An Intelligent Interactive Simulator of Clinical Reasoning in General Surgery

Shengrui Wang[1], Béchir El Ayeb[1], Vincent Echavé[2] and Benjamin Preiss[3]

[1]Department of Mathematics and Computer Science, Faculty of Sciences
Department of [2]Surgery and [3]Biochemistry, Faculty of Medicine
Université of Sherbrooke, Sherbrooke
Email: wang@dmi.usherb.ca, bpreiss@vm1.si.usherb.ca

ABSTRACT

We introduce an interactive computer environment for teaching in general surgery and for diagnostic assistance. The environment consists of a knowledge-based system coupled with an intelligent interface that al lows users to acquire conceptual knowledge and clinical reasoning techniques. Knowledge is represented internally within a probabilistic framework and externally through a interface inspired by Concept Graphics. Given a set of symptoms, the internal knowledge framework computes the most probable set of diseases as well as best alternatives. The interface displays CGs illustrating the results and prompting essential facts of a medical situation or a process. The system is then ready to receive additional information or to suggest further investigation. Based on the new information, the system will narrow the solutions with increased belief coefficients.

INTRODUCTION

Systems designed to provide assistance in clinical reasoning to medical students and practitioners have to deal with many issues. These include knowledge representation and manipulation as well as user-machine interaction. Among the most difficult problems are reasoning with multiple and hierarchical causal relationships and building an intelligent user interface. There exist numerous approaches to modelling clinical reasoning. Among recent probabilistic causal models are Cooper[1], Pearl[2], Neapolitan[3] and Peng-Reggia[4,5,6]. The predominance of probability based models for clinical reasoning can be attributed to the uncertainty and incompleteness inherent in medical knowledge. Although several other approaches have been proposed such as weighted rule-based reasoning[7], fuzzy-logic theory[8], and Dempster-Shafer theory [9], they lack either a solid theoretical foundation or they are equivalent, to some extent, to a probability based model [10,11].

Intelligent interface design has also been of great interest to researchers in this domain. An interface should not only provide a user-friendly environment but also help the user establish or evoke mental images of medical concepts and their component sub-concepts. For example, specific pathologies proposed as solutions to diagnostic problems should be displayed in a form that permits the user to see at a glance: the site, cause, major manifestations, age or sex related prevalence and warnings where needed. Concept Graphics (CGs) are designed to give such "disease pictures"[12,13]. If CGs of similar but different diseases are displayed, an observer should be able to "filter out" common features and concentrate on relevant differences. Therefore we believe that an integration of CGs into a clinical reasoning model will greatly enhance interaction between human users and an expert system that best serve clinical decision making and the acquisition of medical knowledge.

Before presenting the system, we describe an example of the target problem:
Patient: A small child of either sex, accompanied by the mother who speaks for and about the child. The child has recently developed the following manifestations:
-not eating well (anorexia) and has vomited once
-not as active as usual
-has constant abdominal pain, possibly on the right side
-physical examination is inconclusive
-moderate fever
-a moderate rise in the leucocyte count discovered through a blood analysis.

The user enters all these manifestations. According to general causal relations and some selection criteria, the expert system would propose the following possibilities with corresponding belief coefficients:
-Appendicitis (0.2)
-Mesenteric Adenitis (0.2)
-Urinary tract infection (0.1)
-Inflamed Meckel's diverticulum (0.05)
-Pneumonia-right lower lobe (0.1)
-Gastroenteritis (0.1)
These are all of the commun diseases that could have caused the afore-mentioned manifestations. The system would also propose several groups of these diseases, each of which is also associated with a belief coefficient for their co-occurance.

At this stage the user enters additional information ei-

0195-4210/92/$5.00 © 1994 AMIA, Inc.

ther of her own choice or after asking the system for advice on the following step. If the user asks the system for advice, the system will propose to do a chest X-ray, a urinalysis for pus (bacteria) and a urine culture, although the surgeon can not wait for the results. If the chest X-ray is negative and no pus is found in the urine both pneumonia and urinary tract infection are ruled out. The system will further ask if the fever is very high, the abdominal pain is crampy and not constant, accompanied by diarrhea and vomiting.These manifestations would make gastroenteritis likely[16]. The additional information now entered by the user should allow the system to narrow the choices. In our model case, after having ruled out pneumonia, urinary tract infection and the likelihood of gastroenteritis, the system will display the remaining alternatives with much more discriminative belief coefficients.

-Appendicitis (0.9)
-Mesenteric Adenitis (0.1)
-Inflamed Meckel's diverticulum (0.025)
-Gastroenteritis (0.025)

The repetitive execution of this process would help the user to make a more and more informed and justified choice.

SYSTEM OVERVIEW

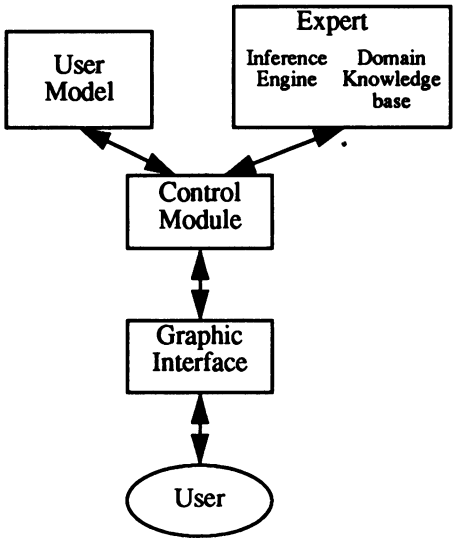

Figure 1.

The simulator has a general architecture (Figure1) which is similar to that of an ITS[14,15]. It is composed of a user model, an expert module, a control module and an icon-based interface. The user model describes different categories of users according to their knowledge levels (beginners, intermediate, and experienced). It provides, for each level of knowledge, a set of test questions related to relevant concepts, relations and clinical reasoning techniques. It allows the system to verify the knowledge level of the user and to suggest appropriate instructions to the user and the level of abstraction at which the expert system should consider when reasoning.

The expert module, as stated earlier, is derived from causal model of Peng-Reggia[4]. Some detailed information about the model, as well as its extension, will be discussed in the following paragraphs. The control module implements general strategies that ensure interface operation sequencing. Finally, the graphic interface is designed to allow a user to have easy access to other modules of the systems. While the whole system is being implemented in the object-oriented language c++ within X-window environment, we focus our attention on design and implementation of the expert and the graphic interface modules.

CONCEPT GRAPHICS

Concept Graphics (CGs) are multi-iconic representations of multivariate systems [12] (Figure 2). CGs offer at least two major advantages assumed to result from the use of Chernoff faces[17,18]. One is the integration of information achieved through the spacial coherence of the displayed pattern or picture, making all the information available to the observer at a single glance. The other is the use of the human ability for pattern recognition. Each display (CG) has its own visual "character" and can serve as a mnemonic device for remembering the features of a situation. However, CGs differ fundamentally from Chernoff faces because their component icons are metaphors of the subconcepts they represent. The icons range from simplified pictures of organs or body parts to abstract terms such as 'pain', 'chills' or 'fear'. The difficulties encountered in the use of Chernoff faces, namely filtering decrement, low psychophysical compatibility and problems arising from the presence of irrelevant features [18] may be avoided with CGs. CGs are expressive, according to the definition of Mackinlay[19], in that they encode all the essential facts of a medical situation or dynamic process and only those facts. We believe that CGs are highly effective [12]. However, as pointed out by Mackinlay [19], no clear criteria for effectiveness with any human population are available to date. Work is in progress on the formalization of the semantics, syntax and grammar of CGs which will permit extention of the existing set and automated translation into and from a large repertoire of CGs

(Kaltenbach, Gonzalez-Rubio and Preiss, unpublised).

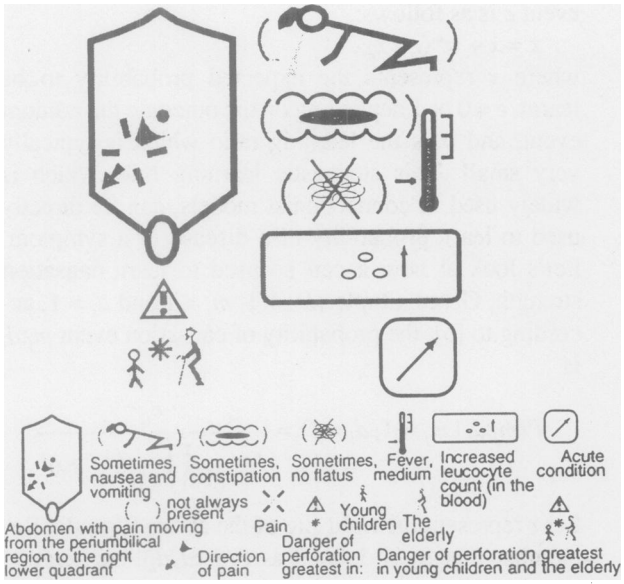

Figure 2. *Appendicitis, Concept Graphic and glossary*

The graphic interface in our system consists of window-based icons and buttons, and is designed to provide an interaction platform between the internal expert system and users. The CGs are actually the part of the interface that mainly represents symbolic knowledge of manifestations, diseases and their relationships. These include general clinical knowledge as well as specific results from diagnostic reasoning of the system. Detailed numerical knowledge can be accessed through buttons whose activation allows to show text information on scrolling windows. Work is in progress to enhance the abilities of the CGs to represent numerical knowledge such as probabilities.

PENG-REGGIA's MODEL FOR KNOWLEDGE REPRESENTATION AND REASONING

Our expert system is derived from the model of Peng-Reggia. However, it extends this model in several ways. Our system has the capacity to reason when the presence or absence of certain manifestations is unknown. It suggests further laboratory tests when necessary and is capable of automatically learning, thus increasing its clinical expertise. This model has been chosen because the problem here consists in the identification of a set of diseases that best account for a set of symptoms. Peng-Reggia's model is based on an extended Bayesian theory and has proved to be very useful in modelling clinical reasoning of this kind.

In their approach, a diagnosis problem is characterized as a 4-tuple:

$$\langle D, M, C, M^{+} \rangle$$

where D is a set of diseases, M is a set of possible symptoms (manifestations), C is a causation relation defined on $D \times M$, and M^{+} is a subset of M representing a set of observed symptoms (observed manifestations). Associated with each possible symptom d_i is a prior probability p_i. To simplify, the symptoms in D are assumed to be independent. A c_{ij} ($0 <= c_{ij} <= 1$) in C stands for causation strength between the disease d_i and the symptom m_j. $c_{ij} = 0$ means that d_i does not cause m_j at all, while a $c_{ij} > 0$ means the strength with which the d_i actually causes m_j. One of their major contributions lies on the fact that c_{ij} is not equivalent to the conditional probability $P(m_j \mid d_i)$ often used in the early Bayesian approaches. Rather, it has the advantage of being unaffected by coincident disorders, i.e. we may expect the frequency with which the d_i causes m_j given d_i to remain stable. Finally, they assume that each symptom in M is caused at least by some disease in D, i.e. for each m_j there exists one di such that $c_{ij} > 0$.

The reasoning process simulated in this model aims at finding the most plausible set of diseases among all possible ones $\{D_I\}$, a concept characterized by the maximum of a "relative likelihood" function defined as:

$$L(D_I, M^{+}, M^{-}) = L_1 L_2 L_3$$

where M^{-} is the subset of symptoms which are known to be absent, and

$$L_1 (D_I, M^{+}, M^{-}) = \prod_{m_j \in M^{+}} \left(1 - \prod_{d_i \in D_I} (1 - c_{ij})\right)$$

is the likelihood that disorders in DI cause the manifestations in M^{+}.

$$L_2 (D_I, M^{+}, M^{-}) = \prod_{d_i \in D_I} \prod_{m_j \in \langle effects(d_i) - M^{+} \rangle \cap M^{-}} (1 - c_{ij})$$

is the likelihood that disorders in DI do not cause the manifestations outside of M^{+}. Finally

$$L_3 (D_I, M^{+}, M^{-}) = \prod_{d_j \in D_I} \frac{p_j}{(1 - p_j)}$$

is the likelihood that a highly probable disorder contributes significantly in the overall likelihood of a diagnosis D_I containing d_i. Thus L_1 forces L to focus on only diagnoses that cover or explain all manifestations in M^{+}, L_2 encourages L to focus on "irredundant" and "relevant" covers, and L_3 forces L to focus on more likely or common disorders.

However, the theoretical model of Peng-Reggia makes an unrealistic assumption on the conditional causation independence, much the same way as other Bayesian models assumed the independence of symptoms of a disease. We will discuss this issu in the section below.

Several other issues such as reasoning with hierachical causal relations, expert knowledge acquisition and heuristics to increase reasoning efficiency are also addressed in our system.

Conditional causation independence

In the model of Peng-Reggia, it is assumed that causation event $m_j{:}d_i$ occurs independently of any of its contexts. Informally, this means that causation strength c_{ij} is constant even though other manifestations of disease d_i are present.

In our system, c_{ij} is assumed to be a basic causation strength that can be increased when other manifestations of the same disease are available:

$$c_{ij} = \min\{1, c_{ij} + h_{ij} * c_{ij}\}$$

where h_{ij} is a multiplier defined as:

$$h_{ij} = \alpha \times p_i \times \sum_{m_l \in effect(d_i) \cap M^+,\, l \neq j} \frac{c_{il}}{P(m_l)}$$

where α is a small positive number, typically $\alpha<0.1$. Thus the multiplier depends only on observed manifestations of disease d_i, although other observed manifestations may also influence the causation strength c_{ij}. It should be pointed out that the impact of such a modification on the model is significant and has to be analysed in both theoretical and practical perspectives.

Hierarchical causal relations

Another important issue on modelling of clinical reasoning concerns hierarchical causal relations. This is out of the scope of the present paper because it requires a profound re-formulation of the model. However, some special cases could be addressed within the theoretical framework of the model, particularly when hierarchy of manifestations (multilevels of abstraction) are considered. More specifically, if a new and more precise manifestation is discovered, then it can either replace an existing manifestation or serve as evidence to increase related causation strengths.

Acquisition of causation strengths

Causation strengths and prior probabilities of causes are principal constituents of our knowledge base. They can be provided by medical experts. In fact, experts can easily enter their knowledge into the system, thanks to the intelligent icon-based interface. However, because of the large number of probabilities and of changing environment, it is important that the system be able to learn by itself. One typical senario of the situation is that experts provides initial probabilities and the system "modifies" these probabilties after a session of reasoning. In another senario, the system could be asked to learn all the probabilities based on information from a medical database.

The basic rule for learning the probability of a random event e is as follows:

$$x = x + \alpha * (e - x)$$

where x represents the expected probability to be learnt, $e = 0$ or 1 depending on the outcome the random event, and α is the learning ratio which is typically very small. This stochastic learning rule, which is widely used in connectionist models, can be directly used to learn probability of a disease or a symptom. Let's look at how it can be used to learn causation strength. Given a tuple $\{D, M\}$, $m_j = 1$ and $d_i = 1$, according to [5], the probability of causation event $m_j{:}d_i$ is

$$P(m_j{:}d_i \mid m_j = 1, d_i = 1) = \frac{c_{ij}}{1 - \prod_{(d_k=1) \in D} (1 - c_{kj})}$$

Let r represent the right site of the above formula. Remember that c_{ij} is defined as $P(m_j{:}d_i|d_i)$, an iterative learning rule for c_{ij} based on the two above formula is:

$$c_{ij} = c_{ij} + \alpha * (e(p) - c_{ij})$$

where $e(p)$ is a random function. It equals 1 with probability p and 0 with probability $1-p$, while

$$p = \begin{cases} r + \beta & \text{if } m_j{=}1, d_i{=}1,\ m_j{:}\, d_i \text{ present} \\ r - \beta & \text{if } m_j{=}1, d_i{=}1,\ m_j{:}\, d_i \text{ absent} \\ r & \text{if } m_j \bullet d_i{=}0 \end{cases}$$

Where $1<\beta<<1$, $p=1$ if $r+\beta>1$, $p=0$ if $r-\beta<0$.

About searching efficiency

Finally, concerning the computation of the diagnoses, which is computationally intractable, Peng-Reggia proposed an efficient algorithm (see [6] for more details) for reducing the searching space. In practice, heuristics can be used to further improve the searching procedure. This can be done through fixing an order of priorities on observed manifestations, including or excluding certain diseases. Again, we should underly the importance of a graphic interface for inspiration and manipulation.

CONCLUSION

We believe that integrating the probabilistic knowledge-based system and the CGs is a promising avenue to the creation of an efficient intelligent tutoring and decision support system. Of the first importance, such a system allows users to visualize final results and the process of reasoning followed by the system, compare visually the solutions provided by the system with their own, and propose new tests. It also allows expe-

rienced users to limit searching space by inclusion and exclusion of certain diseases in the searching process, schedule searching sequencing according to their preference (ex. based on severity or importance of manifestations), and to modify causal relationships.

ACKNOWLEDGEMENTS

This work was supported in part by grants OGPO121680 and EQPO139397 of the Natural Sciences and Engineering Research Council of Canada.

Reference

1. Cooper, G. NESTOR: A Computer-Based Medical Diagnostic Aid that Integrates Causal and Probabilistic Knowledge. Stanford University, Department of Computer Science, 1984. Ph.D. Dissertation Tech. Rep. No. STAN-CS-84-1031.
2. Pearl, J. "Fussion, Propagation, and Structuring in Belief Networks." Artificial Intelligence 29 (1986): 241-288.
3. Neapolitan, R. "Properly Using Probability and Statistics to Rank Explanations." (1988):
4. Peng, Y. and J. A. Reggia. Abductive Inference Models for Diagnostic Problem-Solving New York: Springer-Verlag, 1990.
5. Peng, Y. and J. A. Reggia. "A Probabilistic Causal Model for Diagnostic Problem Solving Part I: Integrating Symbolic Causal Inference with Numerical Probabilistic Inference." IEEE Transaction on Systems, Man, and Cybernetics SMC-17 No.2 (1987a): 146-162.
6. Peng, Y. and J. A. Reggia. "A Probabilistic Causal Model for Diagnostic Problem Solving Part II: Diagnostic Strategy." IEEE Transaction on Systems, Man, and Cybernetics SMC-17 No.3 (1987b): 395-406.
7. Shortliffe, E.H. and B.G. Buchanan. "A Model of Inexact Reasoning in Medicine." Mathematical Biosciences 23 (1975): 351-379.
8. Zadeh L. "Knowledge Representation in Fuzzy Logic." IEEE Trans. on Knowledge and Data Engineering, 1, No. 1, (1989): 89-100.
9. Shafer G. A Mathematical Theory of Evidence. Princeton: Princeton University Press, 1976.
10. Heckerman, D.E., E.J. Horvitz, and B.N. Nathwani. "Toward Normative Expert Systems: Part I The Pathfinder Projet." Methods of Information in Medicine 31 (1992): 90-105.
11. Heckerman, D.E. and B.N. Nathwani. "Toward Normative Expert Systems: Part II Probability-Based Representations for Efficient Knowledge Acquisition and Inference." Methods of Information in Medicine 31 (1992): 106-116.
12. Preiss, B., R. Black, C. Caron, and D. Shapcott. "Graphic summaries of expert knowledge for the medical curriculum I. An experiment in second year nephrology." Meth Inform Med 31 (1992a): 303-309.
13. Preiss, B., M. Kaltenbach, J. Zanazaka, and V. Echavé. "Concept Graphics: A language for medical knowledge." In The 16th Annual SCAMC in Baltimore MD, McGraw-Hill, 515-519, Year.
14. Micarelli, A, F. Mungo, F. S. Nucci, and L. Aiello. "Reasoning With Worlds and Truth Maintenace in an Intelligent Tutoring System." Expert Systems With Applications 4 (1992): 147-155.
15. Sleeman, D.H. and J.S. Brown, ed. Intelligent Tutoring Systems. New York: Academic Press, 1982.
16. Lacharité S, Echavé V. "L'abdomen aigu chez l'enfant et l'adolecscent." L'actualité Médicale Jan. (1991): 39-42
17. Chernoff H. "The use of faces to represent points in k-dimentional space graphically." J. Am Stat Assoc 68 (1973): 361-368.
18. Naveh-Benjamin M, Pachella RG. "The effect of complexity on interpreting "Chernoff" faces." Human Factors 24 (1982): 11-18.
19. Mackinlay J. "Automating the Design of Graphical Presentations of Relational Information." ACM Transactions on Graphics 5 No. 2 (1986): 110-141.