Generation of Dynamically Configured Check Lists for Intra-Operative Problems Using a Set Covering Algorithm

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ABSTRACT

We present a prototype of a decision support system for anesthesia that applies set covering theory. The system is designed to generate dynamically configured check-lists for intra-operative problems. These lists have the potential to help anesthesiologists detect and manage problems in a timely manner. The items in the lists consist of major complications that should be considered for a particular case. A set covering algorithm that accommodates multiple problem sets was used to implement the prototype. A simulated case and the system behavior are presented. The ultimate goals of a system such as the one presented are to function as an intelligent alarm module for electronic monitors and to facilitate the task of correcting intra-operative problems.

INTRODUCTION

Increasing efforts have been made to reduce mishaps in medical management since the Institutes of Medicine reported that human error is a leading cause of death in the hospital[1]. The anesthesia community has been aware of the impact of human error on patient safety for a long time. In 1978, Cooper et al examined 359 preventable incidents and reported that 82 percent of the preventable incidents involved human error[2]. Since that historical report, tremendous efforts have been made to reduce anesthesia errors. Gaba et al[3] introduced into the anesthesia domain crisis management strategies previously reported in non-medical, dynamic and complex domains such as aviation, nuclear power generation, and military situations[3].

In anesthesia, trivial incidents may rapidly evolve into adverse outcomes[4]. The use of check-lists has been suggested as a means to prevent crisis from occurring in the operating room[5]. Anesthesiologists are trained to exert thorough and systematic checking of anesthesia machines, equipments, and medications before administration. To support anesthesiologists, we designed a prototype that generates dynamically configured check-lists for intra-operative problems. The dynamic check lists are tailored to the specific case at hand.

Decision Making in Anesthesia

The purpose of anesthesia is to provide optimal operating conditions to the surgeon while securing patient safety and comfort during the operation. General anesthesia provides unconsciousness, removes pain, and immobilizes the patient with strong medications. In this condition, patients require artificial respiration and stabilization of homeostasis, at different levels depending on the anesthetic agents. Anesthesiologists watch the condition of the patients using their sensory perception aided by multiple electronic monitors, including electrocardiograph (ECG), pulse-oximeter, and blood pressure monitors. They tailor the administration of medications according to the condition of the patients.

A model of the anesthesiologists' real-time decision making and actions in the operating room was proposed by Gaba et al[5]. A primary component of the model is a loop of observation, decision, action and re-evaluation. In observation phase, the role of anesthesiologists is to watch the patient by their perception and through electronic monitors. In this phase it is also important to manually verify the reliability of the data derived from the monitors. Once an abnormality is detected and verified, anesthesiologists make decisions and take appropriate actions. If the abnormality is eliminated and the patient's safety is confirmed in the re-evaluation phase, the observation phase starts again. Computers have been utilized to detect abnormalities in data/signal from electronic monitors and to facilitate appropriate decision-making[6, 7]. In this study, we implemented a prototype system that can be utilized in the decision and action phase. Once abnormalities are detected and confirmed, anesthesiologists have to consider all potential problems associated with these abnormalities. The process of decision making is generally done by systematic checking of all possibilities. As intra-operative problems are not only caused by pathophysiological processes, but also by non-pathological processes (e.g., equipment failure), systematization of this checking is essential.

Set Covering Theory and Reggia's Algorithm

Set covering theory has been previously applied in medicine in search for optimal sets of diseases given a set of symptoms. In our context, the "symptom" is the abnormality detected by monitors or anesthesiologists, and the "disease" is the intra-operative problem.

Let $\mathbf{A} = \{a_1, a_2, \ldots, a_k\}$ be a set of abnormalities and let $\mathbf{P} = \{p_1, p_2, \ldots, p_l\}$ be a set of intra-operative problems. A binary relation, $\mathbf{K} \subseteq \mathbf{A}\times\mathbf{P}$ ($\times$ represents Cartesian product) can be considered as a knowledge base, where $(a_i, p_j) \in \mathbf{K}$ represents "p_i can cause a_i." Given **A**, **P**, and **K**, the following sets can be defined (Figure 1):

$causedby(p_j) = \{a \mid (a, p_j) \in \mathbf{K}\}$

A set of abnormalities can be caused by p_j.

$causes(a_i) = \{p \mid (a_i, p) \in \mathbf{K}\}$

A set of problems can cause a_i.

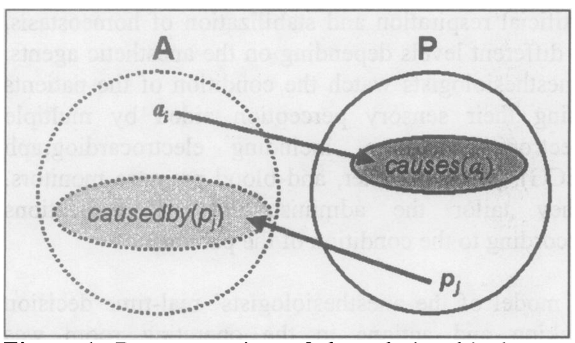

Figure 1: Representation of the relationship between A and P[9]

With these definitions, the diagnostic task can be stated as a search for a set of problems that can cover all observed abnormalities.

Application of the set covering theory was reported by Reggia et al[9]. A variation of his work was given by Wu[10]. A neural network approach for seeking optimal disease sets was given by Cho and Reggia[11]. Vinterbo and Ohno-Machado[8] reported a genetic algorithm approach for searching optimal disease sets.

Reggia et al proposed an algorithm to implement the set covering theory[9]. The algorithm requires a data structure consisting of following three elements[9].

ABN: a set of abnormalities observed so far

SCOPE: a set of all problems that cause **ABN**

FOCUS: diagnostic hypothesis

Given the data structure, the algorithm can be described as following:

1. Accept an abnormality a_i
2. Retrieve $causes(a_i)$ (i.e., a set of problems corresponding to a_i) from the knowledge base
3. Update **ABN** with $\mathbf{ABN} \cup \{a_i\}$
4. Update **SCOPE** with $\mathbf{SCOPE} \cup causes(a_i)$
5. Adjust **FOCUS** to accommodate a_i:
   (a) if $\mathbf{FOCUS} = \phi$, $\mathbf{FOCUS} \leftarrow causes(a_i)$
   (b) if $\mathbf{FOCUS} \cap causes(a_i) \neq \phi$, $\mathbf{FOCUS} \leftarrow \mathbf{FOCUS} \cap causes(a_i)$
   (c) if $\mathbf{FOCUS} \cap causes(a_i) = \phi$, $\mathbf{FOCUS} \leftarrow \mathbf{FOCUS} \times causes(a_i)$ and restructuring of the **FOCUS** by producing a new combination of subsets (see [9] for details)
6. Go to 1 until no further abnormalities are observed

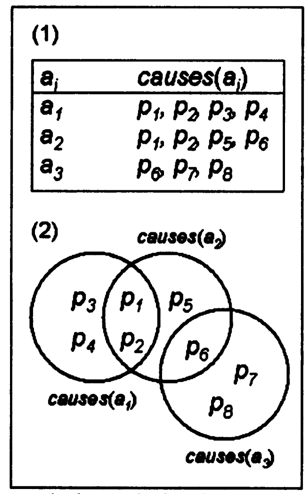

Figure 2: A sample knowledge base (1) and its schematic representation (2).

We present a sample knowledge base in Figure 2. Given the knowledge base in Figure 2, the changes of the elements in the data structure are illustrated in Figure 3. Initially, **ABN**, **SCOPE** and **FOCUS** are empty. When a_1 is observed, **FOCUS** is adjusted to $\{p_1, p_2, p_3, p_4\}$. Subsequently, when a_2 is observed, **FOCUS** is adjusted to the intersection of current **FOCUS** $\{p_1, p_2, p_3, p_4\}$ and $causes(a_2)$ $\{p_1, p_2, p_5, p_6\}$. Therefore, **FOCUS** becomes $\{p_1, p_2\}$. With the observation of a_3, **FOCUS** is updated to the Cartesian product of current **FOCUS** $\{p_1, p_2\}$ and $causes(a_3)$ (i.e., $\{p_1, p_2\} \times \{p_6, p_7, p_8\}$). Also, restructuring results in another combination of subsets ($\{p_6\} \times \{p_3, p_4\}$).

A sequence of observations	ABN	SCOPE	FOCUS
Initial state	ϕ	ϕ	ϕ
a_1	$\{a_1\}$	$\{p_1,p_2,p_3,p_4\}$	$\{p_1,p_2,p_3,p_4\}$
a_2	$\{a_1,a_2\}$	$\{p_1,p_2,p_3,p_4,p_5,p_6\}$	$\{p_1,p_2\}$
a_3	$\{a_1,a_2,a_3\}$	$\{p_1,p_2,p_3,p_4,p_5,p_6,p_7,p_8\}$	$\{p_1,p_2\}\times\{p_7,p_8\}$ and $\{p_6\}\times\{p_3,p_4\}$

Figure 3: Application of Reggia's set covering algorithm[9] to the sample knowledge base in Figure 2

Sequential ruling out process

We introduce the notion of high-impact abnormality. It is defined as an abnormality that is uniquely associated with a problem. Additionally, the problem can be ruled out if the abnormality does not exist. In Figure 4, suppose the current set of abnormalities is {high blood pressure, low SpO_2, high end-tidal CO_2}. Given the abnormalities, consider only two problems, endotracheal-tube (ET) obstruction and pulmonary embolism. In this context, {lost patency of ET tube} is uniquely associated with the problem {ET obstruction}. And the problem {ET obstruction} can be ruled out if the ET is patent. Some high-impact abnormalities lead to major complications if left undetected and/or can be easily checked for. It is these abnormalities that we are interested in detecting.

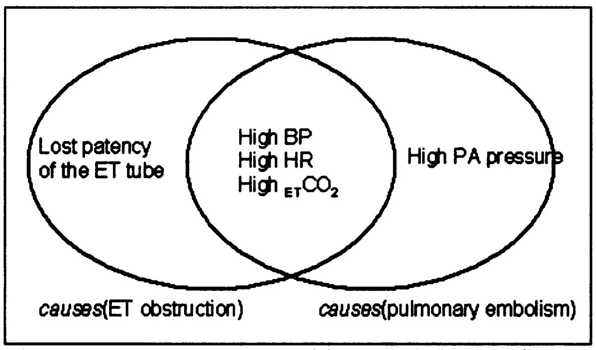

Figure 4: Intra-operative problems and abnormalities (ET obstruction and pulmonary embolism)
ET: EndoTracheal, BP: Blood Pressure, HR: Heart Rate, ETCO2: end-tidal CO2

With a hypothesized set of problems in **FOCUS**, our system sequentially searches for high-impact abnormalities. Detected high-impact abnormalities are presented to users as closed type questions (i.e., they can be answered as "yes" or "no"). The algorithm used is the following:

1. For the next p_i in **FOCUS**
2. Retrieve *causedby*(p_i) (i.e., a set of abnormalities associated with p_i) from the database
3. Calculate a difference between **ABN** and *causedby*(p_i)
4. If a difference exists and high-impact abnormalities are present inquire about the abnormality and adjust **FOCUS** accordingly. Else go to (1).

In step 4, the user enters information as requested by the system (based on the current FOCUS) so that certain problems can be ruled-out and therefore removed from the list. A pre-defined set of options is available, so the interaction is efficient.

Searching for potentially existing abnormalities

The system is also equipped with optional functionality to display potentially existing abnormalities. The algorithm of this function is similar to the one presented for the sequential ruling out process, except that all listed abnormalities are considered (i.e., not just the high-impact ones).

This functionality helps anesthesiologists alert for potentially existing abnormalities when necessary.

System Implementation

Knowledge base and inference engine

A database was built based on two anesthesia textbooks[5, 12]. There are two entities in the database: problems and corresponding abnormalities. The simplicity of the database structure is useful for the maintenance of the knowledge base. The database consists of 600 entries, which include problems of general anesthesia but exclude those of sub-specialty area such as obstetrics, pediatrics and cardiac surgery. All high-impact abnormalities were ranked in the order in which they should be checked by the inference engine.

The inference engine was implemented based on Reggia's algorithms[9]. The program was implemented in Perl based on a previous version written by Szolovits[*].

There is currently no graphical user interface for the prototype system.

Example

We present a case simulation of intra-operative problem. Suppose a pulseoximeter detects low oxygen saturation (SpO_2). The system generates a hypothesis (**FOCUS**) for low SpO_2. The content in **FOCUS** is presented in Figure 5. Problems in the list are those that expert anesthesiologists would consider. Subsequently, the blood pressure monitor detects high blood pressure (BP). According to the algorithm presented above, the system calculates the intersection between current **FOCUS** and *causes*(high BP).

[*] Personal communication.

acute hemorrhage
airway rupture(tracheobronchial tree)
anaphylaxis/anaphylactoid
aspiration
atelectasis
breathing circuit problems
cardiomyopathy
CHF
decreased chest wall/diaphragmatic compliance
elevated intrathoracic pressure
endobronchial intubation
esophageal intubation
ETT problem
hypovolemia
inadequate alveolar ventilation
inadequate muscle relaxation
low CO
low FIO2
malignant hyperthermia
narcotic induced chest wall rigidity
O2 supply problem
patient position
pneumothorax
pulmonary edema
pulmonary embolism
raised intra-abd pressure
sepsis
shunt
side effects of drugs
surgical maneuvers restricting venous return
V/Q mismatch
valvular heart disease

Figure 5: Problems caused by low SpO_2 (abnormality)

Figure 6 represents the updated hypotheses (**FOCUS**). The number of problems in the list is reasonably reduced given the new information (i.e., high BP). All questions are asked as a closed question format and the user can interact with the system efficiently.

airway rupture(tracheobronchial tree)
aspiration
atelectasis
breathing circuit problems
decreased chest wall/diaphragmatic compliance
endobronchial intubation
esophageal intubation
ETT problem
inadequate alveolar ventilation
inadequate muscle relaxation
low FIO2
malignant hyperthermia
narcotic induced chest wall rigidity
O2 supply problem
patient position
pneumothorax
pulmonary edema
shunt
side effects of drugs
V/Q mismatch

Figure 6: Problems in FOCUS updated by high blood pressure

Figure 7 shows a question list based on **FOCUS** in Figure 6. Most of these abnormalities can be easily detected and/or may lead to major complications if left undetected. Lastly, Figure 8 is a demonstration of the reminding function which displays potentially existing abnormalities associated with the current **FOCUS**.

airway injured?
aspirated?
Endobronchial intubation?
ET in esophagus?
ETT kinked/obstructed?
inadequate muscle relaxant?
inappropriate patient position?
inappropriate ventilator setting?
low FIO2?
machine failure?
narcotics given recently?
O2 supply problem?

Figure 7: A list generated based on the FOCUS from Figure 6

*** check suggestions for malignant hyperthermia ***
check ABG for metabolic acidosis AG+
check BP for high BP
check BT for high temp
check capnography for high etCO2
check CK for high CK
check ECG for arrhythmias
check ECG for high HR
check lytes for high K
check PE for muscle rigidity
check urinalysis for myoglobinuria
check visual inspection for cyanosis
check visual inspection for high RR
check visual inspection for sweating

Figure 8: An example of potentially existing abnormalities

DISCUSSION

We implemented the prototype of a decision support system for anesthesia that applies set covering theory. The system was designed to generate dynamically configured check-lists for intra-operative problems. The elements of the check-lists are sequentially presented to the user in the form of closed questions so that problems can be sequentially ruled-out.

In our prototype, the nature of the sequential checking process was not taken into account thoroughly. Although the contents of the lists may be clinically reasonable, the order of the items presented to the user may not be effective. Checking processes of experts are natural, fluent, systematic and thorough. In the future, our system needs to emulate the sorting process that experts use. We are aware, however, that the sorting of checking process varies among experts. Some experts sort by organ system while others sort by type of mechanical/pathological causes. Experts also switch and combine these sorting mechanisms depending on the situation. It is difficult to integrate the practice "style" of anesthesiologists into the system.

Additional functionality would also be necessary to make the system usable in practice settings.

Currently, the inference engine treats most abnormalities equally (except for the distinction between high impact ones and others). Adding a probabilistic reasoning engine based on the frequencies of abnormalities would improve the accuracy of diagnoses. The availability of real data might allow the replacement of the reasoning engine by one that more formally addresses the probabilistic nature of this domain, as well as the utilities related to detecting each problem. In the same context, temporal reasoning would be useful. For example, it is known that the hypoxia causes tachycardia initially, and it sometimes causes bradycardia as time passes. The temporal reasoning engine would contribute to solve this paradoxical phenomenon. Another useful function would be the capability of triggering rules for detailed instructions. For example, with an oxygen supply problem, the system would propose detailed instruction rather than alert the problem itself (as shown in Figure 4). In this case, the system could generate instruction lists including the following items: checking wall O_2 supply gauge, wall O_2 pipe connection, anesthesia machine O_2 pipe connection and anesthesia machine O_2 supply gauge. This functionality would be especially useful for novices.

The user interface of the system should be implemented so that the user can interact the system with minimum time and effort. As most of the abnormalities in the database are detected by the anesthesia monitors, data input can be automated by directly connecting to the monitors. Text-to-speech engine would enable the check-lists presentation process to be more efficient. As all questions are of closed type, voice recognition devices may not be unrealistic for the user interface.

Currently, the alarms of anesthesia monitors are simply triggered by preset thresholds. Although many studies have been done to reduce false alarms, all false alarms may not be eliminated to maintain the sensitivity of the monitoring system. Therefore, instead of reducing the sensitivity of monitors, double-checking by humans is necessary for patient safety. In this context, our system may be useful to aid the anesthesiologist in the checking process.

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