Temporal Expert System Approach to the Interpretation of ICU Cardiovascular Data

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Abstract

Intensive Care depends on sophisticated life support technology. Effective management of device-supported patients is complex, involving the interpretation of many variables, comparative evaluation of numerous therapeutic options, and control of various patient-management parameters. Raw data, when taken literally, can lead to the wrong interpretation of the patient state. We propose a system which processes raw data as it arrives for intelligent alarming and retrospectively for summarisation and state assessment, using a temporal expert system which incorporates both associational and model-based reasoning.

Introduction

The domain of our project is the Medical Intensive Care Unit (ICU) into which patients are admitted for the management of a wide variety of severe illnesses. Our area of interest is the cardiovascular data produced by the monitors: Heart Rate, Blood Pressure (BP), Central Venous Pressure (CVP) and Pulmonary Arterial Pressure (PAP). There is also scope for working with other ICU data.

Medical staff are confronted with large amounts of continuous data and it is far too time consuming to look at it all to make clinical decisions. Single channels are rarely interpreted on their own - it is usually necessary to compare several channels, often in the context of past events. This leads to the need for data summaries in which greater level of abstraction are achieved. Clinical staff are interested in temporal intervals during which data have abstractions such as *steady, increasing* and *decreasing*. For such classification, one has to remove non-physiological events which would otherwise give an inaccurate history of the patient. A state assessment of the patient may also be required e.g *patient is suffering from cardiogenic shock*.

Presently most alarms in the ICU are based on a single monitored parameter passing a preset limit e.g an upper threshold for a systolic pressure and a lower threshold on a diastolic pressure. If the monitoring limits are set to the maximum allowable physiological deviation from the normal or expected value, a monitor alarms when the patient already is in a serious condition. On the contrary, if the limits are adjusted to increase sensitivity, the monitor is prone to giving false alarms. Another important deficiency is the inability of the present monitors to detect slow trends in a patient's physiology and to regard them as important indicators of the development of the patient's state. Finally, only very simple technical faults can be detected in the signal, such as simple signal cutoff or input overload conditions. More subtle technical faults can not be distinguished from a disturbance in patient physiology. For example, an occlusion in a pressure catheter may go unnoticed or may produce an alarm, not a technical warning as it should. It is rare for current patient monitors to make a cross comparison between physiological signals to verify that an abnormal situation is a result of an actual physiological change [Makivirta et al,1987] .

There is, therefore, a strong practical need for intelligent alarming. While medical staff can recognise an unsatisfactory development in a patient's state, the monitoring equipment cannot. An intelligent alarm should be able to alarm at an early stage of problem development and should be able to differentiate between an artefact and a medical disorder and process them accordingly.

These features, we feel, can be incorporated into a bedside workstation, acting as a ***background*** monitor.

The temporal cardiovascular data produced by the monitors in the ICU can therefore be considered in two ways:

1. *historically* - when considering a given time in the past, we have available data relating to times both *before* and *after* that time. This data can be used to generate summaries of past events and patient state to assist clinical decision making.
2. *'real-time'* - when considering a given time we only have available data relating to times *before* that time. We are not concerned at present with the problems

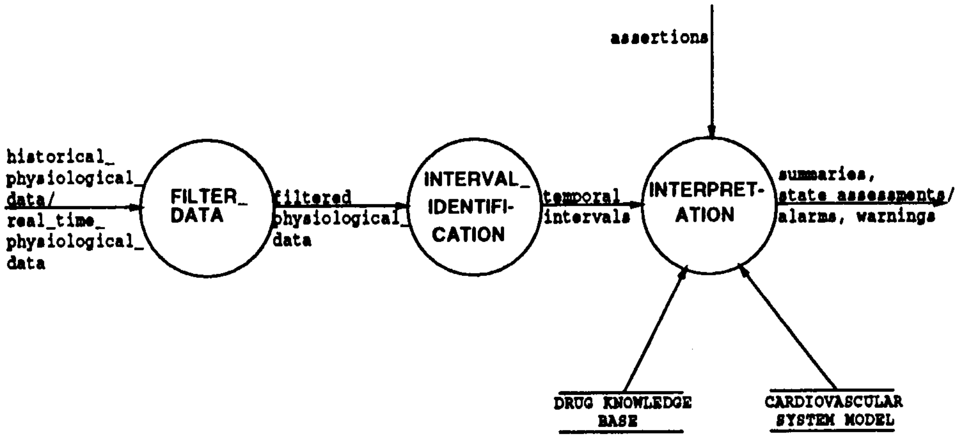

Figure 1: System Design

of handling data at the rate at which it would arrive. This data can be used as the basis for intelligent alarming.

A large volume of data is collected for each patient. The challenge is to interpret these signals and to distinguish between clinically significant and insignificant events.

We, therefore, divide our research into two activities: *summarising historical data* and *real-time intelligent alarming*. Each activity, in turn, can be viewed as following three consecutive processes: *filtering*, *interval identification* and *interpretation*, and part of the focus of our work is in investigating which techniques are common to both activities.

System Design

Figure 1 depicts the three consecutive processes which summarising and intelligent alarming make up.

Filtering

Filtering is a method of identifying and removing non-physiological events (blood samples, line flushes etc) from the data. This is required for summarisation, otherwise a distorted view of the patient will be generated. Likewise, filtering is required for intelligent alarming otherwise unnecessary alarms will be set off. The non-physiological events which have been removed must be classified and stored for audit purposes.

Some non-physiological events are represented as high frequency components in the signal. *High-pass filters* retain non-physiological events. *Average filters* smooth the value of the non-physiological event and hence distorts the baseline signal. However, *median* and *low-pass* filters show promise. When a signal is filtered with a median filter having a moving window of length n, all spikes in the signal shorter than $\frac{(n-1)}{2}$ are removed from the signal. This length is called the *cut-off length* t_c of the filter. Despite this, even a sudden change in a signal is accurately reproduced if the signal continues at the new, changed level.

Low-pass filters allow signals which have a frequency less than a *cut-off* frequency to pass through and discards signals (this should include non-physiological events).

For summarisation, filtering can be based on a window *centred* on a point. However for intelligent alarming we are constrained to using a window *ending* with the latest data item - such a window will inevitably introduce a delay.

Interval Identification

Since monitor data can arrive at a high rate it is impractical to carry out complex processing on each data value. *Interval identification* is the classification of event-free data generated by the filtering process into temporal intervals in which data is symbolised as *steady*, *increasing*, or *decreasing*. One must decide the beginning and end of an interval.

In the spirit of [Shahar et al,1992] , intervals can be identified by using a combination of temporal and statistical reasoning. This involves temporally interpolating between data points to obtain temporal intervals. These temporal intervals are temporally inferenced to obtain *super-intervals*.

With summarisation one is able to look around a point. In real-time, deciding the timing of the transition from one abstracted interval to another is more complex - one can only look backwards.

Interpretation

Interpretation is the process of using the temporal intervals for the purposes of summarisation and intelligent alarming and will be implemented using YAQ which is a hybrid system of associational and model-based reasoning [Uckun,1992].

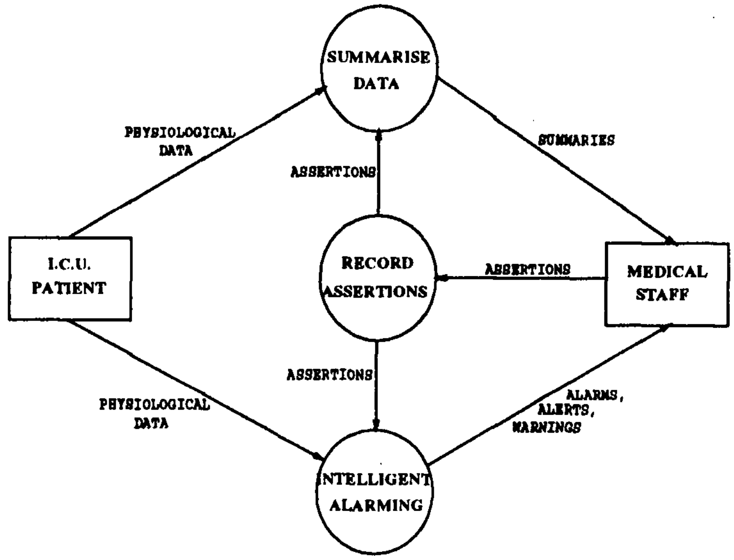

Figure 2: Proposed System

Interpretation involves a model of the cardiovascular system, knowledge of drugs, and knowledge of exogenous variables (assertions).

A *Cardiovascular Model* will define cardiovascular parameters as quantities together with their quantity spaces e.g the quantity *Heart Rate* with a rate below 60 can be classified as *bradycardic*. Since there are no absolutely defined ranges for quantities, the quantity spaces can be changed dynamically. The model also defines the relationships between cardiovascular parameters e.g *Heart Rate varies inversely with parasympathetic tone*.

A *Drug Knowledge Base* will define the effects on the cardiovascular parameters made by the administration of a specific drug. For example, the drug *Noradrenaline* (which acts primarily upon the *alpha* receptors but also on the $beta_1$ receptors in the heart) causes an increase in peripheral vascular resistance which in turn causes a rise in BP and a reflex slowing of the heart. This knowledge base also holds such information as estimated times from administration to the time of action of the drug, used to create expectations of how the drug will act in the future.

Assertions include a description of the patient (age, sex, history etc), mode of ventilation, administration of oral drugs, drug infusion rates, lab results etc. These can change quantity spaces, assist in diagnosis or affect other quantities in the system.

For Summarisation, interpretation of historical data involves the analysis and presentation of (overlapping) temporal intervals of symbolised physiological data and the generation of state assessments.

For Intelligent Alarming, interpretation involves predicting and informing clinical staff of imminent events e.g *potential cardiac tamponade* or *potential haemorrhage*.

YAQ currently reasons between discrete points in time. For the purposes of intelligent alarming and summarisation, YAQ needs to be extended to reason about intervals.

Proposed System

Figure 2 depicts the system are developing for clinical decision support in the ICU; it consists of two main processes: *SUMMARISE DATA* and *INTELLIGENT ALARMING* together with the administrative process *RECORD ASSERTIONS*. We will describe each of these :

RECORD ASSERTIONS

This process simply records the time of each event taken by medical staff. This could be the rate of drug infusions, mode of ventilation, amount and kind of intravenous fluid given, dosage, time and kind of drug taken orally etc. This will assist in intelligent alarming and summarisation.

SUMMARISE DATA

In order to make clinical decisions, meaningful summaries of past data are required.

For a medical computer system to be truly effective, 'the patient data must be as complete as possible and that stored data should be free from artefact' [Gardner et al,1982]. The process *SUMMARISE DATA* takes as input historical physiological parameters relating to the cardio-vascular system and :

1. extracts events together with their time and type for classification - this will be stored for audit purposes.
2. using symbolic interpretation, generates accurate reports as requested by medical staff - these reports can be in the form of *trends, means, graphs* etc.

Figure 1 depicts the non real-time subprocesses involved in *SUMMARISE DATA*.

Past data is filtered by the process *FILTER DATA*. Here, *events* such as *blood sample* are recognised, removed and stored in the an *audit* database. At time points (or intervals) where events occurred, they could be replaced by an approximate value relative to the past or have *null* values. The subsequent *filtered physiological data* is then passed onto the process *INTERVAL IDENTIFICATION* where meaningful temporal intervals are generated.

Using these temporal intervals and audit data, the process *INTERPRETATION* serves two purposes;

1. meaningful summarises of temporal abstractions together with events which had occurred e.g *heart rate was steady with a mean of 100* ±5 *beats per minute between 7a.m and 10a.m - during this interval 2 blood samples were taken at times 8:30a.m and 9:30a.m. Patient proceeded with Intermittent Mandatory Ventilation at 9.45a.m.*
2. state assessment of the patient - this will involve utilising the knowledge bases and assertions. This will be implemented in YAQ.

INTELLIGENT ALARMING

The process *INTELLIGENT ALARMING* is a temporal expert system which takes various inputs and generates *meaningful* and *minimal* alarms or alerts. These can be simple alerts such as abnormally high CVP due to miscalibration of the measuring device after the bed was raised (CVP rarely jumps). Alarms based on past trends and expectations of the future can also be generated. Alternatively they can be more complex alarms based on expectations of the results of administering a drug which were not met within a certain time interval. The purpose of this process is to inform and warn clinical staff of imminent events before they happen. Alarms will be generated when dangerous events have happened.

The process *INTERPRETATION* utilises the temporal intervals together with the drug knowledge base, cardiovascular system model and assertions and generates alarms, alerts and warnings to medical staff. This will be implemented using YAQ.

For testing purposes, we will use historical data and treat it as though it were arriving in real-time.

Progress To Date

The sub-processes *FILTER_DATA* and *INTERVAL_IDENTIFICATION* for the process *SUMMARISE_DATA* have been implemented, based on observations in the ICU at Aberdeen Royal Infirmary to establish the wave-forms corresponding to non-physiological events. The results are encouraging. Discussions with anaesthetists have generated characteristic profiles for physiological events which will be used for *INTERPRETATION* in both *FILTER_DATA* and *SUMMARISE_DATA*.

We have partially completed the Drug Knowledge Base and the Cardiovascular System Model.

Summary

We propose a system which processes raw data as it arrives for intelligent alarming and historical data for summarisation and state assessment. These two activities can be viewed as following three consecutive processes: filtering, interval identification and interpretation. Interpretation will use a temporal expert system which incorporates both associational and model-based reasoning.

References

[Gardner et al,1982] Reed M. Gardner, Blair J. West, Allan Pryor, Keith G. Larsen, Homer R. Warner, Terry P. Clemmer, James F. Orme, *Computer-based I.C.U. data acquisition as an aid to clinical decision-making*, Critical Care Medicine, Vol 10 No. 12, 1982.

[Makivirta et al,1987] A. Makivirta, E. Koski, A. Kari, T. Sukuvaara, N. Saranummi, *Knowledge Based Alarm Management and Analysis in Intensive Monitoring*, Medical Engineering Laboratory, Technical Research Centre of Finland, P.O.Box 316, SF-33101 Tampere, Finland and Kuopio University Central Hospital KYKS, SF-70210 Kuopio, Finland.

[Shahar et al,1992] Yuval Shahar, Samson W. Tu, Mark A. Musen, *Temporal-Abstraction Mechanisms in Management of Clinical Protocols*, Proceedings of the Fifteenth Annual Symposium on Computer Applications in Medical Care, American Medical Informatics Association, pages 629-633, 1992.

[Uckun,1992] Nuri Serdar Uckun, *An Ontology For Model-Based Reasoning in Physiologic Domains*, PhD Thesis, Vanderbilt University, Nashville, Tennesse, August 1992.