INTEGRATION OF MONITORING FOR INTELLIGENT ALARMS IN ANESTHESIA: NEURAL NETWORKS—CAN THEY HELP?

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ABSTRACT. Although there has been a decrease in the number of anesthesia-related critical incidents, there are still opportunities for further improvement. We discuss the potential of integrated monitoring and artificial neural networks as a means of vigilantly watching for patterns in multiple variables to detect incidents and reduce false alarms. We estimate that half the anesthesia-related events could be detected with integrated monitoring using only 5 variables. A review of research using artificial intelligence/expert systems indicates limited potential for success using these tools alone for integrated monitoring in the operating room. We present artificial neural networks as an approach that is more suited to the type of multivariable monitoring and pattern recognition required. Along with rule-based artificial intelligence, these now have the potential to help develop innovative monitoring in the operating room.

KEY WORDS. Equipment: monitors; alarms. Complications: anesthesia.

There have been many studies of operating room deaths and mishaps, with clear indications that a significant number of preventable critical incidents have taken place [1,2]. Several investigators refer to falling malpractice litigation and liability insurance costs as an indication that new monitors and monitoring standards have decreased the number of incidents [3–5]. Many anesthesiologists feel this decrease is related to the introduction and widespread use of pulse oximetry and capnography [2,6]. However, there is still ample opportunity for further improvement as the potential of integrated monitoring is exploited. We discuss the potential of integrated monitoring and neural networks as a means of vigilantly watching for patterns of change in the integrated database for the generation of intelligent alarms.

PROBLEMS IN ANESTHESIA MONITORING

Vigilance

Decreased vigilance is a contributing factor in many preventable anesthesia-related critical incidents and accidents. Vigilantly observing a repetitious event for possible deviation is not a human strength nor should we attempt to make it one. Currently, the anesthesiologist is expected to watch multiple variables for meaningful changes (individually or in combination), integrate this information with other knowledge and experience, and continually make decisions concerning present status, appropriate interventions, and expected results. Alarm

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systems have been developed to enhance vigilance by alerting the anesthesiologist when changes have occurred and pointing to the need to more carefully examine the monitored variables.

False Alarms

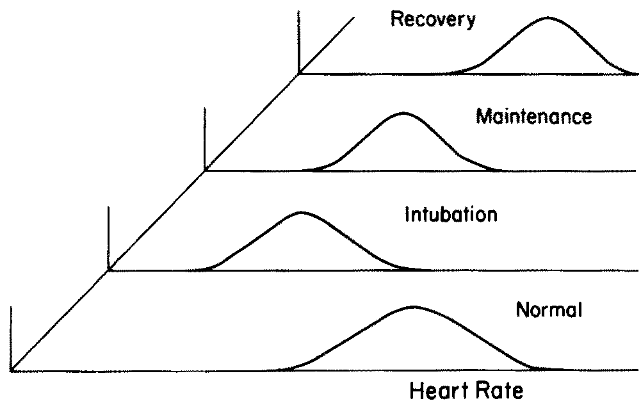
The growing number of monitors in the operating room, however, may actually be decreasing patient-directed vigilance. There is now an unacceptable number of isolated alarm situations and a cacophony of audio warnings. False alarms remain a significant problem. Studies of spurious alarms have revealed that 40 to 75% of all alarms are false. Typically, 1 alarm sounds every 4.5 to 18.8 minutes of operating time [7,8]. Individual monitors average 1 alarm every 34 minutes [9].

One way to reduce the number of false alarms is to cease considering warning devices in isolation and to develop a rational and integrated framework for monitoring and alarming [10]. Currently, each new monitor that is added to the monitoring array comes with its own separate alarms, which are independent of all other alarms. When all variables and alarm limits are considered together, the integrated system has the potential for detecting most problems without generating so many false alarms.

To increase noise immunity (interference or artifacts), alarm delays are usually added. Fewer false alarms may be possible by automatically changing alarm limits during a procedure. The Figure shows relative changes in the "acceptable range" of heart rate during induction (intubation), maintenance, and recovery. Shifts also can occur with drug administration, incision, etc. Automated event recognition and limit adjustment, using multivariable analysis, could provide these corrections. Recognition of intubation has been accomplished using measured variables from clinical monitors interfaced to a personal computer [11]. Recorded data from 20 general surgical cases were used to test a rule-based algorithm for detecting changes in oxygen level, breathing rate, and heart rate to identify preoxygenation, start of intubation, and completion of intubation. Fifteen of 19 intubations were recognized (second intubation attempts were missed), producing a 42% reduction in "low CO_2" false alarms. Determination of appropriate limits could be further enhanced using information on initial patient status and diseases.

Proliferation of Monitoring

Another approach to reducing false alarms is to reduce the number of monitors. Davis suggests that it may be better to monitor only one very fundamental variable: brain tissue oxygenation [4]. Weingarten, however, suggests that monitoring a single variable has limitations that could delay identification of a potentially disastrous event [12]. In addition, one of the primary functions of a monitor is to announce or help identify the basic cause of a problem.



Example of changes in the acceptable range of a variable during a procedure. Multiple variable analysis is required to automatically identify different periods and adjust alarm limits.

We examined 10 published reports of operating room critical incidents, accidents, and deaths since 1975 to determine the percentages of anesthesia-related critical incidents that could have been detected with knowledge of patient airway variables [3,4,13–20]. From each report we estimated the number of anesthesia-related critical incidents and the number that could have been detected with integrated monitoring of 5 airway variables: anesthetic agent concentration, oxygen concentration, carbon dioxide concentration, flow, and pressure. We determined that 47% of 1882 anesthesia-related critical incidents could have been detected. Ten to 25% of the incidents were categorized as unavoidable and not identifiable with current monitored devices. Thus, our estimates indicate that integrated monitoring of the 5 patient airway variables could potentially identify and warn when 50 to 60% of the preventable anesthesia mishaps occur.

Beneken and Blom suggest a minimum of 3 monitored variables for simple cases, increasing to 10 or more for complex surgery and 30 or more when derived measurements are included [21]. They also indicate that monitoring only a few signals (with minimal signal processing) is too simplistic, while monitoring 30 or more variables (without additional processing) is incomprehensible, and that the use of models or interrelation among variables is simply impossible with current signal processing capability. Meijler has analyzed the anesthesia delivery process and provides a perspective on monitoring and the anesthesiologist's activities in the operating room as they relate to the development of a data acquisition and display system [22]. Her system provides some integration of alarm functions, but was primarily designed for multivariable acquisition and display. The continuing discussion of monitoring standards and the effectiveness of monitoring modalities indicate less than universal acceptance of available technology [23–27].

Pace cautions that monetary (insurance) incentives may be driving the use of monitoring while we still await the data to show their effectiveness [28]. However, cost-benefit analyses of monitoring versus safety show the economic advantages of using selected monitors [29]. Effective monitoring may cost as little as $7 per case [30].

INTEGRATION OF MONITORING AND ALARMS

Definition

Integrated monitoring is the simultaneous and interdependent evaluation of multiple measurements to produce an ongoing status assessment and to identify the source of a real or potential problem. This integration is currently accomplished by the anesthesiologist, who assesses patient status and makes decisions based on input from multiple monitors. However, the need for vigilance and to simultaneously follow many variables makes the task more suitable for computer technology than for humans.

Some limited integration of monitoring already has been achieved in hardware. One device combines the signals from a noninvasive blood pressure monitor and a pulse oximeter to avoid pulse oximeter alarms when the pressure cuff in inflated. Another includes multiple sourcing for heart rate (electrocardiography, plethysmography and invasive pressure) to avoid false heart rate alarms and to report accurate heart rate even when one or more of the signals are lost. Time averaging and trending of selected variables is also a way of facilitating human integration and summarizing multiple measured variables [31].

Simultaneous monitoring and display of multiple variables is a step forward, but does not correct the alarm problems unless the information is combined and used for noise immunity, more accuracy, or derived variables. An example of noise immunity is the use of multiple sources of heart rate data (electrocardiograph, pulse oximeter, and blood pressure wave) to preclude an alarm if one signal is noisy or disappears. This multiple sourcing along with identifying abnormal rates of change has been shown to reduce false alarms and increase true positive alarms for heart rate [32].

Improved accuracy and an indication of measurement reliability can be provided by using information from other monitored variables. Noninvasive blood pressure (NIBP) measurements (oscillometric) assume mean blood pressure at the point of maximum oscillations. This assumption loses accuracy at higher pressures but could be corrected from pressure readings [33]. A model built into the calculations for NIBP could provide corrections for pressure and for arterial stiffness, which also affects pressure determinations. At the very least, an indication of the reliability of the measurements is possible. Oxygen saturation from pulse oximetry is also pressure dependent and can be made more accurate (RS Clark, Department of Medical Informatics, University of Utah, personal communication, 1990).

Anesthesia should be viewed as a whole: patient, anesthetist, operating room personnel, and multiple pieces of equipment. Anesthesia delivery systems are far from optimal [34], with redundant data available from a variety of monitors. New integrated systems have been suggested [35–39]. Our challenge is to use a systems level design to develop the decision-making rules to more effectively use these data and reduce false alarms.

Forms of Integration: Hierarchy

Alarm hierarchy is a way to integrate data, showing the relative importance of each alarm and giving textual informative messages about each alarm [40]. Some new anesthesia systems already include a 3-tiered alarm system [41]. Specific alarm signals, having spectral richness, frequency modulation, and temporal patterning, can be used to convey priority [42]. However, totally acceptable alarm strategies have been lagging from industry due to the multiplicity of manufacturers involved, the medical liability issues, and the general difficulty in designing reliable and broadly functional alarm systems [43].

Multiple Variable Analysis

Multiple variable analysis has been used to identify problems related to the anesthesia machine and its proper connection to the patient. Monitoring gases, pressures, and flows in the breathing circuit provides a number of waveforms from which multiple features can be extracted and combined, using rule-based artificial intelligence, to identify specific problems. Feature extraction is the identification of one or more characteristics from a measurement, e.g., end-tidal CO_2 concentration as derived from the CO_2 waveform. Derived features include maximum or minimum values, derivatives, integrals, time durations, etc. For example, breath-by-breath and total anesthetic uptake have been determined by continuously integrating agent concentration [44,45]. Measurements and derived features can be combined for multivariable analysis. The goal is to discriminate between real problems, artifact, and normal variations in the signal. The complexity of rule-based logic expands rapidly with large numbers of input variables and potential events, and research has concentrated on a specific set of problems, usually related to the gas delivery and patient interface.

Artificial Intelligence/Expert Systems

Integrated monitoring requires the simultaneous evaluation of numerous primary and derived variables. For all but the simplest of medical applications, their wide ranges and diverse variations make it almost impossible to use rule-based expert systems to identify specific abnormal situations. Systems using rule-based artificial intelligence have been developed for medicine but not adopted, even though this technology has been readily integrated into other fields [46]. At the University of Arizona, anesthesia-related incidents were created in animals to identify predictable changes in physiologic and machine variables for use in an intelligent alarm system [47]. Results showed unpredictable variability in many physiologic variables. Beneken and Blom found that the analysis of decision rules followed by an anesthesiologist became too demanding a project [21], and Blom suggests that expert systems cannot handle the huge data flow necessary for comprehensive and generalized patient monitoring [48]. However, in specific limited surgical situations and/or narrowly defined monitoring tasks, rule-based expert systems have been successfully applied [48–53].

Specific Applications of Artificial Intelligence

The anesthesia bioengineering group at the University of Utah has developed a computer-assisted anesthesia work station that combines 17 monitored variables and extracted features to detect faults in the breathing circuit and anesthesia machines [54]. This system includes a central display, assistance in controlling and monitoring anesthesia delivery, and rule-based analysis of multiple variables to detect changes in the delivery system. In laboratory tests with 26 different critical events the alarm system produced 88% correct responses. Only 8 false-positive alarms occurred during 20 hours of testing.

At the University of Arizona, 6 clinical monitors were interfaced to a personal computer and operating room data were collected at 5-second intervals through 21 procedures [11]. The data were used to formulate rules for recognition of incidents such as intubation and false heart rate alarms using multivariable analysis and abnormal rate of change. Heart rate alarms were significantly improved. True-positive alarms were increased when compared with an electrocardiogram monitor ($p = 0.022$) or pulse oximeter ($p = 0.04$) and false-negative alarms were significantly reduced when compared with an electrocardiogram monitor ($p = 0.0005$) or pulse oximeter ($p = 0.02$) [32].

At the University of Florida rule-based logic has been used with 3 measured variables (CO_2, pressure, and flow) and multiple extracted features to monitor the integrity of the anesthesia circle breathing system [53]. This system was tested on an anesthesia simulator and correctly identified 93% of the simulated malfunctions.

At Stanford University researchers have implemented a logical alarm reduction mechanism using calculated probabilities for differential diagnosis based on available data and prior probabilities of diseases [52]. Statistical inference was used to identify predetermined probabilities of specific incidents using multiple variables in multidimensional space with previously identified diseases or problems. In an operating room evaluation, the system, which looks for 9 specific problems for patients on a mechanical ventilator, correctly identified 71% of the test cases.

Another example of combining multiple primary variables and extracted features is a prototype ventilator monitor and alarm system developed for the NASA space station [50]. Eight transducer signals and 15 derived variables are processed with rule-based logic to identify and interpret critical events. This system, used in a less complex and demanding environment than the operating room, had a 99.2% success rate in identifying critical events when tested on healthy volunteers.

Summary of Rule-based Systems

Work on artificial intelligence in medicine has stimulated creative thinking about the problems of anesthesia monitoring, and some ideas from this research have been incorporated into new anesthesia equipment. However, none of the systems has been sufficiently successful to warrant complete acceptance as a system. There are many reasons for this.

A recent tutorial by Rennels and Miller explains the difficulties in incorporating artificial intelligence systems into medicine and why knowledge-based expert systems have remained in the prototype stage in medicine while these tools have been used successfully in other domains [46]. They cite social factors and diverse, incomplete, and anecdotal medical knowledge, all of which must be integrated into a defined accessible structure. Successful expert systems are typically implemented in situations in which complete knowledge exists.

Rule-based expert systems, performing multivariable analysis, require a priori human determinations of appropriate variables and features, alarm limits, acceptable probabilities for disease identification, etc. An expert system can be thought of as "a computer program that contains and can apply specialized knowledge," i.e., knowledge-based consultation, with knowledge in this context distinguished from data [55]. Complex medical problem solving may be better suited to pattern recognition methods than to rule-based analysis. This is one of the key differences between rule-based expert systems and neural networks [56]. The latter are able to assimilate data and provide meaningful alarms and recommendations on a real-time basis without first analyzing and summarizing the data.

NEURAL NETWORKS IN ANESTHESIA: A FIRST EXAMPLE

Neural networks represent an expanding field of computerized decision theory, being developed and successfully implemented mainly for image and voice recognition. Extensive software and dedicated hardware are being created, which very well may be applied to patient monitoring during anesthesia because of their speed and their ability to recognize complex relationships in data. One might visualize a model created when the airway pressure, airway flow, and CO_2 concentration are plotted in three dimensions. This model has a characteristic appearance when all is normal. The model changes form when a critical event occurs. In preliminary studies, we created a breath-to-breath model using 39 features extracted from airway flow, pressure, and CO_2 sensor signals [57,58]. We showed that from these features a neural network can detect that a change has occurred and can specifically identify, from 14 listed critical events, the one that caused the change. We believe that a neural network can be developed to detect and specifically diagnose many other critical events and that it will do so much more effectively than can threshold or expert system-based alarms.

The first neural network used for integrating anesthesia data was developed at the University of Utah, where three signals (CO_2, pressure, and flow) were monitored at the mouthpiece in an attempt to identify alarm conditions and incidents [57,58]. Twenty-five features, such as duration, slope, and magnitude, were extracted on a breath-by-breath basis from the three analog waveforms and used as inputs to a three-layered neural network (one hidden layer). The network had 25 input cells, 40 cells in the hidden layer, and 14 output cells. The network was programmed in Pascal and ran on an IBM PC with 1 Mbyte RAM. Once trained, the program produced its results in 60 milliseconds and displayed responses on a breath-by-breath basis. Analysis of multiple breaths was required to avoid artifactual responses.

The system was trained with data from an oil/water lung model [59] using 45 repetitions of 13 critical events. Training the network required approximately 24 hours on a DEC MicroVax II (Digital Equipment, Maynard MA) to repeatedly cycle through the 585 simulated critical events and corresponding alarm conditions. After training, the system was 99.5% accurate in identifying the 13 critical events recreated on the lung model.

The network was trained further with 57 repetitions of the 13 critical events reproduced on 5 mongrel dogs. With controlled ventilation the system was 95% accurate in identifying the events. When tested with spontaneous breathing the system was 87% accurate. During 44 hours of clinical testing the system detected 57 critical events. The neural network correctly reported 94.7% of the events [60].

These are impressive results for a first attempt to use this tool for an integrated breathing circuit alarm system. There are many possibilities for increasing the accuracy and the breadth of uses for this system. These include using the digitized analog signals as direct inputs to the network, additional training perhaps including more spontaneous breathing, and expanding the number of input signals used. Some of these studies are already under way.

POTENTIAL OF INTEGRATED MONITORING

It is unlikely that neural networks will by themselves produce a panacea to the problem of integrated monitoring. Logic rules will be required to encompass the wide variety of patients, diseases, and surgical situations seen during anesthesia. Also, techniques for error reduction can be used to increase the accuracy of both individual measurements and the integrated information. However, we believe that the addition of pattern recognition capability using neural networks will allow the development of systems that will meet the stringent and complex requirements of the medical environment.

As a beginning, neural networks might be trained to recognize "normal," "minor changes," and "problems." This might be viewed as a vigilance alert with green, orange, and red lights to indicate "all is well," "some things may need your attention," or "panic time." The key to such an alarm will be a low rate of false negatives.

Neural networks can be more easily updated to incorporate new information since the retraining process is simpler than rewriting the rules in an artificial intelligence system and making sure that the changes are consistent with existing rules. Training a new neural network with a subset of data and operating the two networks in parallel may be a possibility. It is possible that neural networks trained on data from a complex simulator will perform appropriately when evaluated in the operating room. This would allow extensive training (more accuracy) with a wide variety of data, and facilitate field modifications and updates.

System performance during missing or spurious data will need to be evaluated. How does the network respond? Can it be trained to recognize and ignore artifact, at least for a period of time, just as humans do? Can expert system techniques be used with a neural network to address these problems? Obviously, there are many unanswered questions that await the ideas and creative intelligence of others.

CONCLUSION

Preventable incidents in anesthesia remain a problem that can be ameliorated by new monitoring capabilities. Increased vigilance and reliable alarms must be part of successful monitoring. Integrated monitoring and pattern recognition software provide an opportunity for significant monitoring improvements.

Neural networks provide a new way of integrating information currently available in the operating room. We can expect their implementation in a variety of modalities, such as interference reduction, preprocessing of data, feature identification, and integrated monitoring. However, they should be viewed as an addition to current methods and not as an "end all." Final systems will combine capabilities of thresholding, expert systems, statistical rules, neural networks, and perhaps new, as yet undiscovered, methodology.

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