A Model-Based Expert System for Interpretation of Hemodynamic Data from ICU Patients

Ruilin Zhao[1,2], Roger G Mark[1], Peter Szolovits[2]

[1]Harvard-M.I.T. Division of Health Sciences and Technology, Cambridge
[2]Laboratory for Computer Science, MIT, Cambridge, MA, USA

Abstract

With the proliferation of modern monitoring and laboratory procedures, physicians in intensive care areas may face "information overload", in dealing with very large, complex and ever-changing quantities of clinical data, which often lacks efficient organization. This research analyzes the medical knowledge required for formulating decision models in the domain of hemodynamics. Based on such analysis, a knowledge based expert system to track a patient's hemodynamic state has been developed and evaluated in a laboratory setting.

The initial phase of the work utilizes a cardiovascular simulator to generate "pseudo-ICU" waveforms as input to the expert system in order to guide the development of the matrix of rules and search strategies. A number of pathological simulations have been successfully analyzed by this model-based expert system, including examples of hypertension, left ventricular failure, hypovolemia, pulmonary hypertension, etc. We conclude that our approach is practical, and provides a mechanism for transforming and reducing real-time physiologic data into pathophysiologic hypotheses relevant to the management of patients.

1 Introduction

Hospital intensive care areas generate enormous amounts of real-time and off-line data relating to the status of acutely ill patients: multi-parameter real-time physiological signals, ventilator data, laboratory tests, imaging studies, medications, clinical observations, etc. Clinical staff must reassess patients frequently, and accurately interpret all of this dynamically changing data. Providing optimal life support in ICUs is becoming an increasingly difficult task as the volume of monitoring data increases. The sheer quantity of available patient data, which often lacks rational organization, may lead to "information overload" for clinicians, and decreased efficiency in translating the data into pathophysiologic hypotheses upon which therapy is based. There have been occasional tragedies, most of which are due to the human error, reported in ICU care[1].

Manufacturers of monitoring equipment are making major progress in developing interfaces between real-time monitoring systems and hospital clinical information systems such that patient data from multiple sources is accessible from a single ICU terminal. In fact, in a number of centers it is already possible to access most real-time and offline patient data from patient's bedside. The next challenge is to explore the extent to which the available clinical data can be used to formulate dynamic pathophysiological models of the patient's changing clinical status. Such models or hypotheses could provide a rational structure around which to present data to clinicians, could play a key role in developing decision support paradigms, and should provide the basis for more sophisticated and sensitive "alarms".

Many researchers have developed techniques to interpret ICU data[2]. Generally, we can divide these techniques into two categories: numeric and symbolic methods. The numeric methods are reasoning processes for providing quantitative analysis; and symbolic methods deal with qualitative analysis. In intensive care areas, the clinical context includes data that are both numeric and symbolic[3].

We have begun our investigations in the restricted domain of hemodynamics. We have designed and implemented a prototype knowledge-based system to interpret observable hemodynamic data (right and left-sided pressures, cardiac output), and limited functional/anatomic data available from imaging studies such as echocardiography. We assume that the patient's hemodynamic status at any particular time can be represented by the simple lumped parameter model described below. Our objective was to design and evaluate the feasibility of an expert system to automatically select that set of parameter values for the CV model which produces outputs closely matching the pressures and flows of the patient.

0276-6547/96 $5.00 © 1996 IEEE

2 Methods

2.1 Cardiovascular Model

A lumped-parameter cardiovascular model was used in our expert system to represent the patient's hemodynamic state. The same model was used during this study to generate "clinical" input data for the expert system. The model is a dynamic computer simulation of human cardiovascular hemodynamics, originally designed as a teaching tool for students of physiology and medicine[4]. It is implemented on workstations running the X window system, and allows students to perform a variety of "investigations" not all of which would be possible in an animal laboratory.

The model is shown in Figure 1. It includes four major sections: the left heart, systemic circulation, right heart, and pulmonary circulation. Each side of the heart is modeled by a variable capacitor (representing the pumping action of both atrium and ventricle), two diodes representing the AV and arterial valves, and outflow resistances[4]. There are 23 parameters for defining the status of the simulator; their normal values are shown in the second column of Table 1.

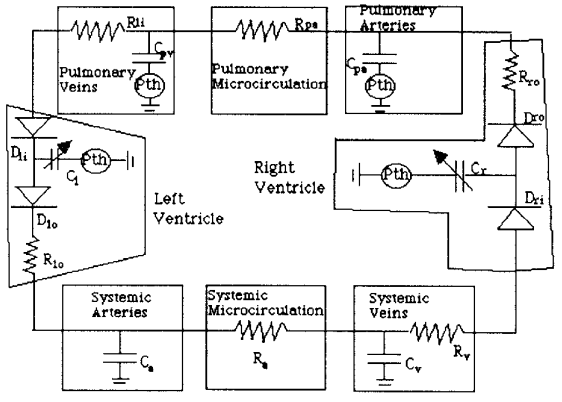

Figure 1: Circuit Diagram Equivalent of Lumped Parameter Model

2.2 Extracting Features from Physiological Waveforms

The CV simulator is initialized by specifying each of the 23 model parameters. The simulator then generates the resultant pressures, flows, and volumes at all sites in the CV system. (See Figure 2.) The raw waveforms are then pre-processed by the "feature detector" which derives a set of 21 clinically observable parameters (features) such as heart rate, mean arterial BP, pulse pressure, central venous pressure, left ventricular end-diastolic pressure, cardiac output, etc. (Note that clinically non-observable parameters are not included in the feature set.) This 21 dimensional feature set is used to characterize the physiologic data generated by the model (or by patients).

In our present study we used the CV simulator to generate "pseudo-clinical" test data which was representative of a variety of disease states. This approach simplified the task of designing the expert system, and also provided a quantitative method to evaluate its performance of the expert system. Since the actual input parameters of the CV model are known for each test case, they can be compared directly with those derived by the expert system.

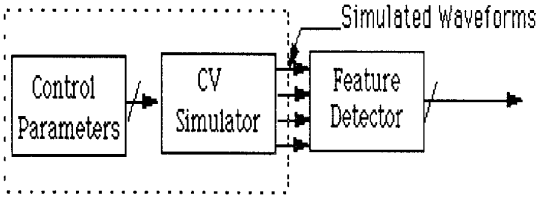

Figure 2: Diagram of Generating and Pre-processing Data

2.3 Design of the Expert System

The task of the expert system is to derive a set of control parameters for the CV model which will result in output waveforms and features which match those of the patient. The input to the expert system is the 21-dimensional feature set from the patient or "pseudo-patient". The expert system then iteratively adjusts the control parameters of its internal copy of the CV model until its output feature set matches that of the "patient". (See Figure 3.) The initial control parameters are established by using the patient data to calculate as many parameters as possible. For example, if the clinical data includes ABP, PAP, C.O., CVP, PCWP it is possible to derive model parameters such as HR, Ca, Ra, Rp, Cp, etc. The remaining parameters are initialized to the normal values.

The CV model is then run, and its output is represented by an 21-dimensional feature vector which is compared to the target feature vector from the "patient". The comparison is made using the error functions Eq. 1 and Eq. 2 :

$$\mathbf{E}_{TOTAL} = \sum_{i=1}^{21} \mathbf{E}_i \qquad (1)$$

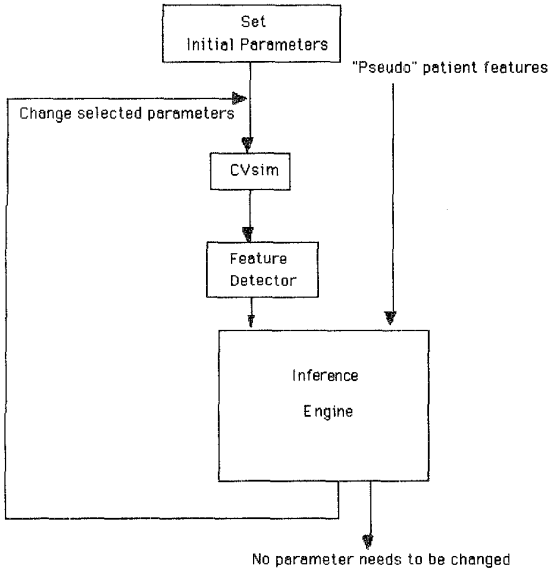

Figure 3: Prototype of Search Control Box

$$\mathbf{E}_i = \frac{|Patient \text{ Value - CVsim Output Value}|}{\text{Normal Value}} \quad (2)$$

For example, the error function of CVP(Central Venous Pressure) is defined as Eq. 3:

$$\mathbf{E}_{cvp} = \frac{|Patient \text{ CVP - CVsim's CVP}|}{\text{CVP Normal Value}} \quad (3)$$

The total error function is compared to a threshold. If the error is below the threshold the iteration stops. If the error exceeds the threshold, the expert system tunes the input parameters of its CV model to more closely represent the status of the "patient". This is a multidimensional search process guided by a priori physiologic knowledge and available clinical data from the patient. The rule-based inference engine which guides the search was developed in the context of analyzing a number of simulated pathological conditions such as hypertension, septic shock, hypovolemia, LV failure, pulmonary hypertension, etc. The performance of the expert system was evaluated by comparing the model parameters and waveforms derived by the expert system to those of the pseudo-patient.

3 Results

Illustrative results are presented in the context of two case studies:

3.1 Case study 1: Hypertension

This case represents a patient with increased peripheral resistance, increased heart rate, increased blood volume, increased LV contractility, decreased LV diastolic compliance, and decreased arterial incremental compliance. After running about 4 minutes on a Sun SPARC station, the iteration stops. Table 1shows the comparison of the actual model parameters to those estimated by the expert system.

The following decision-making strategies were employed in this case:

1) Set up the resistance and heart rate based on direct calculation;

2) Estimate the value of arterial capacitance based on "patient's" stroke volume and pulse pressure;

3) If the "patient's" right heart pre-load is high, then increase total blood volume of CV simulator;

4) If the "patient's" stroke volume is low and left heart pre-load is high, then change the diastolic capacitance and systolic capacitance of left ventricle of CV simulator.

From Table 1, we can see that the estimated values of heart rate and microvascular resistance match with the actual values very well. The estimated value of effective blood volume (up 300 cc in total blood volume) is identical to the actual effective volume (300 cc squeezed out of the veins by decreased zero-pressure volume). The system was not successful in distinguishing LV systolic and diastolic dysfunction, however.

3.2 Case study 2: Vaso-dilation

This case represents a patient with decreased microvascular resistance and increased arterial capacitance. After running about 1 minute on a Sun SPARC station, the iteration stops. Table 2 shows the comparison of real values with estimated values in this case.

The following decision making strategies have been used for this case:

1) Set up the resistance and heart rate based on direct calculation;

2) Estimate the value of arterial capacitance based on "patient's" stroke volume and pulse pressure;

3) If the "patient's" cardiac output, left ventricular end-diastolic pressure and central venous pressure are the same with those of CV simulator, but the "patient's" pulse pressure is low, then increase arterial capacitance of CV simulator.

From Table 2, we can see that the estimated values of arterial capacitance and microvascular resistance match with the real values well.

Parameter	Normal	Actual	Estimation
Heart Rate	72	**100**[1]	**100**
Total Blood Volume	5000	5000	**5340**
Trans-thoracic Pressure	-4	-4	-4
Capacitances:(ml/mmHg)			
LVsyst	0.4	**0.30**	**0.50**
LVdiast	10.0	**6.0**	**8.7**
Arterial	1.5	**0.9**	**1.12**
Venous	100.0	100.0	100.0
RVsyst	1.20	1.20	1.20
RVdiast	10.0	10.0	10.0
Pulm. Art.	4.30	4.30	4.30
Pulm. Venous	8.40	8.40	8.40
Zero-Pressure Volumes:(ml)			
LV	15.0	15.0	15.0
Arterial	715.0	715.0	715.0
Venous	2500.0	**2200.0**	2500.0
RV	15.0	15.0	15.0
Pulm. Art.	90.0	90.0	90.0
Pulm. Venous	490.0	490.0	490.0
Resistances:(mmHg*sec/ml)			
LV Inflow	0.01	0.01	0.01
LV Outflow	0.0	0.0	0.0
Microvascular	1.0	**2.00**	**1.96**
Venous	0.01	0.01	0.01
RV Outflow	0.00	0.00	0.00
Pulmonary	0.08	0.08	0.08

Table 1: Comparison of Actual Values with Estimated Values for Hypertension Patient

Parameter	Normal	Actual	Estimation
Heart Rate	72	72	72
Total Blood Volume	5000	5000	5000
Trans-thoracic Pressure	-4	-4	-4
Capacitances:(ml/mmHg)			
LVsyst	0.4	0.4	0.4
LVdiast	10.0	10.0	10.0
Arterial	1.5	**1.6**	**1.8**
Venous	100.0	100.0	100.0
RVsyst	1.20	1.20	1.20
RVdiast	10.0	10.0	10.0
Pulm. Art.	4.30	4.30	4.30
Pulm. Venous	8.40	8.40	8.40
Zero-Pressure Volumes:(ml)			
LV	15.0	15.0	15.0
Arterial	715.0	715.0	715.0
Venous	2500.0	2500.0	2500.0
RV	15.0	15.0	15.0
Pulm. Art.	90.0	90.0	90.0
Pulm. Venous	490.0	490.0	490.0
Resistances:(mmHg*sec/ml)			
LV Inflow	0.01	0.01	0.01
LV Outflow	0.0	0.0	0.0
Microvascular	1.0	**0.496**	**0.500**
Venous	0.01	0.01	0.01
RV Outflow	0.00	0.00	0.00
Pulmonary	0.08	0.08	0.08

Table 2: Comparison of Actual Values with Estimated Values for Vaso-dilation Patient

4 Discussion and Conclusions

Based on approximately 15 typical case studies examined, we found that:

1) The system usually can converge in less than 5 minutes;

2) Heart rate and most resistances can be directly calculated, so their values are quite accurate;

3) The system can only be used to determine the *effective blood volume* and cannot differentiate whether the change of effective volume is due to changes in total blood volume or to changes in zero-pressure filling volumes;

4) Systolic and diastolic LV dysfunction cannot be clearly differentiated on the basis of hemodynamics alone. Additional information (such as cardiac echo) is needed;

5) The system cannot be used to analyze some cases such as mitral regurgitation due to constraints of the model.

This iteration approach can be used as a way for model-based expert system to solve system identification problems when these problems are underdetermined. Clinical rules and other available test results have been used to guide the direction of the iteration in our system. The results of our case studies have shown that this approach is promising to solve other underdetermined clinical problems.

[1]The items in bold type are different from the normal values.

5 Acknowledgement

This work has been partially supported by Hewlett Packard Company and by An Wang Graduate Fellowship. Timothy Davis helped us to be familiar with Cardiovascular Simultor. George Moody provided us lots of helpful hints.

References

[1] Abramson N., et al., Adverse Occurrences in Intensive Care Units, JAMA, 244: 1582-1584, 1980.

[2] Uckun S., Model-based reasoning in biomedicine, Critical Reviews in Biomedical Engineering, 19(4): 261-292, 1992.

[3] Rutledge G. W., Dynamic Selection of Models, Ph.D. thesis, Department of Computer Science, Stanford University, March 1995.

[4] Davis T. L., Teaching Physiology Through Interactive Simulation of Hemodynamics, MIT M.S. Thesis, February 1991.