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Artificial Intelligence for Decision Support: Needs, Possibilities, and Limitations in ICU

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Abstract: This paper discusses how Artificial Intelligence (AI) could be used for decision support in modern intensive care units (ICUs), namely using knowledge-based techniques. First, the specific needs for decision support in ICU will be analyzed, which results in the most urgent need with regard to the different tasks of monitoring and therapy planning. Second, a definition for AI will be presented. Third, methods to solve the two essential parts of monitoring and therapy planning, namely data validation and abstraction in real-world environments, will be exemplified. Finally, basic requirements and limitations for knowledge-based decision support will be summarized.

1. Introduction: The needs for decision support

The complexity of medical knowledge has been steadily increasing, the cost of health care services has surged over the years, and growing demands exist for assessing and improving the quality of health care services.

For example, the care of critically ill patients in modern intensive care units (ICUs) is increasingly complex, involving interpretation of many variables, comparative evaluation of many therapy options, and control of many patient-management parameters. Even experienced physicians have difficulties in facing the important and relevant continuous data and in reacting in a time-constraint, critical situation. Not only the amount of information to be processed limits the quality of intensive care, but also human factors, like the problem of vigilance, varying expertise, and human errors. These frequently lead to errors in diagnosis and in the selection of appropriate treatments.

Dealing with decision support in medical domains the real-world environments have to be taken into account. Data are usually more faulty than expected and the knowledge available is fuzzy and incomplete. Additionally, data analysis has to deal with different observation frequencies, different regularities, and different data types.

The medical staff have to act and to react in time-constraint and critical situations. Therefore she/he needs the essential and context-relevant information about the health condition of the patient displayed on the screen. The continuous and discontinuous data have to be visualized in a self-explaining form so that the medical staff can cope with the situation as quickly as possible.

Knowledge-based decision support might provide considerable help in solving many of these problems. But it cannot solve management problems or improve the relationship between physician, nurses, patients, and health care administrators. Knowledge-based decision support can promote a deeper level of understanding of the data under investigation and foster new insight into the underlying process.

In my opinion, the need for support is most urgent with regard to the different tasks of monitoring and therapy planning of severely ill patients. I will neglect all administrative and organizational aspects that are covered in patient data management systems (PDMS) and hospital information systems (HIS). Additionally, the decision support presented is mainly concerned with physicians and nurses to improve the patient-oriented medical care. No aspects of health care administrators are involved. In the next sections I will clarify the term AI.

2. What's AI?

The official birthplace of AI was during a two-month workshop at Dartmouth in the summer of 1956. AI is one of the extensively and broadly discussed disciplines. Therefore a generally accepted definition is hard to find. According to [1] the definitions of AI vary along two main dimensions: first it is concerned with thought processes and reasoning, second it deals with behavior. Additionally, it is concerned with human performance or rationality (an ideal concept of intelligence). Table 1 shows the main four categories.

Systems that think like humans	Systems that think rationally
Systems that act like humans	Systems that act rationally

Table 1: Some definitions of AI organized into four categories.

The subareas of AI range from fundamentals, like knowledge representation, knowledge acquisition, problem solving and search, to specific concepts, like knowledge-based systems, intelligent agents, natural language processing, machine learning, computer vision, or impacts. In the following I will not discuss AI in general. My main focus is the use of knowledge-based systems in intensive care medicine.

In 1982 Peter Szolovitz [2] defines the three main aims of knowledge-based systems in medical care in general. Their importance is still relevant and applicable to intensive care medicine:

"(1) To develop expert computer programs for clinical use, making possible the inexpensive dissemination of the best medical expertise to

geographical regions where that expertise is lacking, and making consultation help available to non-specialists who are not within easy reach of expert human consultants;

(2) To formalize medical expertise, to enable physicians to understand better what they know and to give them systematic structure for teaching their expertise to medical students;

(3) To test AI theories in a "real world" domain and to use that domain to suggest novel problems for further AI research."

3. Monitoring and therapy planning

Monitoring and therapy planning involve observing and guiding the behavior of a system with real-time constraints. In contrast to diagnosis, which tries to find the best explanation for the actual situation of a patient, monitoring and therapy planning imply actions: *monitoring* indicates observing the course of a patient's condition under a given therapy, and assessing whether the selected therapeutic action is effective and the predicted improvement of the patient's condition occurs. *Therapy planning* involves selecting which therapeutic actions may improve the patient's condition, predicting the outcome, and adopting a therapeutic plan according to some explicitly defined preferences on the predicted condition of the patient [3].

The building of a knowledge-based monitoring and therapy planning system can be divided into several steps: data selection, data validation, data abstraction (interpretation of the patient's status), determination of proper therapy recommendations and the short or long term predictions of the effects of a therapy. All these steps are involved in a single cycle of data interpretation. These knowledge-based techniques are implemented and evaluated in VIE-VENT, a monitoring and therapy planning system of artificially ventilated newborns, which we are currently developing at my institute [4, 5]. In the following I will discuss two essential parts, namely data validation and data abstraction.

3.1 Data validation

A critical aspect of effective knowledge-based data analysis is the data validation. The central aim of data validation is to detect faulty or contradictory input data and to arrive at classified data (e.g., reliable, inconsistent, unknown) for further analysis tasks.

Nowadays, data validation does not work well. Several monitors have built-in modules for recognizing faulty data, especially those arising from hardware problems. However, these built-in modules often trigger false alarms and the medical staff, especially the nurses, are suffering under wrong alarms. A context-sensitive examination of the plausibility of input data based on different temporal ontologies improves the data validation process [5]. The data validation process uses discontinuously and continuously assessed numerical and qualitative data as well as derived qualitative descriptions. The latter are received from the data abstraction process described in the next section or are given by the users (e.g., user's requests). We distinguish four data validation concepts based on their underlying temporal ontologies: time-point-, time-interval-, trend-based, and time-independent validation.

The time-point-based concept uses the value of a variable at a particular time point for the reasoning process. This concept can handle all kinds of data. It benefits from the transparent and fast reasoning process but suffers from neglecting any information about the history of the observed parameters. We apply range checking as well as causal and functional dependencies.

The time-interval-based concept deals with the values of different variables within an interval. We use three methods: temporal validity, allowed changes/values of a single variable during an interval and allowed changes/values of interdependent variables during an interval.

The trend-based concept tries to analyze the development of a variable during an interval. A trend is a significant pattern in a sequence of time-ordered data. Therefore the following methods can only handle continuously observed variables. It benefits from the dynamically derived qualitative trend-categories (descriptions) which overcome the limitations of predefined static thresholds. We apply trend-based functional dependencies of different dependent variables and an assessment procedure of the development of a variable.

The last concept is based on time-independent priority lists of variables and constraints. The data validation process allows to identify less reliable variables or constraints in case of conflicts. The result is a reliability ranking. This method is triggered, e.g., if an ambiguous classification of values (e.g., "some are wrong") has been derived.

3.2 Data abstraction (interpretation of the patient's status)

Monitoring data are observed by the trained medical staff. However, these single observations may only be recognized for being "normal" or "abnormal". Information about trends, "natural" oscillations, etc. is very difficult to gather. Therefore, inexperienced personnel may have difficulties in interpreting a clinical picture from single monitoring data in limited time.

Some of the variables are influenced by other clinical variables that may not (continuously) be determined (like cardiac output, pulmonary perfusion).

The most common methods to interpret continuous data are time-series analysis techniques [6]. Furthermore, probabilistic and fuzzy classifiers are useful approaches to classify values. However, they contain crucial shortcomings. In the absence of an appropriate curve-fitting model time-series analysis techniques are not applicable. Domain specific characteristics, like dynamically changing degrees of parameters' abnormalities depending on the changing states of the environment can not easily be integrated in probabilistic or fuzzy classifiers. Classifications through value interval assignments (point data abstraction methods) are insufficient in dynamically changing environments where the temporal dimension covering the course of a parameter and the interdependencies of different parameters over time have to be taken into account. These shortcomings lead to apply knowledge-based approaches to solve the troubles.

The data abstraction process should lead to unified qualitative descriptions of point and interval data as well as verbal problem descriptions. The advantage of qualitative values is their unified usability in the data validation, therapy planning, and data visualization, no matter of which origin they are. Adaptation to specific situations can easily be done by specific transformation tables without changing the model of data interpretation. According to our temporal ontologies we define three types of qualitative abstraction: time-point-, time-interval- and trend-based abstraction.

The time-point-based abstraction transforms quantitative data points into qualitative values. It is usually performed by dividing the numerical range of a variable into regions of interest. Each region stands for a qualitative category. The time-interval-based abstraction classifies a property of a variable to a time interval. A specific case of the previous abstraction mechanism is the trend-based abstraction, which classifies the development of a variable during a predefined time interval.

4. Basic requirements for integration in routine clinical practice

Decision support techniques have been available for about three decades. In retrospect, application of knowledge-based techniques are rather limited. Routine clinical use is rather the rare exception [7]. To change this situation a set of basic requirements must be put forward

- integration into clinical practice is vital
- integration of diverse information sources to give a coherent picture of the situation of the patient and her/his history
- assessment of users' needs is necessary (involving the medical staff really using the systems in the future)
- knowledge-based support system should deal with defined areas of clinical medicine
- user interface must be easy to use
- appropriate explanations should be provided
- the user needs to be informed of the quality of the system (intensive evaluation)
- the user needs a secure and legally valid system
- intensive training of the medical staff (the real end users) and

additional support must be guaranteed

5. Conclusion

No perfect knowledge-based system will exist in the future, especially in the field of medicine. The knowledge is changing too quickly. However, we could develop a workbench of useful tools to make the daily routine easier, like tools for data validation, data interpretation, or context-relevant data visualization. We need intelligent assistance to ease the burden of filtering, sorting, filing, and archiving the information that we daily receive.

The presentation is based on the traditional AI method of designing knowledge-based systems. I did not apply methods like neural nets, machine learning, or natural language processing to improve the decision support in medicine. The reason lies in facing the decision making in real-world environments: data available are usually more faulty than expected, data based on different observation frequencies, different regularities, and different data types, and knowledge available is fuzzy and incomplete. Other techniques would not succeed without preprocessing and additional knowledge.

Shortliffe [8] analyzes the evolving role of computers in medical care and the impact that evolution will have on the delivery of medical care. Starting his paper he tells a typical newspaper story on the clinical use of computers. The story presents a perspective on the future and must quickly attract the public's attention [8].

"*The semiconscious patient lies in a futuristic intensive care unit, tubes protruding, wires emerging from under the sheets and connecting to a host of monitor carts or wall-mounted devices, and intravenous fluids with computer-controlled infusion pumps circling the bed. The beeps of the* *monitors are not interrupted by footfalls of nursing staff, for health workers seldom have to enter the room. Instead, intelligent devices measure every pertinent physiological parameter, deciding how to adjust infusion rates, when to alter the respirator settings, and whether to sound alarms for the intervention of nurses or physicians.*"

I hope that computer-controlled therapy offering sterile, impersonal, and dehumanizing care will never be reality. The limits of automation will help to avoid such nightmare.

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