TOWARDS INTELLIGENT DIAGNOSIS FOR EFFECTIVE KNOWLEDGE COMMUNICATION

Bienvenido Jose A. Juliano Jr. and Wyllis Bandler
Department of Computer Science and Institute for Cognitive Sciences
The Florida State University, Tallahassee, Florida 32306-4019

Abstract

In this paper, we present an interpretive perspective in accomplishing intelligent diagnosis for effective knowledge communication. We focus on the *epistemic* level of diagnosis — that which is concerned with knowledge states and aspects of both a model of the domain and of strategic knowledge [WEN87] — and propose some extensions for a more hybrid approach involving certain issues for the *individual* level as well. The formulations we present here are based on an earlier proposal for comparing fuzzy cognitive structures [JU89b,JUL90]. It is projected that this approach will facilitate the management of multiple evidence and uncertainty propagation.

Keywords: Cognitive diagnosis, fuzzy cognitive maps, intelligent tutoring systems, chains-of-thought.

1 Introduction

1.1 Preliminaries

Computer-Assisted Instruction (CAI) is an explicit attempt to instigate and control learning. The goal of CAI research is to build instructional programs that incorporate well-prepared course material in lessons that are optimized for each student. These programs were described as branching programs [CLA87]. At each point during attempts to solve a particular problem, some form of evaluation is undertaken by the program by relying on pre-computed, built-in answers. Clearly, no coherent model of patterns in the student's performance is recorded. Conventional programming techniques allow the recording of histories regarding the branches the program made. Hence, each new decision about where to branch next would depend on the history of what branches have occured earlier. This process could be very complex, since all possible histories would have to be anticipated.

The incorporation of some artificial intelligence programming techniques into CAI software not only allows the inclusion of sophisticated models of concepts and operations in the subject domain of concern. But it also facilitates the simulation and approximation of the process of intellect — comprehension of anything regarding the student, the course material, or the pedagogical approach [DED86]. Such research, owing its beginnings particularly to John Seely Brown, Alan Collins, and Ira Goldstein [CLA87,SLE82] initiated the development of *intelligent CAI* (ICAI) programs. The name *intelligent tutoring systems* (ITS) means the same thing.

Perhaps the most important reason for attributing intelligence to these programs is their ability to solve the same problems that they present to students [CLA87]. This capability greatly enhances student modeling and explanation. The student model allows the program to behave and respond correspondingly; hence, enhancing the interaction. These important developments affected much of these instructional devices — the system architecture, the development time, the complexity, and more.

Our goal is to attempt to facilitate the combination of the ideal features in *coaching* and *tutoring*. This would result in a partially non-intrusive pedagogical strategy, based on the idea that people should just solve the problem and continue on their own. All responses would be based solely on the student's actions as observed and/or approximated by the system.

1.2 Intelligent diagnosis

Diagnosis is an integral function for any intelligent tutoring system. This entails the collection and deduction of information pertaining to a user or any observed, related set of actions. Focusing on its interpretive task, it is asserted that any intelligent system designed to be *user-friendly* must have the facility for modeling some aspect of its users. In this paper, we present our proposal for achieving plausible diagnosis at the epistemic level — the level dealing with knowledge states and certain aspects of both domain and procedural knowledge.

The DIPS project [GOO86,JU89a,SZA87] of the Florida State University's Department of Computer Science and Institute for Cognitive Sciences is concerned with a paradigm referred to as Diagnosis for Instruction in Problem Solving. Some of the questions the project focuses on are

- How does an accomplished teacher diagnose the problem-solving difficulties of a student during an individualized help session?
- How can this form of human diagnosis be simulated by a machine?
- How accurate can a computer approximate cognitive activities based on our current state of technology?

and, rather indirectly

- Can human cognition be approximated and predicted?
- What cognitive phenomena for tutoring can we approximate?
- Can we achieve worthwhile goals by concentrating on diagnosis?

The main focus of our research efforts are *diagnosis* and *problem-solving*.

2 Epistemic Diagnosis

For our diagnostic approach, we list the following assumptions for an underlying theory of these knowledge states which can conveniently be represented in a computer. What, if anything, this says about the processes of actual human cognition is a deep topic beyond the scope of the present paper. Our basic assumptions are:

1. The knowledge of the system and the knowledge of the user constitute an *overlay* [GOL79] as depicted in Figure 1. In other words, expertise is decomposable into independent components that may be used to define various dimensions of knowledge. Hence, *subsets* inherit essential characteristics of this "full" model and the user's level of mastery of a particular component can somewhat be deduced.
2. The granularity of items in the knowledge state has been established. Here we assume that a knowledge state describes a set of concepts and the set of relations among them, as well as specific routine procedures.
3. Goal structures, heuristics, and the indication of the context or *viewpoint* of a knowledge state are embodied in the *functional* or *performance* level of diagnosis (refer to Figure 2). Furthermore, this knowledge is encoded in a form that is useful or relevant to the student.

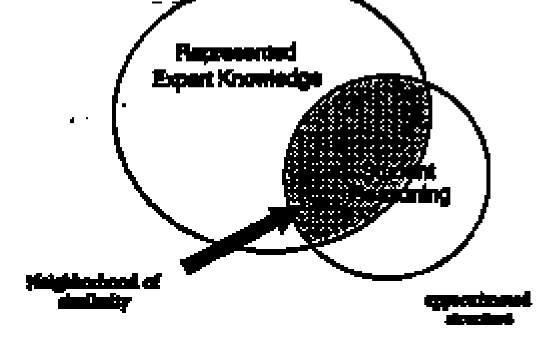

Figure 1 The *overlay* assumption (adopted from Goldstein's idea as presented in [CLA87]).

4. Based on item (1), it should be possible to reconstruct and generate the user's current knowledge state from observed deviations or *bugs*. Hence, this task of attempting to reconstruct (some aspect of) the student model is *data-driven* and so it must be a *bottom-up* approach. This entails the generation of "lines of reasoning", which we call *chains-of-thought*, to account for each observed action.
5. Since the system must be able to learn and reason in the vague and fuzzy tutoring environment whereby decisions are primarily based on imprecise, qualitative data, it is plausible to represent uncertainty through *fuzzy sets theory* [ZAD65]. The theory is highly suitable for tasks involved with the modeling of human cognitive processes.
6. The system's knowledge must include both *knowledge of the world* or domain knowledge, and *knowledge of reasoning strategies* or procedural knowledge. Relative to our previous work on *fuzzy cognitive maps* [JU89b,JUL90] (refer to the next section), the set of relations, $R_{\mathcal{M}}$, may be partitioned into "pure" relations and "transitional" relations, correspondingly.

This interpretive perspective requires the system to "understand" the user prior to attempting to communicate knowledge in any way. The system must be able to explain any observation and inference pertinent in an on-line session. Positing chains-of-thought, knowledge structures and internal states to account for a generalized student model attempts to incorporate inferential capabilities to diagnosis as well.

2.1 FCMs: An overview

Define a *fuzzy cognitive map* [JU89a,JU89c], $\mathcal{M} = (C_{\mathcal{M}}, R_{\mathcal{M}})$ over the finite universe X as a *fuzzy graph* that is a 2-tuple where

- $C_{\mathcal{M}} \in [0,1]^X$ is a *fuzzy concept space of X*.
- $R_{\mathcal{M}}$ is a *fuzzy multirelation*; that is, a finite sequence of relations $(R_{j_1}, R_{j_2}, \ldots, R_{j_m})$ on $C_{\mathcal{M}} \in$

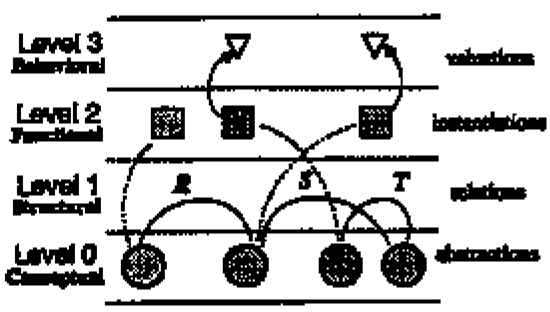

Figure 2 Proposed diagnostic levels.

$[0,1]^X$. In other words, assuming that the FCM $\mathcal{M}$ is clear from the context, each component R_{j_k} (where $1 \leq k \leq m$) of the multirelation $R_\mathcal{M}$ is a fuzzy relation on the fuzzy subset $C_\mathcal{M}$ of X. Therefore, each R_{j_k} is defined by a function $\rho_{R_{j_k}} : C_\mathcal{M} \times C_\mathcal{M} \rightarrow [0,1]$. Furthermore, the values in $R_\mathcal{M}$ are restricted by

$$\rho_{R_{j_k}} \leq \mu_{C_\mathcal{M}} x_i \wedge \mu_{C_\mathcal{M}} x_j$$

for all $x_i, x_j \in X$.

Various operations on FCMs are proposed in [JU89a, JU89c] for creating, generating and modifying these structures. Of the structural relations suggested, perhaps the most interesting is the *fuzzy equality* or *fuzzy similarity* relation

$$\pi(\tilde{M} = \tilde{N}) \;=\; \pi(\tilde{M} \lessdot \tilde{N}) \wedge \pi(\tilde{M} \gtrdot \tilde{N}) \qquad (1)$$

which derives a degree to which a pair of FCMs are similar. The indicated degree may be used as a *distance metric* or as an expression of coherence toward global interpretation. This is pertinent to comparing and analyzing approximated structures with idealized ones. The interested reader may refer to [JU89a,JUL90] for our mathematical formulations. From these, and the assumptions indicated earlier, we note that we have considered the following epistemic elements:

- concepts
- conceptual relations; these also cover
  - *rules*; and
  - *procedures*

which may be represented as relations themselves.

2.2 Student modeling and diagnosis

Structure–mapping in the framework of comparing cognitive structures must be done systematically. Any arbitrary pairing of structures, or constituents, would result in combinatorial explosion. Random methods are useless; the generation and verification of hypotheses regarding candidate matches becomes an alternative. In [JU91a], we refined the idea of structure–mapping of our proposals in [JUL90] by the concept of *homomorphisms* between FCMs. These mappings are *structure–preserving* — they maintain certain characteristics deemed pertinent for the task under consideration. We contrast this with approaches in analogical mapping in the following section.

Notice that structure–mapping imposes some constraints meant to achieve a level of consistency within the knowledge states. Coupled with other constraints that deal with consistency between knowledge structures over time (*e.g.* genetic constraints, as in the context of an overlay based on Goldstein's *genetic graph* approach), we may formulate a rigid set of *consistency rules*. These are relevant in reducing the number of knowledge states that must be considered as possible (interpretations of) student models.

To determine which knowledge elements have been directly involved in the currently available account of the user or his behavior, the use of FCMs facilitate model tracing and the reconstruction of solution paths. These collectively form the basis for epistemic inferences. Furthermore, the mathematical characteristics of FCMs facilitate the integration of epistemic inferences into the existing student model. We divide this modeling task into two levels:

- global (model–based) modeling; and
- local (concept–based) modeling.

The former is achieved through FCM structures, while the latter is embodied in chains–of–thought that are treated as FCM substructures. Loosely speaking, global modeling can be viewed as an intricate web or network of associations between learned and established facts and concepts. On the other hand, local modeling is concerned with concepts specific to the current task in hand. In this modeling task, interpretation of the performance of a user, whom we can refer to as the *approximated system*, is required. This is done by initially constructing analogue approximations of localized information made available in an ongoing session. The fact that chains–of–thought are treated as substructures of FCMs facilitates the generation and approximation of the *target* FCMs — expert knowledge encoded in the tutoring system.

3 Discussion

As we have indicated earlier, homomorphisms between FCMs are reminiscent of approaches in analogical mapping. Analogy is more inferential. Such a mapping is made from a *base–structure* pertaining to established knowledge, to a *target–structure* denoting some knowledge whose fundamental characteristics need to be inferred from the former:

$$\textit{base–structure} \longrightarrow \textit{target–structure}$$

In our approach, we want to establish an *interpretive* mapping. Hence this must occur in the reverse direction: from an *approximated* structure that we want to interpret to a known structure called the *target* structure. This terminology is based on the fact that, ideally, the main objective for tutoring is to achieve student performance (as indicated by the student model) comparable to the model of expertise.

Of course, the reliability of interpretive diagnosis is amplified when coupled with inferential diagnosis. This is relevant in the reconstruction of chains-of-thought. The current knowledge state and underlying reasoning strategy must be deduced by relying on whatever input is provided to the system on a minimum bandwidth communication channel determined by a corresponding interface.

Assumptions (1) to (6) itemized above mostly pertain to diagnosis at the functional and epistemic levels. It may be argued that the distinction between the issues covered by these levels overlap. Certainly, we would like these levels to interact in some way to maximize the plausibility of our approach.

In the literature, all other non–functional and non–epistemic constituents of diagnosis are refered to as the *individual* level. Using FCMs and homomorphisms for intelligent diagnosis partially considers the following aspects of the individual level:

- *Architectural.* FCMs are used to embody global, conceptual knowledge. And chains–of–thought, being sparked by the existing conceptual relations, are basically substructures of FCMs representing more local or specific knowledge. These relations and their structure facilitate how approximated knowledge states fit within the cognitive architecture of the perceived student model.
- *Learning.* Interpretive and inferential diagnosis at the epistemic level allows the system to follow (by model tracing of the conceived student chain–of–thought) and anticipate (by reconstruction or generation of conceptual associations from the system's own structures) knowledge acquisition by the user. For example, by embedding genetic graphs [GOL79] into the relational space $R_{\mathcal{M}}$ we can deduce learning styles.
- *Reflexive.* Fuzzy linguistic variables [SCH85, ZAD75,ZAD76,ZAD83] may be utilized at the interface module to indicate degrees of certainty the user has with responses provided to the system. Since the user is, in essence, trying to recall knowledge that is pertinent to the solution of the problem at hand, then the given responses are relative indicators of the user's model of himself.

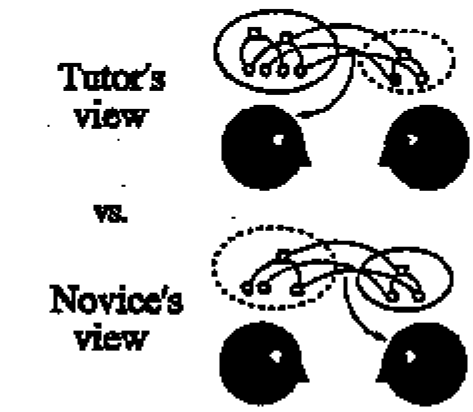

Figure 3 The *reflexive* view.

- *Reciprocal.* Similarly, the questions posed by the student indicate to the system which pieces of information the student expects the system to have; a relative indicator of the user's model of the system.

The latter two items were pointed in [JU89a]. It was asserted that the user performs a modeling scheme similar to the underlying student modeling by an intelligent system. "Similarity" here refers to the goals of the modeling tasks: they both attempt to be as close as possible to the *target* expert model; to the trajectory of an *ideal* chain–of–thought (refer to Figure 3).

With regards to the levels of abstraction depicted in Figure 2: we are not, in any way, making a claim that these are intensive and exhaustive. We merely point out that we perceive these as abstract levels pertinent to our particular conceptual framework.

As with other approaches to epistemic diagnosis, limitations prevail with the one we propose. Most of them are deduced from the assumptions we have enumerated. The most constraining of these is that concerning the user interface. This affects the granularity of incoming data. Of course, the strength of any knowledge communication paradigm lies on how well it captures the significant aspects of the natural phenomena. We hope to have an empirical application available to support our claims.

4 Summary and Conclusions

In this paper, we presented an interpretive perspective in accomplishing intelligent diagnosis for knowledge communication. We use fuzzy cognitive maps