Roles of Shared Ontology in AI-ED Research
-- Intelligence, Conceptualization, Standardization, and Reusability --

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This paper discusses long-term perspectives of AI-ED research aiming at giving a clear view of what we need for further promoting the research and for enjoying the bright prosperity of AI-ED community. The main topic here is how to engineer knowledge in IESs. To do this, we analyze intelligent systems and show one of the essential properties common to existing intelligent systems is "Declarative representation of what the system knows". On the basis of this observation, we discuss the importance of ontology engineering which is a innovative research area in artificial intelligence. Ontology plays several roles critical to overcoming the drawbacks which the current IESs have. (1) It makes systems smart and reflexive. (2) It explicates the conceptualization on which the system is based. (3) It contributes to standardization of vocabulary. (4) It enables them to be literate and hence to communicate with humans. (5) It makes knowledge reusable, and so forth. In this paper, we discuss how ontology contributes to IES research in general and exemplify how it makes authoring systems smarter.

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Key words: Ontology, Knowledge engineering, Shared vocabulary, Smart authoring systems, Reusable components

1. INTRODUCTION

A lot of research on AI-ED has been done to date. Several learning paradigms such as CAI, ICAI, Micro-world, ITS, ILE, and CSCL have been proposed and many systems have been built within each paradigm. And, innovative computer technologies such as hyper-/multi-Media, virtual reality, Internet, WWW have significantly affected AI-ED community in general. We really have learned a lot from our experiences and we could say the results are very fruitful. But, we still need promising directions to which effort should be devoted for further progress of AI-ED research.

AI-ED research consists of the following three major research areas in addition to Computer science:
(1) Artificial intelligence theories and techniques.
(2) Educational technology
(3) Cognitive science

As far as the authors know, some AI technologies have successfully been introduced into AI-ED community to bring fruitful results in building various IESs(Intelligent Educational Systems). However, the interaction between AI-ED and AI communities has been not so active compared to those with Educational technology and Cognitive science communities. Considering the future of AI-ED research, the authors believe promotion of more active interactions between AI-ED and AI communities would be beneficial, especially for us AI-ED researchers.

This paper discusses long-term perspectives of AI-ED research aiming at giving a clear view of what we need for further promoting the research and for enjoying the bright prosperity of AI-ED community from AI point of views. The main topic here is how to engineer knowledge in IESs. In the next section, we enumerate shortcomings the current AI-ED research suffers from and discuss how the four concepts intelligence, conceptualization, standardization, and reusability relates to them. In section 3, we overview what is happening in knowledge-based systems community to learn how ontology research plays roles critical to overcoming the problems common to interactive systems. On the basis of the observations, we discuss the importance and general utility of ontology in AI-ED research in section 4. A rough sketch of educational task ontology designed is shown in section 5. We show some specifications of IESs in terms of task ontology desgined in section 6 and finally, we exemplify the concrete utility of ontology by showing how an ontology-based authoring system works in section 7.

2. ANALYSIS OF CURRENT STATE OF THE ART OF AI-ED RESEARCH

Let us first enumerate drawbacks of current IESs from computer science and AI points of view.

(1) There is a deep conceptual gap between authoring

systems and authors.
(2) Authoring tools are not intelligent or very friendly.
(3) Building an IES(Intelligent Educational System) requires a lot of work because it is always built from scratch.
(4) Knowledge embedded in IESs does not accumulate well.
(5) It is not easy for us to specify functionalities of components in IESs.
(6) It is not easy for us to compare or assess the existing systems of different types.
(7) Communication among agents or modules in IESs is not fluent or principled.

All these issues are of content-related ones. In other words, any inference techniques or beautiful theoretical formalism cannot contribute to improvement of the situation. So, we could say what we need to overcome these drawbacks is a theory of content, that is, ontology. Now, let us go into the detailed discussion about the issues.

2.1 Intelligence

Adaptability is the heart of intelligent systems. It comes from the declarative representation of what the system knows about the world it is in. In IESs cases, the world consists of a learner and the system itself. So, such a system behaves adaptively to the learner's understanding state. Learner model, which is a representation of system's knowledge about the learner, serves as the source of intelligence. The system can investigate the learner model to adapt its behaviors to the learner. In this sense, the model should be represented declaratively in order for the system to investigate it.

What about authoring systems? What is the source of existing authoring systems? Do they have such a model or declarative representation of what they know? Unfortunately, the answer is NO. This is one of the major reasons why authoring systems are not so intelligent. Intelligence of authoring systems is not a specific but a general issue of AI-ED research, since it is deeply related how to build IESs.

As is discussed above, the source of intelligence of the existing systems is declarative descriptions the knowledge they have. They can inspect such declarative descriptions in order to adapt its behaviors to situations where they are operating. We could say intelligent systems KNOW what they know and what they are doing. Thus, lack of intelligence causes the following two:

(1) There is a deep conceptual gap between authoring systems and authors.
(2) Authoring tools are not intelligent or very friendly.

Authoring is viewed as kind of knowledge acquisition from teachers / instructors / trainers. This view gives us many constructive suggestions to improve the performance of authoring tools. We could learn from the research of knowledge acquisition in knowledge-based systems community in which task / domain ontologies for knowledge modeling has been extensively discussed.

2.2 Conceptualization

Conceptualization consists of objects and relations among them existing in the target world. It is the basis of intelligent systems whose performance heavily depends on it. One of the major difficulties common to most of the existing systems is the lack of an explicit representation of the conceptualization the systems are based on. Taking an expert system as an example, it has a knowledge base in it which declaratively represents what it knows about the problem solving in the task domain. It is OK for ordinary use. Once a user tries to modify the knowledge base or to reuse some portion of existing knowledge base developed by other persons, however, he / she immediately finds a big difficulty in doing it. That is, the design rationales of the knowledge base is implicit as well as other underlying philosophies assumed. Even worse, the same terms may have different meanings. In general, such information is rarely represented explicitly, which has been a serious cause of many drawbacks current expert systems have.

The same applies to IESs. Few IESs has an explicit representation of its conceptualization. While they know about the understanding state of the learner and tutoring knowledge, etc., they do not know any concept which the knowledge it has is composed of. We could say such systems are illiterate because they do not know the basic concepts. Therefore, such systems never be able to communicate with users(authors) about the fundamental knowledge.

Thus, the lack of an explicit representation of conceptualization is the cause of the following drawback indicated earlier.

(1) There is a deep conceptual gap between authoring systems and authors.

2.3 Standardization

Needless to say, industries have attained todays high productivity due to standardization of components, say, bolts and nuts. It is a pity that we have no such standardized components in knowledge base technology. In order to model target objects, such components would help a lot and facilitate model-based problem solving. For example, standardization of a pipe and pumps in qualitative modeling of a plant, that of enterprise ontology, and that of task ontology. Standardization of components does not necessarily imply that of knowledge in general. We are not claiming that all the knowledge should be standardized. Using standardized basic components, one can easily design their own knowledge by configuring them, which is proved by the current engineering production.

Standardization is mainly for providing us with a common vocabulary for understanding what have been done to date with less ambiguity. It never implies any restriction of exploration of the future research activities. The main rason why humans can communicate with each other is we have a common platform we can rely on and concepts in terms of which we can express our ideas. In this sense, we can say standardization is crucial to further success of AI-ED research. A project called "P1484: Standard for information technology for education -- Personal Learning System -- Learner model"(Schoening, 1996) has been set up in IEEE and started its official activities since December 4th. It aims at establishing standards of several issues related to computer-based learning systems. I believe the project will have some fruitful results. However, one may say AI-ED research is premature to establish a standard. We could agree with that opinion. If standardization is a bit too strong, we could call it reference models. But, we still think something similar to standard is badly needed to further progress of the research. Let us call it shared vocabulary. It sounds much more softly and acceptable.(Murray, 1996)

Let's see the role of shared vocabulary. One of the most critical impact can be seen in Motivational theory(del Soldato and Boulay, 1996)(del Soldato, 1992) in which we discuss about how to get learners motivated. No body is against the importance of "motivation" in Learning support systems. The mental or affective state is rather vague, which makes it difficult to communicate with each other what they mean by "motivation". According to the recent progress of motivational theory, "Motivation" is divided into "Intrinsic motivation" and "Extrinsic motivation". Generally speaking, the former is better appreciated than the latter. However, the latter has non-negligible importance. Further, the importance depends largely on respective learners and situations. In some situations, learners can be better motivated by extrinsic motivation than by intrinsic one.

Motivation is a complex of several sub-mental and emotional behaviors such as Curiosity, Challenge, Control, Confidence. Motivation in collaborative environments becomes more complex. Clarification of the concept of Motivation and sharing it among the researchers is critical to the success of the research. Establishing relations between existing or new tutoring tactics and each motivation-related behaviors is also highly appreciated. Ontology of motivation could contribute a lot.

Specification of functional components should be described in terms of common vocabulary. The problem, however, is the terminology used by teachers, authors, and developers are different from each other. As is discussed above, implemented systems do not understand either of the vocabulary. In short, all the four participants, three humans and one computer, do not share common vocabulary. This has caused a lot of misunderstanding and disorder.

Even among human participants, furthermore, when they start discussion on comparison among several IESs of different domains, it is not easy for them to properly perform the comparison because of the different terminologies used in the respective systems.

The same applies to communication among component modules in IESs. Because no common functional specifications and no common protocols are available, the components can not communicate with each other properly. This is one of the serious preventive factors of reusability of them.

Thus, lack of shared vocabulary is the cause of the following three drawbacks.

(5) It is not easy for us specify functionalities of components in IESs.
(6) It is not easy for us to compare or assess the existing systems of different type.
(7) Communication among agents or modules in IESs is not fluent or principled.

2.4 Reusability

Lack of reusability of software components is a universal problem in computer science. Nevertheless, we cannot avoid the ambitious issue, i.e., how to make knowledge and component modules reusable. One of the key issues is "de-contextualization" of the knowledge. Needless to say, every piece of knowledge is tuned to a context in which it is expected to apply. The first thing we have to do is to formalize the context and then, to establish a shared terminology. These two are not sufficient but necessary for making knowledge and components reusable. Reusability is one of the most serious issues in knowledge-based systems, since it implies a lot. Imagine a case the knowledge in a knowledge base is not reusable. Then, no one tries to accumulate his knowledge in a knowledge base since it is of no use if it is not reusable. Thus, lack of reusability causes the following two drawbacks:

(3) Building an IES(Intelligent Educational System) requires a lot of work because it is always built from scratch.
(4) Knowledge embedded in IESs does not accumulate well.

3. KNOWLEDGE AND ONTOLOGY ENGINEERING

3.1 Knowledge-based systems

An expert system consists of a knowledge base and an inference engine. The knowledge base contains mainly heuristics of human experts in solving a specific task in a certain domain. It is interpreted by the inference engine to perform a task given, say, diagnosis of artifacts. This knowledge-based system architecture enables expert systems not only to solve problems like human experts do but also to explain how they have solved the problem, which has given a considerable impact to the industrial applications. We could say "an expert system KNOWs what it is doing how" in this sense. It is a typical intelligent behaviors enabled by a declarative representation of knowledge.

Does this mean an expert system is very intelligent? Unfortunately, the answer is no. The problem was uncovered when developers built the knowledge base, that is, in the process of knowledge acquisition. To acquire necessary and sufficient knowledge, developers, called knowledge engineers, have to interview human experts who are the major source of the knowledge. What they found then was they do not know the knowledge to acquire at all. Even worse, the human experts do not know what computers can do and cannot do either. The is called "knowledge acquisition bottle neck" This difficulty has stimulated the new research on "knowledge modeling". The knowledge base building process has been called "knowledge engineering process".

Knowledge modeling is a technology of building expert systems. It has contributed to eliciting expertise, organizing it into a computational structure, and building knowledge bases. While rule base technology has dominated until recently, a new technology based on knowledge modeling has appeared such as KADS project in Europe(Wielinga, 1992), PROTEGE project in USA(Puerta, 1992), and MULTIS project in Japan(Mizoguchi, 1992)(Mizoguchi, 1995). All these technologies are originated from the idea of Generic tasks(Chandra, 1986) and heuristic classification(Clancey, 1985). The latest knowledge modeling research comes up with an idea of task ontology which serves as a theory of vocabulary / concepts used as building blocks for knowledge-based systems(Mizoguchi, 1993, 1995). We consider ontology consists of task ontology which characterizes the computational architecture of knowledge-based systems and domain ontology which characterizes the domain knowledge.

Especially, task ontology, which is discussed below, provide us with an effective methodology and vocabulary for both analyzing and synthesizing knowledge-based systems. It is a system of knowledge about concepts in terms of which expertise of human experts is described. We could say ontologies implemented declaratively in knowledge-based systems are "Meta-models" of expertise because "Knowledge model" is described in terms of ontologies. Task ontology is what we need to make knowledge-based systems be aware of what they know about the task they are performing, on what conceptualization the knowledge in the knowledge base is based, etc. Such research on ontology is called ontology engineering.

Task ontology of IES consists of taxonomy of concepts and axioms among them. The educational behaviors of IESs can be represented in terms of the concepts under the constrains and preferences represented by axioms. An authoring system with, say, tutoring task ontology knows what a tutoring task is and knows what type of domain knowledge is necessary to perform the task, which enables the authoring system behave intelligently in authoring support process.

3.2 Form vs. Content

The above discussion shows the importance of both content of knowledge and its declarative form of representation. The two stuff nicely contrasts with each other as "Form" and "Content" of knowledge.

In AI research history, we can identify two types of research. One is "Form-oriented research" and the other is "Content-oriented research". The former deals with logic and knowledge representation and the latter content of knowledge. Apparently, the former has dominated AI research to date. Recently, however, "Content-oriented research" has become to gather much attention because a lot of real-world problems to solve such as knowledge reuse, facilitation of agent communication, media integration through understanding, large-scale knowledge bases, etc. require not only advanced theories or reasoning methods but also sophisticated treatment of the content of knowledge.

Although importance of "Content-oriented research" has been recognized a bit these days, we could enumerate its shortcomings as follows:

1) It tends to be ad-hoc, and

2) It does not have a methodology which enables the research results to accumulate.

In order to establish the content-oriented research, we do need a theory of content which enables us to discuss "content" as formally as possible without losing "meaning" of the concepts. Ontology serves for that purpose. It gives us design rationale of a knowledge base, kernel conceptualization of the world of interest, strict definition of basic meanings of basic concepts together with sophisticated theories and technologies enabling accumulation of knowledge which is dispensable for modeling the real world. Ontology provides us with what we need to overcome the shortcomings the current IESs have we discussed above.

4. TASK ONTOLOGY

4.1 What is task ontology

Ontology in philosophy contributes to understanding of the existence. While it is acceptable as science, its contribution to engineering is not enough, it is not for ontology engineering which has to demonstrate the practical utility of ontology. It is true that every software has an ontology in itself and every president of a company has his / her own ontology of enterprise. But, such an ontology is "implicit". An explicit representation of ontology is critical to our purpose of making computers "intelligent".

FIrst of all, we would like to declare the ultimate purpose of ontology engineering is:

"To provide a basis of building models of all things, in which information science is interested, in the world".

Task ontology is a system / theory of vocabulary for describing inherent problem solving structure of all the existing tasks domain-independently. It is obtained by analyzing task structures of real world problems. It does not cover the control structure but do components or primitives of unit inferences taking place during performing the tasks. The ultimate goal of task ontology research includes to provide theory of all the vocabulary necessary for building a model of human problem solving process.

When we view a problem solving process based on search as a sentence of natural language, task ontology is a system of semantic vocabulary for representing meaning of the sentence. The determination of the abstraction level of task ontology requires a close consideration on granularity and generality. Representations of the two sentences of the same meaning in terms of task ontology should be the same. These observations suggest task ontology consists of nouns, verbs, adjectives, and constraints. Task ontology for training tasks, for example, looks as follows:

Nouns: “Problem”, “Scenario”, “Answer”, “Example”, “Accident”, “Operation”, “Hint”, etc.
Verbs: “Provide”, “Show”, “Ask”, “Simulate”, etc.
Adjectives: “Unsolved”, “Easy”, “Correct”, etc.
Constraints: “Rationality”, “Preference”, “Condition”, etc.

Verbs are defined as a set of procedures representing its operational meaning. So, they collectively serve as a set of reusable components for building IESs.

4.2 Roles of task ontology in IES

Considering the shortcomings the current IESs have and characteristics of task ontology, the roles of task ontology are summarized as follows:

(1) To provide us with a shared vocabulary which facilitates fluent communications among all the participants including modules.

While this is at the shallowest level of meaning, its contribution is of the most practical.

(2) To structure terms under the upper model to help us have a better picture of the terms.

This also brings benefits mainly for humans. For example, well organized taxonomy gives users a clear understanding of concepts structure in which each terms / concepts fit.(Schoening, 1996)

(3) To help fill the gap between humans and computers by representing some essential portion of meaning of terms and constraints among them in a computer understandable way.

Our task ontology support three levels of ontology such as lexical, conceptual, symbol level ontologies to maintain continuous mapping from human conceptual level to computer execution level.(Mizoguchi, Tijerino, and Ikeda, 1995)

(4) To facilitate formalization of the processes of learning and tutoring.

According to the definition of task ontology, it formally represents the tutoring / learning process at various levels domain-independently. The representation is intelligible for both humans and computers, which enables both agents to hare the same understanding.

(5) To specify the tutoring / training context which contributes to making it easy to put domain knowledge into a right context, since it provides us with abstract roles of various objects which could be instantiated to domain-specific objects.

One of the key roles of task ontology is its role-limiting function which is inherited from McDermott's half-weak methods idea(McDermott, 1988). Task ontology has several key concepts each of which represents the role of the objects in the problem solving context. Each verb knows how to do with the objects associated with the roles specified. Thus, task ontology contributes to building and analyzing knowledge bases.(Mizoguchi, Sinitsa, and Ikeda, 1996a)

(6) To help us make authoring tools more intelligent by providing sophisticated axioms representing constraints among concepts.

Authoring systems can know what is tutoring and what is a learning environment, what combination of actions and objects are valid, what would be better done in a certain situation, etc., which enables authoring systems to behave intelligently.(Mizoguchi, Sinitsa and Ikeda, 1996b)

(7) To help us describe knowledge such as tutoring strategies at the conceptual level and share them with others.

Using the vocabulary contained in task ontology, one can easily represent tutoring strategies, or some other type of knowledge developed at the conceptual level which allow us to share them easily with other.(Mizoguchi, Sinitsa, and Ikeda, 1996a)

(8) To provide us with an innovative manner of ITS / ILE development, that is, ontology-based system building.

Most of the conventional software is built with an implicit conceptualization. The new generation AI systems should be built based on a conceptualization represented explicitly.(Ikeda, Seta, and Mizoguchi, 1997)

5. PRELIMINARY DESIGN OF TASK ONTOLOGY OF IESs

We are currently designing task ontology for IESs and trying to represent it in an ontology description language. Because of the space limitation, we only present higher level description of task ontology designed thus far. Details of it is found in (Mizoguchi, Sinitsa, and Ikeda, 1996a) and http: / / www.ei. sanken.osaka-u.ac.jp / announce / ITS.ws.html.

The top-level categories of task ontology of IESs consist of Goals of education, Learner's state, System's functionality, Learner-system interaction, and Teaching material knowledge because an IES is characterized as an interaction between a system and a learner in which the system's activity is based on its functionality which is performed in a domain according to the learner's state under a certain goal. Then, we have the following top level categories of concepts.

5.1 Goals of education

Let us investigate Goals of education first. There have been proposed a number of paradigms for IESs to date. While they are seemingly conflicting each other, the reality is not. When we carefully investigate the paradigms, we easily understand most of the them can co-exist, since they have different educational goals. In this sense, goals enable one to distinguish and identify an appropriate paradigm for his purpose.

Goals of education are first divided into two categories such as augmentation of Domain-independent and Domain-dependent capabilities. The former is mainly related to Reasoning capability which has various kinds of subcapabilities. The latter is divided into three subcategories such as Deep understanding of concepts(declarative knowledge), Problem solving capability(procedural knowledge) and Skills.

5.2 Learner's state

Learner's state is composed of Historical state, Learning style, Phase in learning process, Knowledge state, and Mental state. Knowledge state consists of Numerical representation and Symbolic representation. Symbolic representation is composed of two components such as Location of bugs and Types of bugs.

5.3 System's functionality

Needless to say, system's functionality is the most important category in IESs. The top level concepts are concerning how to teach which characterizes the type of IESs. Assuming autonomous systems, it includes One-to-one interaction and Group learning. The former incudes Repetitive practice, Learning by doing, Free exploration in a learning environment, Interactive learning environment, Coaching, Tutoring, Training and the latter Collaboration, Coordination, Cooperation, Game-playing, Argumentation, etc.

We also identify non-autonomous systems, that is, tools used with the aid of a human teacher. In this paper, however, we only discuss tutoring systems as a typical autonomous system. Functionality of an ITS includes Modelling and Tutoring. The former characterizes capability of an ITS to model a learner as well as the problem domain which is critical to make an IES behave intelligently. Tutoring activity is composed of Tutoring objectives, Control, and Methods. Methods are composed of Actions and Objects. The former includes Help which simply gives information required upon request, Getting learners motivated which encourages and compliments learners, Exercise which gives learners problems to solve, Guide which gives Explanation or Hints appropriate for the learner's understanding state and context, and Evaluate / Assess. Objects includes Problems, Explanation, Hints, Advice, and Learner's performance.

5.4 Interaction between the system and the learner

Learner's activity, both internal (mental) and external (actions, communication) also seems to play an important role. However, as we cannot directly assess / evaluate his / her mental activity and student model construction is mainly consists of filling the chosen framework using learner-system communication as an information source, we will concentrate here on Learner-system interaction. At the top level we suggest to characterize interaction by the following categories: Mode of interaction, Communication roles, Content type and Control / Sequencing / Protocol. The first concerns technical means and recognition techniques incorporated in IES, Communication roles reflect learner's attitude to IES, Content types describe cognitive content of communication and Control - a communication order.

5.5 Teaching material knowledge

Teaching material is a heart of education. To make it easier to manipulate various teaching material, it is important to characterize it in terms of a few concepts. We analyzed various teaching material knowledge from the viewpoint of effectiveness of tutoring strategy applications to them. Details are omitted here because of space limitation(for details, refer[Ikeda et al., 1994]).

Teaching material knowledge includes Domain knowledge, Search control knowledge and Strategic knowledge. The former is composed of Nodes and Links. Nodes have several attributes such as mandatory / optional, difficulty to master, etc. and include Concepts, Facts, Rules, and Principles. Links includes Prerequisite, Objectives, is-a, part-of, order, etc. Search control knowledge includes Goals, Cost / Score, Preference, Focus, etc.

6. SPECIFICATION OF IESs USING TASK ONTOLOGY

Let us show how existing IESs are specified in terms of our educational task ontology. Capital letter words represent terms included in our task ontology. We take WEST(Burton, 1982) and GUIDON(Clancey, 1982) as examples.

(1) WEST

WEST is a typical COACH system for a GAME, so it plays both the ROLE of a COMPETITIVE PARTNER and a COACH. Therefore, COMMUNICATION SEQUENCE is IN-TURN, breaking by Learner's HELP and System's advice as a HINT or EXPLANATION. Regular CONTENT of COMMUNICATION is a result of calculation. MOTIVATION is supported by GAME situation and COMPLIMENTs from system. PROBLEM SELECTION is based on RULE in FOCUS. FOCUSing uses one of strategies: "FOCUS on the same RULE until it is MASTERed" or "FOCUS on the poor-known RULE that was not mentioned for the longest time". System INTERRUPTs as a COACH only on certain conditions (see example). The only TYPE OF BUG is LACK OF RULE.

(2) GUIDON

GUIDON is a TUTORING system, playing the ROLE of an EXPERT (Diagnostician). COMMUNICATION is SYSTEM-DRIVEN, breaking by HELP and QUESTIONs of a Learner. COMMUNICATION CONTENT includes Learner's QUESTIONs, HYPOTHESEs and FACTORs, supporting them; System's QUESTIONs, RULEs, GOALs, and EXPLANATIONs about FACTORS, HYPOTHESES, and RULEs. PROBLEM SELECTION is done once based on a set of chosen RULES, then communication is within one problem. System provides IMMEDIATE FEEDBACK. TYPE OF BUGS recognized - INCORRECT RULE (FACTORs, HYPOTHESIS), LACK OF RULE. MOTIVATION is not considered.

(3) Comparison

Although both IESs teach to apply RULEs for problem solving, WEST mentions the RULE as a whole and compares RESULTs of RULE application, whereas GUIDON discusses RULE components - FACTORS and HYPOTHESES, existence of a RULE to connect some FACTORs to HYPOTHESIS, and GOALs in solution process. Improved version of GUIDON is based on NEOMYCIN framework for problem domain knowledge representation, including concept structuring and strategic knowledge about diagnostic problem solving. To describe these improvements current ontology must be supplied with vocabulary to represent diagnostic problem solving.

7. HOW TO MAKE AUTHORING SYSTEMS SMARTER

The authors have developed a Computer-Based Training(CBT) system for operators of substations in electric power networks. It is called SmartTrainer. On the basis of its development, a new ontology-based authoring system is under development. What the instructors did roughly consists of preparation of:

A) knowledge needed for target operation,
B) training scenario, and
C) simulator of a target system.

except interface design.

The instructors compiles these three items into the skeleton of a CBT system. The typical work of the compilation is to put a fragment of knowledge into the target operation context appropriate for training. What they need while engaged in the authoring task is guidance on structuring fundamental scenarios.

Our educational task ontology has a set of terms to express the training task of the electric power substation operations. So, the author's task is to build a model of the intended training task in terms of the task ontology as a result of the compilation. Such terms / concepts are provided by an ontology server named CLEPE(Seta, Ikeda, and Mizoguchi, 1996) (Ikeda, Seta, and Mizoguchi, 1997), which maintains the consistency between the task ontology and the model built based on the ontology. On the top of CLEPE, we have been developing an authoring system for CBT systems. Figure 1 shows a prospective screen image of the authoring system interface.

When the authoring system is activated, the author is asked to create a training scenario which is a series of question and answer sessions. The window (1) is for editing a question / answer session. Before the window appears, the author was asked to select one from several question / answer types defined by CBT task ontology. In this case, the author selected “ordering question.” And then he / she inputs the components of the question / answer, that is, “question”, “items to be ordered” and “correct answer.” After inputting the question, the author edits a set of learner's errors , called “symptom” in the window (2). The author inputs the possible symptoms as one of “reversing”, “missing”, “superfluity”, which are defined as subcategories of the symptom for ordering question in CBT task ontology. In addition, the author is asked to clarify the cause of the symptom by selecting one node from the domain knowledge shown in the window (3). Since SmartTrainer adopts overlay learner model, the cause is formalized as missing of the selected node. Although we assume that domain knowledge is prepared in advance, the author can modify it at anytime when needed. Once the author completes inputting a symptom, the symptom / treatment window (4) will appear. In this window he / she specifies the treatment for the symptom. The possible treatments are listed in the window (5) based on tutoring strategy concept defined in CBT task ontology. The treatment selected by the author is “let him / her do operation under the help of simulator”. However, the selection violates the constraint on symptom / treatment rationality. It says that direct explanation is better than indirect treatment when the question asked to the student is not very difficult. The window (6) shows the rationality and recommends the “explain the principle” treatment instead.

8. CONCLUSIONS

We have discussed task ontology and its roles in AI-ED research. Our goal is to come up with a clear view of what we need to do for the promising future of AI-ED from AI point of view. Necessity of sophisticated theory and technology for knowledge manipulation was discussed for that purpose. Our conclusion is that ontology engineering will play several crucial roles in overcoming some of the existing difficulties in AI-ED research. A rough sketch of educational task ontology and its utility has been demonstrated, though details are omitted because of space limitation. We are currently developing a sophisticated ontology representation language with an environment and an ontology-based authoring system to show a concrete example of the real utility of task ontology in AI-ED research. As we see in the activity in IEEE P1484 project(Schoening, 1996), we do need a consortium to come up with a shared task ontology.

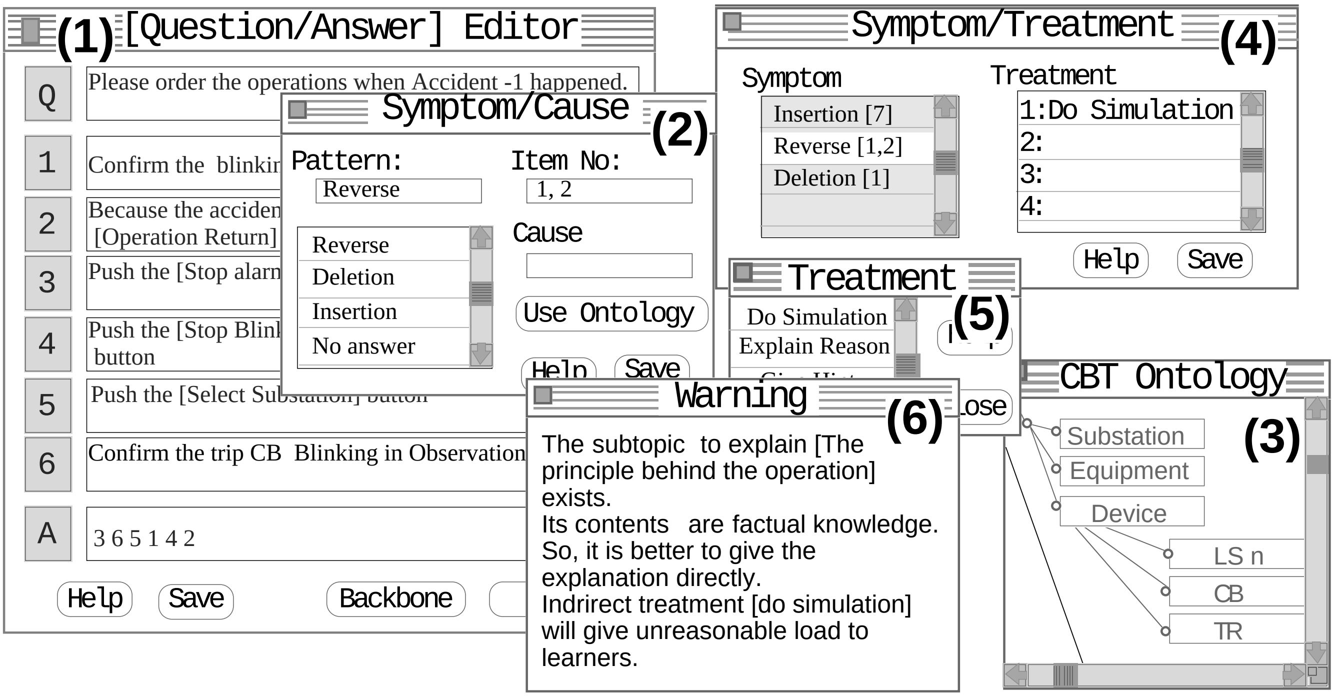

Fig. 1 A prospective screen image of our ontology-based authoring system.

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