to reduce the response time and amount of time a patient is hypotensive. We are confident that the total percentage of cases of hypotension and loss of BP measurement will be greatly reduced after the system is deployed in the OR.

Table 3. Hypotension occurrence and time to intervention for retrospective analysis.

Hypotension Threshold	Cases	Overall events	Time to intervention (events per time interval)		
			0-10 min	10-20 min	> 20 min
SBP <80	34,857 (58%)	115,466	106,698 (92%)	7,057 (6%)	1,643 (1%)
SBP <70	18,105 (30%)	40,916	39,346 (96%)	1,391 (3%)	173 (<1%)
SBP <60	8,281 (14%)	16,589	15,926 (96%)	579 (4%)	82 (1%)
SBP <50	4,335 (7%)	8,576	8,081 (94%)	441 (5%)	54 (1%)
SBP <40	2,693 (5%)	4,920	4,488 (91%)	384 (8%)	49 (1%)

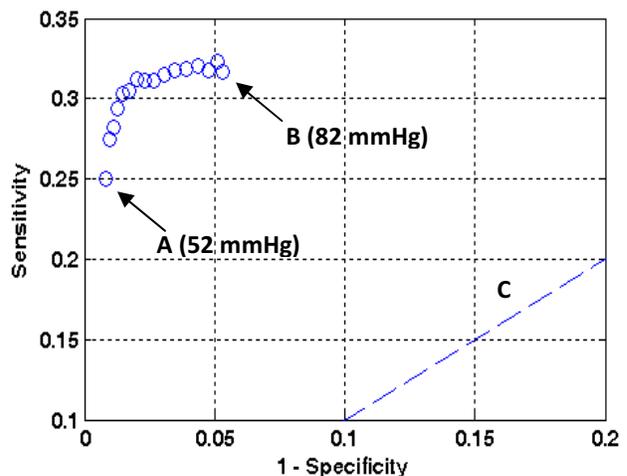


Figure 6: ROC curve of potential hypotension alert rule performance analysis showing true and false positive rates for various blood pressure thresholds.

6. CONCLUSION

We have developed a graphical display, integration and monitoring reactive agent system operating on top of the medical information system at the University of Michigan Hospital with the goal to assist anesthesiologists improve patient care and outcomes in the OR. This system successfully integrates patient monitor data, lab results and additional case information of the patient from distributed sources on the hospital information network and incorporates expert rules to determine patient physiological states, generate alerts and provide suggestions and reminders to clinicians. We begin the analysis of the system by reporting on preliminary results of the analysis of a BP measurement gap alert and potential hypotension alert rule. Results reveal that extended intervals between BP cuff measurements are fairly common, during which changes in patient state are undeterminable. Also, the retrospective study shows that at times various degrees of hypotension exist. To reduce the potential for these events to impact patient outcomes we have developed a simple rule to alert physicians if BP measurements are delayed as well as a simple linear predictor to alert as to the potential onset of hypotension. The future work involves the improvement of the prediction and classification algorithm as well as the deployment of our system to the OR as part of a prospective study to evaluate the effect on patient care provision.

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