An Architecture for Automated Development of Clinical Practice Guidelines in Critical Care: Preliminary Report

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Clinical practice guidelines constitute a major component of evidence-based medicine that emphasizes the effective use of information to improve quality, reduce variation, and manage resources in health care procedures. Clinical practice guidelines filter the large amount of disease- or procedure-related information to concise, relevant, and validated operational summaries for effective communication to the health care providers and practitioners. Usually commissioned and ordered by the government or regulatory bodies, including hospital or managed care administrations, they promote standardization of complex care procedures to assure quality and manage costs.

Current approaches for developing clinical practice guideline involve gathering of clinical evidence and management of information from multiple subjective and objective sources. Due to the dearth of scientific evidence, the uncertainty in guideline development is difficult to deal with. In addition, physician or patient preferences cannot be explicitly expressed in these guidelines. Often, based on the same medical literature, different expert panels would produce different guidelines. In recent years, various computer-based technologies have been developed to facilitate clinical practice guidelines development. Most of these efforts, however, focus on supporting guideline representation, editing, and delivery, instead of information integration and interpretation [1][2].

This paper introduces a decision-analytic artificial intelligence architecture based on the DynaMoL family of tools [3], which center on a dynamic decision modeling language, to automate clinical practice guideline development in critical care management. The proposed architecture establishes the base “engine” that supports modeling of the underlying pathophysiological processes, integrating relevant information from multiple sources, manipulating the uncertainties and preferences involved, updating and maintaining the medical and procedural content, and presenting multiple-level recommendations. The output produced can then be integrated or translated into other computerized guideline representation formats for evaluation and implementation.

1 THE DynaMoL FRAMEWORK

The DynaMoL framework supports dynamic decision problem formulation and parameter visualization in multiple perspectives at multiple levels of details [4]. The underlying mathematical representations of semi-Markov decision processes (SMDPs) support concise formulation of the decision problems. The framework adopts a translation convention which establishes automatic transformations among the different graphical representations and between the high level dynamic decision grammar and an SMDP. These language features, together with the auxiliary system components that include a parameter learning system from large medical databases [5], a probability elicitation system that facilitates knowledge acquisition from domain experts [6], and a knowledge-based model construction system [7], facilitates modeling of a large class of dynamic decision or management problems. A well-formed dynamic decision model representing a specific decision situation can be automatically evaluated or solved, with respect to some prespecified optimality and evalua-tion criteria, e.g., cost and quality of life, to determine an optimal decision policy.

2 THE PROPOSED ARCHITECHURE

We formulate, solve, and analyze the underlying dynamic decision making process of critical care guideline generation in the DynaMoL framework. Continuous physiologic monitoring devices and bedside computers in the intensive care unit (ICU) produce large quantity of patient-specific data in electronic form, repeated measurements can reveal the dynamic disease-related and treatment-related trends, which represent the temporal property in the patient conditions; the parameter learning system of the DynaMol framework can extract parameters from these data useful for guideline generation. Many relevant dynamic decision problems, including discrimination of sequential strategies and generation of optimal course of action over multiple stages can be handled by the modeling system of the DynaMoL framework.

We adopt the explicit guideline development approach advocated by Eddy [8]. This approach specifies the benefits, harms, and costs of potential interventions and derives explicit probability estimates for each outcome. Whenever possible, scientific evidence and formal analytic methods (e.g., mathematical modeling) are used to generate the estimates. Estimates are also generated by expert opinion. The proposed architecture is depicted in Figure 1.

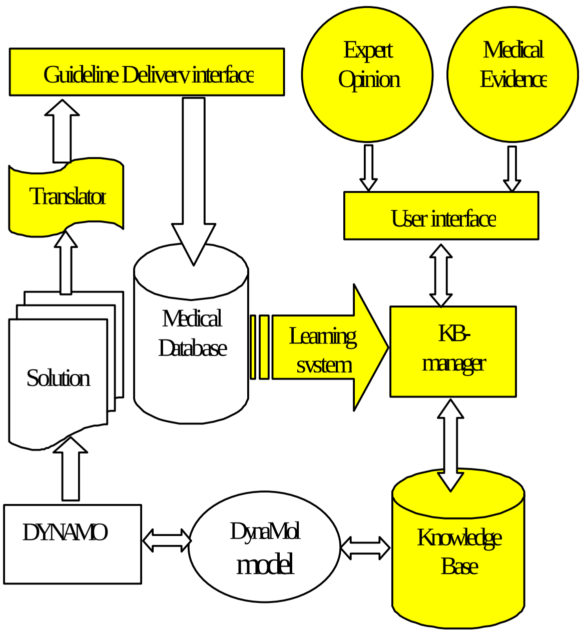

Figure 1: The Proposed Architecture.

2.1 Functionality of the Proposed System

By modifying the underlying DynaMoL models and adding new knowledge into the knowledge base, the system aims to fulfill the following objectives:

1. Generating Clinical Practice Guidelines:

   Medical evidence, expert opinion, relevant information from large population databases and public policy regulations are integrated to facilitate generation of broad-based clinical practice guidelines.

2. Generating Patient-specific Recommendations:

   Patient history and abstracted temporal trends from real-time data are integrated and interpreted into a detailed DynaMoL model to provide recommendations for a specific patient in critical care.

3. Facilitating Guideline's Delivery and Updating:

   The generated optimal policies are translated into various proper guideline formats to be flexibly delivered. The guidelines should be easily updated by modifying the parameters of the underlying DynaMoL models.

2.2 Components of the Proposed System

The proposed architecture consists of the following components:

Expert Opinion and Medical Evidence

Scientific evidence and expert opinion are two principal information sources about clinical benefits and harms. The relevant information is gathered to reduce the uncertainty in decision making. Admissible evidence may be limited to published studies or may include unpublished evidence. Expert opinion is important because reliable scientific evidence is often lacking for most clinical practices [8].

The User Interface

The interface enables access to the knowledge base-system. It facilitates guideline developers or knowledge engineers to input specification of expert opinion and medical evidence and manage the knowledge in the knowledge base.

The DYNAMO System

DYNAMO is the prototype dynamic decision modeling system for the DynaMoL framework that supports formulation and solution of the dynamic decision models.

The Knowledge Base System

The knowledge base system stores and maintains the domain information to support model formulation. Domain knowledge base encodes general facts and relationships of the domain. Structured expert opinion and medical evidence are included. Probabilistic and temporal dependence relationship are captured. Wang and Leong [7] have developed such a component knowledge-based system for the DynaMoL framework. Since DynaMoL supports problem formulation with multiple perspectives and multiple levels [4], various models for a single guideline topic can be constructed from different perspectives and at different levels of details.

The Learning System

The learning system connects the knowledge base system with the relevant medical databases. The probabilistic distribution parameters can be automatically generated from the medical databases by the learning system [5]. Such information can be augmented by expert opinion or prior believes [6] in case of insufficient or incomplete on-line data. Other useful information, such as cost-effective information based on large populations, can also be learned from large commercial medical databases such as SIS and NIS of HCUP [9].

The Translator

The translator translates the solutions for the resulting-dynamic decision model into an established guideline format such as GLIF [10] to facilitate its delivery.

The Guideline Delivery Interface

This interface separates the guideline development details from the end user.

3 DISSCUSSION

The evidence-based approach to health care practice is credited with enhancing the scientific rigor of practice guideline development. The major problem with this approach, however, is that it is often unable to produce recommendations in the absence of acceptable evidence. Neutral recommendations, neither for nor against the procedure, are often issued. Some machine learning methods have been proposed to develop practice guidelines [11]. But these methods only make use of information from medical databases; they do not explicitly capture many important factors in decision making, such as local limitations of health-care resources and decision criteria that involve some kind of utility, e.g. patient preferences and other health related quality indicators. Our approach aims to address these limitations.

Our future work will focus on developing 1) interpretation techniques for temporal trends in pathophysiological data collected at the ICU to support parameter specifications; 2) interfaces and representations for effectively integrating and interpreting knowledge from multiple sources; 3) techniques to organize, reason with, and combine partial models at different levels of details to form guidelines at different levels of generality; and 4) translators for translating the resulting dynamic decision model and solution int to and from standard guideline formats.

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