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Diagnostic reasoning and medical decision-making with fuzzy influence diagrams☆

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ABSTRACT

Influence diagrams have been widely used as knowledge bases in medical informatics and many applied domains. In conventional influence diagrams, the numerical models of uncertainty are probability distributions associated with chance nodes and value tables for value nodes. However, when incomplete knowledge or linguistic vagueness is involved in the reasoning systems, the suitability of probability distributions is questioned. This study intends to propose an alternative numerical model for influence diagrams, possibility distributions, which extend influence diagrams into fuzzy influence diagrams. In fuzzy influence diagrams, each chance node and value node is associated with a possibility distribution which expresses the uncertain features of the node. This study also develops a simulation algorithm and a fuzzy programming model for diagnosis and optimal decision in medical settings.

1. Introduction and background

There are several important missions of a medical reasoning system: diagnosis, prediction, treatment planning, etc. [1–3]. Among the tasks, diagnosis is the process of reconstructing the past facts from the observed evidence; prediction is the process of projecting the evidences from hypotheses; treatment planning is reasoning about the costs and effects of treatments on patients. Usually, medical practice requires various kinds of reasoning simultaneously. Hence, the capability for multiple reasoning tasks is critical to the performance of medical decision support systems. Besides, medical expert systems become more complex when considering the mechanism of human bodies and their mutual interactions with the environmental factors.

In medical informatics and other domains of applications, e.g. business, finance, engineering, bioinformatics, etc., graphical decision models such as Bayesian networks and influence diagrams have been widely used as knowledge representation and decision models [4–9]. Influence diagrams were originally proposed as a compact representation of decision trees for symmetric decision scenarios, and now regarded more as an extension of Bayesian networks [8]. An influence diagram is a directed acyclic graph with three types of nodes: decision nodes, chance nodes, and value nodes. Decision nodes, shown

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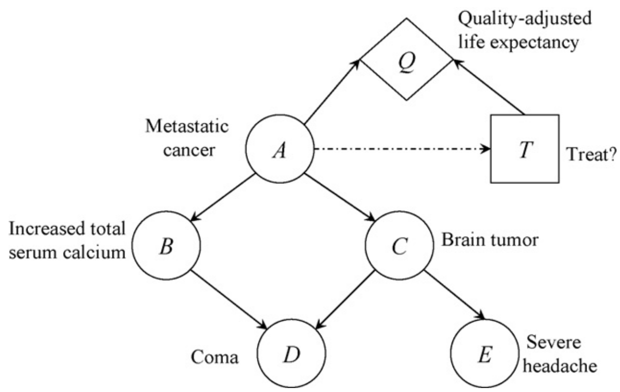

Fig. 1 – The influence diagram for metastatic cancer.

as squares, stand for the actions available to the decision-makers. Chance nodes, or random nodes, shown as circles, represent random variables of interest. Value nodes, or utility nodes, shown as diamonds, stand for the objectives or utilities to be optimized [4,7–8].

An example of influence diagrams for metastatic cancer and treatment is extended from Pearl [7] as Fig. 1. In Fig. 1, there is one decision node *T* ("treat?"), which has two alternatives to take: yes or no. Five chance variables are relevant to the biological test and treatment problems: *A* (metastatic cancer), *B* (increased total serum calcium), *C* (brain tumor), *D* (coma), and *E* (severe headache). Finally, the utility function *Q* (quality-adjusted life expectancy) is to be maximized. In influence diagrams, the meanings of the arcs depend on their destinations. Arcs pointing to value nodes represent approximate or functional dependence. Arcs into decision nodes imply time precedence and are informational; that is, they show which variables will be known to the decision-makers before the decision is made. Conventionally, the knowledge of chance nodes is expressed with probability distributions while the outcomes of the value node are projected with a value table. This paper uses uppercase letters to represent the variables and lowercase letters for its value; that is, x is the value of X. Particularly, for the nodes having two states, this study uses positive and negative to stand for their states; for example, $+a$ stands for $A = 1$ (with metastatic cancer) and $-a$ stands for $A = 0$ (without metastatic cancer).

However, when incomplete knowledge or linguistic vagueness is involved in the reasoning systems, the suitability of probability distributions can be questioned. For example, the states of severe headache and coma may fall into an ambiguous spectrum instead of a specific value. Besides, the quality-adjusted life expectancy may be hard to estimate due to incomplete knowledge and other latent factors. In such cases, the probability distributions and crisp utility become inadequate for the uncertain causal effects in influence diagrams.

Yamada [10] addresses uncertain reasoning with multiple causes and conditional possibilities on a causal network model. However, the work focuses on the causal effect in two layered networks. If the network is multi-layered, the complexity may be hard to reduce. Besides, medical reasoning systems need to provide diagnosis and optimal treatment suggestion as well. Kao and Li [11] solve diagnostic reasoning and optimal treatment problems in influence diagrams with fuzzy multi-objective programming, but they ignore continuous cases and do not handle fuzzy random variables with possibilities [10,12–14]. Rodríguez-Muñiz et al. [15] explore the statistical rules for modeling fuzzy random variables and utilities in influence diagrams mainly based on the value-preserving transformations. Later, López-Díaz and Rodríguez-Muñiz [16] analyze how to evaluate influence diagrams with multiple value nodes in terms of fuzzy random variables by dynamic programming. Both ignore diagnostic reasoning.

To make up the gap between previous researches and practical demands of medical reasoning, this study is devoted to a fuzzy influence diagram involving discrete as well as continuous nodes, where uncertainties are modeled with possibility distribution functions. This design also develops a simulation algorithm and a fuzzy programming model for diagnosis as well as optimization in the graphical model. In short, this study provides the following features distinct from previous investigations.

(a) Propose an alternative numerical model for influence diagrams, possibility distributions, which can formulate knowledge for discrete and continuous variables under uncertainty and imprecise information.
(b) Treat discrete as well as continuous variables in influence diagrams, so the constructs in medical settings will not be limited to binary or discrete.
(c) Develop fuzzy reasoning algorithms for answering queries in medical decision settings. The algorithms are applicable to two-layered as well as multi-layered influence diagrams. Different types of queries for medicine, e.g. diagnosis, prediction and optimal treatment can be done more compactly and flexibly.

The remaining sections of this article are organized as follows. In Section 2, the author defines a fuzzy influence diagram with possibility distributions as the numerical model under uncertainty. Section 3 describes the problems and designs the fuzzy reasoning algorithms for answering queries from fuzzy influence diagrams. Section 4 presents the experimental results. Finally, Section 5 gives the conclusions and the future study suggestions.

2. Fuzzy influence diagrams

This section defines fuzzy influence diagrams, including notations and possibility distribution expression.

Generally, an influence diagram (ID) can be defined as (2.1)–(2.3).

$$\mathrm{ID} = (V, L, P), \tag{2.1}$$

$$V = V_D \cup V_R \cup V_U, \tag{2.2}$$

$$L \subset V \times V. \tag{2.3}$$