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Decision Analytic Approach to Severe Head Injury Management

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Severe head injury management in the intensive care unit is extremely challenging due to the complex domain, the uncertain intervention efficacies, and the time-critical setting. We adopt a decision analytic approach to automate the management process. We document our experience in building a simplified influence diagram that involves about 3000 numerical parameters. We identify the inherent problems in structuring a model with unclear domain relationships, numerous interacting variables, and real-time multiple inputs. We analyze the effectiveness and limitations of the decision analytic approach and present a set of desiderata for effective knowledge acquisition in this setting. We also propose a semi-qualitative approach to parameter elicitation.

INTRODUCTION

Decision support in critical care involves timely intervention recommendations under uncertainty and constant information updates. This project aims to automate treatment planning support for severe head injury patients using decision analysis techniques. Severe head injury management is very challenging because of the unclear domain relationships, numerous interacting variables, and real-time multiple inputs. Our long term objective is to develop computerized, customizable clinical guidelines that integrate with the information system at the neurosurgical intensive care unit to replace current paper guidelines. Such automated guidelines can be used as both consultation and educational tools in critical care.

Existing works on the decision support for treatment of severe head injury mostly focus on early prediction of outcome of severe head injury (e.g., [3]). These results help to specify preference models and allocate scarce resources, but do not recommend specific treatment selection for a particular patient.

General decision support for critical care medicine is discussed in many publications, e.g., [14, 9]. Most of these works, however, focus on the logistics of critical care rather than on the decision making process itself. The efforts that focus on the decision making process itself mainly adopt heuristic approaches. With few exceptions [13] decision analysis has not made significant inroads into the current critical care medicine.

This paper examines the feasibility and effectiveness of a decision analytic approach to critical care. In the first phase of the project, we build a simplified influence diagram in head injury management and analyze the knowledge acquisition requirements. We address the issues of training the domain experts on medical decision analysis concepts, systematically constructing a decision model, and assessing numerous numerical parameters, with the aim of transforming the process and the experience gained into a real-time setting in future. Based on our observations, we identify a set of desiderata for effective knowledge acquisition and propose a semi-qualitative approach to parameter elicitation.

SEVERE HEAD INJURY

Severe head injury involves traumatic damage to the brain. The most common causes of severe head injuries in Singapore are motor vehicle accidents, especially motorcycle accidents, and accidents at construction sites. The injured is often unconscious; he does not respond to visual or verbal stimuli, and has impaired movement ability. The traumatic head injury usually has debilitating consequences ranging from a mild disability to a vegetative survival and death. These consequences are often caused by a secondary brain injury resulting from lesions, raised intracranial pressure, etc. Fast and aggressive treatment is therefore essential for increasing the chances of a good outcome. Although our understanding of the pathophysiological processes involved in head injury has progressed substantially in the last two decades, the pathophysiology is still not understood well enough so

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that a universally acceptable treatment protocol can be established [12]. Many uncertainties remain to be resolved. The immediate treatment goals for severe head injury patients are to keep cerebral perfusion pressure above 70 mm Hg and prevent intracranial hypertension [11]. The treatment options range from simple ones like tilting patient's head to those requiring constant monitoring like inducing a barbiturate coma.

THE DECISION MODEL

Our decision problem is to prescribe an optimal treatment to a severe head injury patient at a neurosurgical ICU setting. We currently only focus on adult patients with a Glasgow Coma Scale Score between 3 and 8, and with no surgically removable lesions.We also set our planning horizon to one hour, i.e., patient status is observed just prior to treatment and evaluated one hour afterwards. This prevents us from considering some of the treatment options with long-acting consequences, e.g., barbiturate coma.

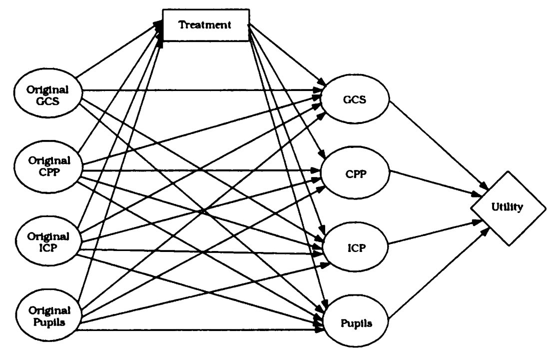
Model Structure

Our current model consists of ten nodes. Eight chance nodes correspond to the four parameters describing patient status: Glasgow Coma Scale (GCS), cerebral perfusion pressure (CPP), intracranial pressure (ICP), and pupillary abnormality (Pupils), one node for pretreatment observation and one node for post treatment observation for each parameter. The model also includes a value node and a decision node. The value corresponds to estimated probability of a good outcome (complete recovery without disabilities) six month after the injury given the current patient status. The decision node represents nine treatment options considered in this model:

none, administer_volume, blood_pressure_increase, blood_pressure_decrease, vent_drain_or_IV_mannitol, adjust_sedation, adjust_barbiturates, hypothermia, hyperventilation.

The model structure is depicted in Figure 1. The chance nodes corresponding to cerebral perfusion pressure and intracranial pressure are two-valued. The values of CPP node are `> 70' (corresponding to cerebral perfusion pressure greater than or equal 70 mm Hg --- the desirable outcome) and `< 70' (less than 70 mm Hg). The ICP node has values `< 20' (corresponding to intracranial pressure less than or equal 20 mm Hg --- the desirable outcome) and `> 20' (greater than 20 mm Hg). The numerical cut-points are based on the current medical practice. The node corresponding to pupillary abnormality is three-valued. Its values are `BB' (both pupils brisk --- the desirable outcome), `BF/FB' (one pupil brisk, one pupil fixed), and `FF' (both pupils fixed). Finally, the node representing the Glasgow Coma Scale was three-valued in the original version of the model, but during the revisions we have changed it to two-valued node by eliminating the best outcome. The original values were `9 - 15' (the desirable outcome), `6 - 8', and `3 - 5'. The labels correspond to the particular interval of the Glasgow Coma Score. We do not consider the highest category because the physicians at the ICU almost never see patients with the score in this category.

Figure 1: Structure of the decision model



Utility Assessment

We followed the value-focused school of decision analysis [8] and built the model from the utility node. We first attempted a direct assessment of the utility function. However, even to linearly order the alternatives was difficult; to assign numerical quantities was infeasible. Therefore, we decided to use the multiplicative utility function as an approximation of the real utility function. We assessed the utilities of the individual factors and then estimated the trade-off weights using the standard reference lottery approach. During the tuning of the model, we had to reassess the trade-off weights again to adjust for the approximation error. The originally assessed utility function was more fine-grained than the one we eventually used in the model. The only place in the whole model where we were able to use observational data was to assess the utility of Glasgow Coma Scale [6].

Probability Assessment

Our model required assessment of 2808 probabilities. Since no data is readily available for specifying the numerical parameters, we relied only on subjective beliefs and elicited all the conditional probabilities directly. The doctors were sitting with the decision analysts in front of the computer and gave the probabilities of the individual events. Usually, we proceeded sequentially for each treatment action. The experts often looked back at the numbers given earlier both for the treatment action currently worked on and for other actions. One could object that this poses a danger of mis-using the Anchor and Adjust heuristic [7], but we believe that it was a very good measure for ensuring the consistency of the probabilities. We have not used any of the indirect assessment methods, such as the betting method, the reference lottery method or the modified AHP method [4, 10], as these methods are significantly more time consuming and their advantages are unclear in our situation. We did not perform comprehensive consistency checking of the elicited probabilities due to the time constraints. However, few incidents indicated that the probabilities are fairly consistent. For example, at the beginning of a session one of the experts started to fill in the probabilities in a particular row of a table. Only after he finished, he went to look at the previous related row and recognized the desired relationship. Also, if more than one expert were present, the numbers they provided often agreed. If there was a disagreement, a short discussion of scenarios behind the numbers always settled the matter.

Challenges

One of the inherent difficulties of performing medical decision analysis is the need to specify a large number of numerical parameters in a decision model. As sufficient data or mathematical models are exceptions rather than rules in the field, the modeler must rely on the experts' subjective judgement. However, physicians do not think about treatment options in probabilistic terms. Therefore, it is sometimes difficult for them to express their beliefs in precise numerical probabilities.

The medical problem itself poses several difficulties by its nature. One of the main problems is the lack of a clear and generally agreed way to judge the patient status. The usual medical evaluation of head injury treatment is based on the Glasgow Outcome Scale [2] measured six months after the injury. This scale has five degrees: complete recovery, moderate disability, severe disability, vegetative survival, and death. Unfortunately, this scale is not very well suited for quantitative modeling as it is very hard to assign quantitative values to the individual degrees. It is also impossible to assess the values for a particular patient in coma. To overcome this difficulty, we decided to use the estimated probability of complete recovery given current status of the patient as the value scale in our model. The problem is also quite complex with many interrelated factors. This means that our model, though small at the moment, turned out to be highly connected, which in turn implied the necessity to assess a large number of parameters.

RESULTS AND ANALYSIS

The solution to the decision model is presented in Table 1.

As mentioned earlier, the doctors made a lot of relational comparisons during the assessment process. Therefore, we believe that the trends in the assessed probabilities faithfully reflect the experts' knowledge or judgement. On the other hand, the exact numbers cannot be taken too literally. The final solution makes sense medically, though it does not conform exactly to the current practice. A possible reason is that the current model is too simple to account for the complexity of the problem. Another is that our current model evaluates only the status of a patient, while the trend in medicine is to look also at a cost-effectiveness of a particular treatment. This may explain why the solution never recommends to do nothing, while the doctors usually do not interfere in some of the situations. We are currently collecting clinical data that will give us some indication about the plausibility of the obtained results.

We performed one-way sensitivity analysis of our model. The results indicate a rather insensitive model to changes in the conditional probabilities of the four main parameters as well as in the utility function.

DESIDERATA FOR A KNOWLEDGE ACQUISITION SYSTEM IN CRITICAL CARE

Our experience in this project has illuminated a set of desiderata for an automated knowledge acquisition system that supports decision modeling in critical care when subjective estimation of parameters are necessary.

First, the system should include an educational component to train domain experts on the basic concepts in medical decision analysis. It should also be linked to a reference or resource component for easy access to the relevant medical literature and the Internet resources.

Second, the system should support systematic elicitation of unbiased probabilities. Some "debiasing" mechanisms for reducing the possible judgmental biases should be built into the elicitation process through comprehensive consistency checking mechanisms and a powerful graphical user interface for visualizing and manipulating the relevant numerical parameters.

Third, the system should incorporate a new set of elicitation methods that allow the experts to avoid direct assessment with point probabilities. Instead, such techniques will allow more qualitative descriptions to

Table 1: Results of the final model

GCS	CPP	ICP	Pupils	Optimal Treatment
6--8	above 70	below 20	B/B	Administer volume/BP increase
6--8	above 70	below 20	B/F or F/B	Vent drain or IV mannitol
6--8	above 70	below 20	F/F	Vent drain or IV mannitol
6--8	above 70	above 20	B/B	Hyperventilation
6--8	above 70	above 20	B/F or F/B	Hyperventilation
6--8	above 70	above 20	F/F	Hyperventilation
6--8	below 70	below 20	B/B	Administer volume/BP increase
6--8	below 70	below 20	B/F or F/B	BP increase
6--8	below 70	below 20	F/F	BP increase
6--8	below 70	above 20	B/B	Hyperventilation
6--8	below 70	above 20	B/F or F/B	Hyperventilation
6--8	below 70	above 20	F/F	Hyperventilation
3--5	*	*	*	Vent drain or IV mannitol

be translated into the relevant probabilities.

Fourth, the system should support easy updating and refinement of the numbers specified, either by the experts or from collected data. An audit trail or log should be maintained for the assumptions and the updates made.

Finally, the system should allow construction and storage of model fragments with the associated numerical parameters. Such fragments may be "re-used" in different decision models to facilitate rapid construction of specific decision problems in the same domain.

TOWARD EFFECTIVE PARAMETER ELICITATION TECHNIQUES

Based on the third desideratum outlined for an effective knowledge acquisition system, we propose two parameter elicitation techniques for large decision models: semi-qualitative assessment and approximation. These techniques would allow the domain experts to express their beliefs in a more natural manner and with greater confidence.

Semi-qualitative assessment is motivated by our observation that the domain experts are quite sure about certain qualitative relationships and trends in the probabilities. We should be able to obtain specifications like "The chance of incurring a brain damage increases exponentially with time of raised intracranial pressure." or "Probability of brain stem damage is at least 0.3." These specifications can be translated either into constraints on an unknown probability or into an imprecise probability [15] modeling the problem. Our experience suggests that these qualitative statements are more reliable than numerical probabilities. The sensitivity analysis results also suggest that in some situations it might be possible, e.g., using the calculus of imprecise probabilities [15], to obtain a unique solution from the constraints alone. Otherwise, a secondary criterion such as max-min rule may be used to obtain a solution. Alternatively, we may use a technique to obtain a point probability from constraints, e.g., maximum entropy, or proceed with normal elicitation but use the constraints to reduce the number of parameters needed.

Approximation techniques can reduce the number of parameters needed for a full specification of the model. These methods include breaking weak dependencies, divorcing parents, using noisy and/or gates, etc. However, the approximations may introduce undesirable artifacts into the model, thus they must be used with caution.

DISCUSSION AND CONCLUSION

We have described our experience in building a decision model of a real critical care problem. We have built a simplified influence diagram, performed basic verification and tuning of the model as well as one-way sensitivity analysis; the model produces reasonable recommendations.

The decision analytic approach allows us to focus on the interactions of the relevant variables, even when we are unsure about their actual relationships. This approach also makes it possible to answer many "what-if" questions about the treatment recommendations. This is important for supporting automated guidelines generation in the future. The main challenge, however, is in specifying the large number of numerical parameters involved, especially when statistical data are unavailable.

To build more realistic models in the domain, we have to consider several other factors, e.g., central venous pressure, as well as possible complications, e.g., diabetes. We should take into the account the dynamic nature of the problem and cover longer time period to account for effects of some treatment options, e.g., hypothermia.

Our decision model is based almost entirely on subjectively estimated parameters. There are not many similar efforts in assessing probabilities and utilities from experts for a practical problem of a substantial size. A notable exception is the HAILFINDER project by Edwards et al. [5, 1]. There are, however, significant differences in the problem characteristics. Edwards et al. describe the elicitation in the context of weather forecasting. Their approach to the assessment of probabilities is very similar to the one we used. Weather forecasting, though very complex and uncertain, is based on reasonably well understood causal mechanisms and processes, while the treatment of severe head injury is mostly based on symptom/results observations and very little is known (at least on the system level) about the underlying processes. In addition, usable multinomial data are unavailable for our case. This implies higher degree of connectedness of our model. Although our model looks much simpler, it required comparable number of probabilities. Another significant difference is that weathercasters are more experienced in working with probabilities than most doctors.

Our experience suggests that an alternative, more efficient strategy for elicitation of numerical parameters is desirable. We have proposed two parameter elicitation strategies for building large decision models: semi-qualitative assessment and approximations. The immediate future agenda of this work include developing these parameter elicitation strategies to facilitate dynamic decision modeling in the management of severe head injury.

Acknowledgments

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